USING COST OF QUALITY TO SELECT ALTERNATIVE SUPPLIERS AND DETERMINE INCOMING INSPECTION IN DYNAMIC CONTEXTS

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ABSTRACT

Process quality planning should establish the incoming quality inspection plan to achieve the desired quality level with minimum Cost of Quality (CoQ). Additionally, the selection of alternative suppliers must be defined, and, in a dynamic context, the best solution may vary. The purpose of this study is to, through a simulation approach, minimize the total CoQ of two related decisions: i) supplier selection and ii) incoming quality inspection selection. We will determine the CoQ of alternative suppliers and determine the CoQ of alternative incoming inspections that are associated with such decisions. The inputs to the model are components costs, inspection costs, proportion of defectives from incoming lots, Type I and Type II inspection errors, alternative control methods, and the cost of delivering defective components to the manufacturing system. The uncertainty of some inputs is modelled through probability distributions and the dynamic context is modelled through different scenarios. The results from simulations estimate the total CoQ of each alternative decision. This model allows to determine the CoQ of the alternative scenarios and to define a best supplier and incoming quality inspection plan. A numerical example based on a manufacturing process demonstrates the applicability of this model and the results indicate that the optimal solution may vary when the model parameters are updated.

Keywords: 100% Inspection, Cost of Quality, Supplier Selection, Incoming Quality Inspection.

1 INTRODUCTION

Generally, manufacturing companies have one or more suppliers for each component/part they need. Companies may assess the quality of their suppliers by doing quality audits or using a set of criteria to evaluate supplier's ability to provide the required parts. Criteria can include price, quality, distance, flexibility, delivery time, or performance assessment of previous deliveries. Usually, once a supplier is selected, a contract is made that describes not only price and part specifications but also the maximum proportion of defective parts per order and other information, such as, penalties due to defective parts or delays or maximum/minimum quantities per period. Before starting mass production, the company must have the necessary components at the right time. Thus, depending on the stock management policy, the company will place orders to the available suppliers. However, selecting a specific supplier may have a direct impact on quality, e.g., if recent deliveries suggest its proportion of defectives is smaller or higher than other alternative suppliers. This selection may not be trivial because the quality level can influence the cost during manufacturing and impact on

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the decision about the type of incoming quality inspection should be done. These decisions can affect the costs and competitiveness of the manufacturer.

Additionally, depending on the company policy, part criticality, expected proportion of defective parts, among other factors, it may be decided to do quality inspection at incoming components, such as, procedures based on sampling inspection to accept or reject a lot or by doing 100% inspection to remove defectives [1], or it can be decided to accept parts without quality inspection. Such inspection implies an additional cost and because the inspection system is not perfect, it is possible to accept defective components (Type II error) or rejecting compliant components (Type I error) [2].

These two decisions, to select a given supplier and to decide which incoming inspection should be done, can be made before the mass production phase, typically, during the process of quality planning. In this paper, we will propose an approach to support this double decision-making process. The approach allows: (1) to store the knowledge of the people who makes these decisions, a relevant feature of knowledge management; and (2) to re-evaluate the decisions in other contexts, allowing the efficient repetition of the decisions.

These decisions may be influenced by the evolution of a dynamic system, e.g., changes in component costs (for example, it can be influenced by an exchange rate or transportation cost), inspection costs, proportion of defectives, effectiveness of the inspection system, and cost of sending defectives to the manufacturing process.

To determine the best decisions (which supplier and which inspection), a set of objectives may be defined, such as, minimizing production delays (due to problems with incoming components), maximizing component quality, or minimizing acquisition and holding costs, while fulfilling company policies, requirements, and contracts. Many authors have suggested different approaches, e.g. analytical models [3, 4] or simulation models [5, 6] as well as other ways of modelling the system under analysis and different variables/parameters [7].

However, the practical application of theoretical models is poor [8]. The literature presents many barriers [9-11] for this application, such as high complexity of models, lack of knowledge/information on how to measure the high number of parameters/variables of the models, company culture that does not promote rigor and evaluation, and difficulty in collecting quality data.

Given the difficulty of modeling and solving such a multi-objective problem, we will use the model of quality costs, particularly the Prevention, Appraisal, and Failure (PAF) costs model [12] to translate operational issues to quality costs and then minimizing the sum of the CoQ. In general, CoQ approaches can be divided into five groups: (i) PAF model; (ii) Crosby's approach; (iii) Opportunity cost; (iv) Process cost; and (v) Activity-Based Costing (ABC) [13]. These approaches offer different ways to identify quality-related costs according to certain categories. The basic assumption of the PAF approach is that investment in prevention and appraisal activities will reduce failure costs and that further investment in prevention activities will reduce appraisal costs. Many quality inspection models are based on the PAF classification [14, 15].

Revision of quality inspection is necessary to reduce appraisal costs and to reduce failure costs e.g., caused by ineffective or inefficient inspection activities [16]. Thus, CoQ assessment concerning quality inspections has potential to be further explored [17, 18]. Determining the total CoQ for the system comprising the two decisions described can motivate top management to reduce it. Thus, by adopting this model, we can support company determination of CoQ and translate a multi-objective problem into a minimization problem.

It is complicated to consider all the different user requirements and contextual variables needed in real manufacturing processes [19]. Some models ignore aspects of the real problem, which can result in the computation of unrealistic solutions that may not capture domain-related characteristics [3]. It is challenging to obtain an optimization model of a problem that reflects all aspects of the real decision-making difficulty. Models may be considered as a simplification of reality, for example, by not considering machine breakdowns [20] or by not modelling inspection errors [21], resulting in inaccurate cost models [4]. To address this issue, in this work, the level of detail modelling or granularity can vary, depending on the available information/data, the experience of the decision-makers and the complexity of the factors involved. We will simplify some parts (e.g., modelling demand will be skipped and only the production of one order is modelled) and we will have more detail associated with the inspection system by modelling their classification errors. This model granularity may be revised because organizations and their contexts are dynamic, leading to rapid changes in models and/or model parameters. Consequently, the method used to determine CoQ must be robust and understandable so that decision makers can adjust it, because some of its parameters change, or because the model is no longer a good representation of reality [22].

Due to the uncertainty and vagueness inherent in a real environment, some model parameters can be difficult to estimate [23]. There are many approaches to represent uncertain and vagueness in parameters [24, 25], such as using intervals, data sets, fuzzy numbers, probability distributions, etc. [26]. Each method requires different relevant information. In this work, we use different methods, depending on the availability and reliability of data. Besides the uncertainty in the cost model parameters, we may also have bigger changes in the system, such as changing the inspection equipment/method or a significant change in the proportion of defects. This uncertainty is addressed by assuming several plausible scenarios.

The main objective of this study is to develop an approach to efficiently select alternative suppliers and alternative incoming quality inspections in dynamic contexts. To limit the size of the paper, only two alternative suppliers and two alternative inspections will be analyzed.

The remainder of this paper is organized as follows. The next section presents the description/assumptions of the supply chain system under study. In Section 3, we present the cost elements associated with each decision, needed to determine the total CoQ. In section 4, an application example is presented, including a discussion of the numerical results of four scenarios with four different decisions. The paper ends with some conclusions and directions for future research.

2 PROBLEM DESCRIPTION AND ASSUMPTIONS

This work focuses on the selection of one amongst two alternative suppliers (*Decision 1 – D1*) for a given part, *Comp1*, needed in a manufacturing company, and the selection of one amongst two incoming inspection alternatives (*Decision 2 – D2*) (Fig. 1). The assumptions used, which may correspond to a specific case for a manufacturer, are:

- There are two approved suppliers, *SA* and *SB*, for *Comp1*. They both comply with quality requirements and other relevant requirements, and deliver lots as ordered with a proportion of nonconforming parts, *PA* and *PB*, below an accorded threshold *P1*. If *P1* is exceeded, according to the contracts, the supplier must compensate all the costs associated with such defective lot and may lose the customer;
- The unitary purchasing cost of *Comp1* is *CA* for *SA* and *CB* for *SB*. We will suppose that, according to the suppliers' contracts, *CA* is more variable than *CB* because exchange rates and transport fees influence *CA* and may vary from order to order.

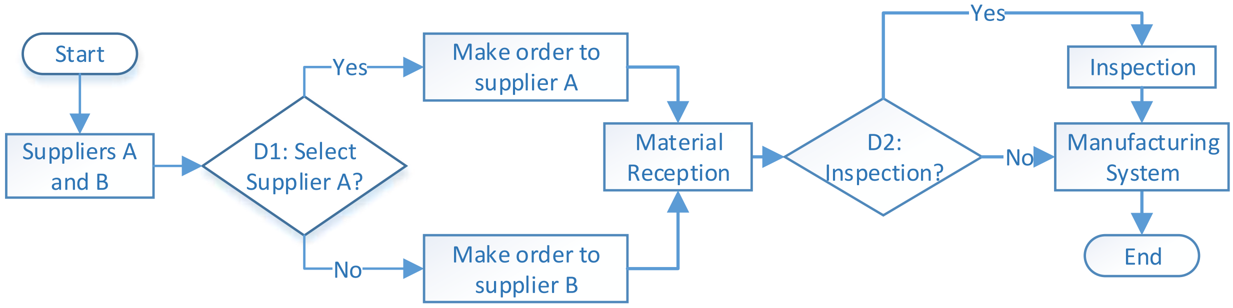


Figure 1: Problem description flowchart / Conceptual model of system

The assumptions about the incoming inspection are as follows:

- It is technically and economically viable to do 100% inspection of *Comp1* critical variables; each part inspection costs on average *Ci*;
- *Fd* is the proportion of compliant parts classified as defective and *Fc* is the proportion of defective parts classified as compliant (imperfect inspection);
- *Cd* is the average cost of dealing with a defective part at incoming inspection after classifying the component as defective (including false defectives);
- *Cr* is the average cost of dealing with a defective part at the manufacturing system;
- *Np* is the number of parts to be ordered.

This corresponds to what occurs in several manufacturing processes of the automotive sector, which receive a given part from more than one supplier and must decide what kind of incoming inspection should be made. As a result of 100% inspection (*100% I*), parts can be classified as compliant and sent to the manufacturing process or non-compliant and segregated. Two different types of errors can occur during the inspection of parts: sending defective parts to the manufacturing process and segregating conforming parts. To represent these situations, four combinations of alternative decisions, here called tactics, including selecting *SA* or *SB* and not doing inspection (*0% I*) or doing *100% I*, were analyzed (Fig. 2).

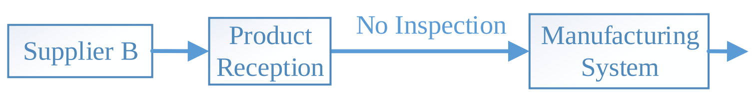
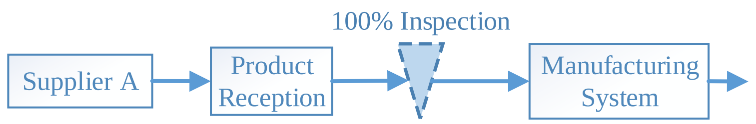
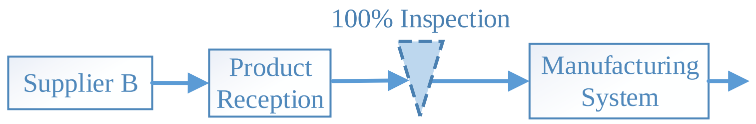
Tactic 1	D1 = SA; D2 = 0% I	
Tactic 2	D1 = SB; D2 = 0% I	
Tactic 3	D1 = AS; D2 = 100% I	
Tactic 4	D1 = SB; D2 = 100% I	

Figure 2: Alternative suppliers and alternative incoming inspections

3 COST OF QUALITY MODEL

Conceptually, this work employs the approach used by Sousa and Nunes [22] to develop a computational model concerned with selecting the best inspection strategy based on an expected CoQ, a non-value-added cost that should be minimized. However, it is developed for a different context, including alternative suppliers and incoming inspection.

To determine the CoQ of each tactic, a computational model was implemented in Microsoft Excel. The uncertainty of some model parameters motivated the use of Monte Carlo simulation.

3.1 Cost of Quality Elements

A set of inputs (parameters) (Table 1) and one output (CoQ) were defined. Four scenarios were analyzed: the first one corresponds to the baseline, i.e., the current situation; the other scenarios correspond to potential changes in the system, which is dynamic, e.g. variable purchasing costs or variations in the inspection system. For each scenario, four analytical models were developed based on the description related to Fig. 2.

The CoQ is obtained as the sum of cost of quality elements, which represent the additional costs added to the strictly necessary cost for manufacturing, such as acquisition, transportation, support/management activities and manufacturing costs. According to the PAF model, the CoQ elements are classified into three PAF categories. Within the supply chain system previously explained we will present the cost elements associated with each decision and then calculate the CoQ for each tactic to select the one with the smallest cost.

3.1.1 Prevention costs

In this context, prevention costs can be considered as the cost of paying an additional value for parts assuming that a given supplier has a lower proportion of defectives and will result in less failure costs. So, when ordering from *SA* (*D1=SA*), if *CA>CB* and *PA<PB,* then the prevention cost will be *CA-CB* (€/unit), otherwise it will be 0. Similarly, when ordering from *SB* (*D1=SB*), if *CB>CA* and *PB<PA*, the prevention cost will be *CB-CA* (€/unit), otherwise it will be 0.

3.1.2 Appraisal costs

Appraisal costs, in this context, are the incoming inspection costs. When ordering from *SA* or *SB*, if 100% incoming inspection is decided (*D2=100% I*), the appraisal cost is *Nc×Ci* (€).

3.1.3 Failure costs

Failure costs are the costs resulting from defective parts. If there is an incoming inspection, we can detect the defective components and deal with them at a given cost (*Cd*). If the defective parts are sent to the manufacturing system, dealing with defective parts will cost more (*Cr>Cd*). Additionally, assuming errors in the inspection system, some compliant parts will be classified as defective (type II error), resulting in a cost (*Cd*). Also, some defective parts may not be detected and pass through inspection to the manufacturing system, also resulting in a cost (*Cr*) per unit. If there is no incoming inspection (D2=0% I), the same proportion of defective components in the received lot will arrive at the manufacturing system, also resulting in a cost (*Cr*) per unit.

4 NUMERICAL EXAMPLE AND DISCUSSION

Based on the context described in section 2, scenario 1 corresponds to the current system's reality. Some input parameters were uncertain and were defined as an uniform distribution whose limits correspond to extreme values [*a*, *b*] (ranging from an optimistic value to a pessimistic value), considered possible for this parameter [27], while others, where a value was more likely than others values, were defined as a triangular distribution [*a*, *b*, *c*] (Table 1). The values of *Ci*, *Fd*, *Fc*, and *Cd* are necessary to determine the CoQ when D2 is 100%I. If other alternatives were assessed, such as acceptance sampling, other parameters would be defined.

Table 1: Control parameters/inputs used in each scenario (Sc)

Sc	*Np*	*CA*	*CB*	*PA*	*PB*	*Ci*	*Fd*	*Fc*	*Cd*	*Cr*
1	1000	9	10	[0.8%, 1%]	[0.6%, 0.8%]	0.3	20%	10%	11	[150, 200, 250]
2	1000	9	10	[0.8%, 1%]	[0.6%, 0.8%]	0.3	<u>10%</u>	<u>5%</u>	11	[150, 200, 250]
3	1000	<u>10</u>	10	[0.8%, 1%]	[0.6%, 0.8%]	0.3	10%	5%	11	[150, 200, 250]
4	1000	10	10	[0.8%, 1%]	[0.6%, 0.8%]	0.3	10%	5%	11	<u>[200, 250, 300]</u>

The values of scenario 1 can be frequently updated depending on changes in the described system and in changes in the availability of data. We may also want to analyze other scenarios, related with potential changes that may abruptly occur, such as an improvement in the measurement system (scenario 2), a price increase of *comp1* from *SA* (scenario 3), and an increase in the costs associated with defective units (scenario 4).

Table 2 shows the CoQ for each scenario for all combinations of decisions. Each combination of two decisions corresponds to a tactic (*TA*). The CoQ is the sum of relevant cost elements previously described and are discriminated by the type of cost (Prevention - P, Appraisal - A, or Failure - F). It can be noted that appraisal costs are zero in the two initial tactics, and the prevention costs are zero when the components' cost is equal (scenarios 3 and 4).

Table 2: CoQ per scenario of each set of decisions assuming deterministic parameters

	TA1: D1=SA; D2= 0% I				**TA2: D1= SB; D2= 0% I**				**TA3: D1= SA; D2= 100% I**				**TA4: D1= SB; D2= 100% I**			
Sc	**CoQ**	P	A	F	**CoQ**	P	A	F	**CoQ**	P	A	F	**CoQ**	P	A	F
<u>1</u>	<u>**1800**</u>	0	0	1800	**2400**	1000	0	1400	**2660**	0	300	2360	**3625**	1000	300	2325
2	**1800**	0	0	1800	**2400**	1000	0	1400	<u>**1570**</u>	0	300	1270	**2532**	1000	300	1232
3	**1800**	0	0	1800	<u>**1400**</u>	0	0	1400	**1480**	0	300	1180	**1462**	0	300	1162
4	**2250**	0	0	2250	**1750**	0	0	1750	**1503**	0	300	1203	<u>**1480**</u>	0	300	1180

As can be seen in Table 2, the minimum CoQ for scenario 1 is 1800, corresponding to the *TA1*, but for scenario 2, which corresponds to a reduction of type I and type II errors from 20% and 10%, to 10% and 5%, respectively, the minimum CoQ is 1570, corresponding to the TA3. If the cost of *Comp1* from *SA* increases from 9 to 10 (scenario 3), the minimum CoQ is 1400, corresponding to *TA2*. This result can be counterintuitive - an increase in price can lead to a smaller CoQ. In this scenario, there are no prevention costs, because both suppliers sell at the same price, despite the better quality of *SB*, so we do not need to pay an extra cost to have the supplier with a lower proportion of defectives. Finally, in scenario 4, which corresponds to an increase of *Cr* from 200 to 250 (the modal value of the triangular distributions), the minimum CoQ is 1480, corresponding to the *TA4*.

In a dynamic context, business conditions can change quickly (here modelled by different scenarios) and uncertainty regarding some parameters of the cost model must be included in the calculations. In this example, the uniform distribution was adopted to model the uncertainty of *PA* and *PB* and the triangular distribution to model the uncertainty of *Cr*. The propagation of the parameters uncertainty to the CoQ value was done using Monte Carlo simulation (MCS) implemented through the add-in tool for Microsoft Excel, @RISK 8.4 from Palisade (https://www.palisade.com/risk/).

Figure 3 shows the results of the simulation for scenario 3, after 10,000 iterations. It shows CoQ values from different tactics *TA2* and *TA4 (*the ones with lowest CoQ). This type of analysis can be performed for any other scenario.

Disregarding the 5% best results and the 5% worst results from MCS, we get the interval [MCS_5, MCS_{95}], which includes 90% of the simulation results. For example, for *TA2*, the 90% confident interval for this tactic is [1108, 1713]. Regarding the *TA4*, 100% of the histogram corresponding to CoQ is contained in this interval but with smaller range. Although the average CoQ value of *TA2* is lower than the average CoQ value of *TA4*, there is a considerable probability of the *TA2* has a higher cost than the cost of *TA4* (this probability corresponds to the entire representation of the histogram of *TA2* shown to the right of the cost histogram of *TA4* (with a CoQ >1490). The greater or lesser risk aversion of the decision-maker will dictate, in this case, which of the two tactics to adopt. This situation does not arise when using the parameters of *scenario 3* without uncertainty, where the best tactic is *TA2* with a CoQ=1400.

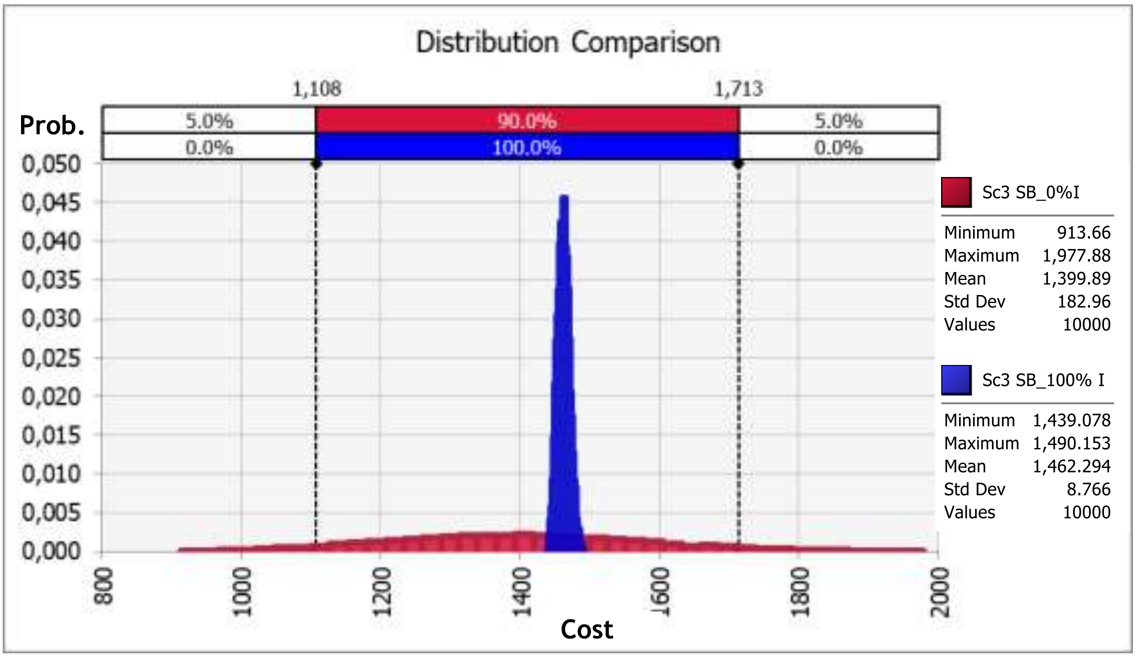


Figure 3: Distribution comparison between *TA2* (SB_0%I) and *TA4* (SB_100%I) from scenario 3.

5 CONCLUSION

The main objective of this study was to develop a framework to efficiently select alternative suppliers and alternative incoming inspections in dynamic contexts. To that end, two decisions were defined in a manufacturing company within a supply chain, and the CoQ associated with each decision is determined, using the PAF model. The approach adopted in this paper is similar to the work of Hlioui et al. [1], having the advantage of translating a multi-objective problem to the financial domain, being easy to model and solve.

The simplicity of the model and the solution can change if other contextual factors are modelled, such as product demand or delivery times. In this paper, we detailed the process of 100% incoming inspection modeling the errors of that system, which some authors do not consider [1]. Thus, it mixes simplicity in modelling and detailing according to data availability and relevant issues that need to be considered in the decisions.

The dynamic system can be delt with frequent reassessment of the best tactic, instead of maintaining the same tactic during mass production, independently of contextual changes. Also, the determination of CoQ of other scenarios provides a view of the solution robustness as in [6], but also deals with the uncertainty of data by using stochastic inputs.

The numerical example shows that in different scenarios the best decisions are not the same, thus, by applying this framework to this type of problem, the company can improve its competitiveness. It also suggests that the decisions are interconnected, despite in many companies these are made by different persons/departments and may not be assessed frequently.

To limit the size of the paper, only two alternative suppliers and two alternative incoming quality inspections were analyzed, but the work can be expanded to include more decisions and to model other aspects that may be relevant in other contexts. As future research direction, the simulation models could be relevant when designing digital twins of supply chain processes.

6 ACKNOWLEDGMENT

This work has been supported by FCT – Fundação para a Ciência e Tecnologia within the R&D Units Project Scope: UIDB/00319/2020.

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