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IFAC PapersOnLine 51-24 (2018) 643–648

Using quality control in optimizing opportunistic maintenance

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Abstract: Nowadays companies are constantly looking for maximum production efficiency. To achieve this goal, the actions taken aim to reduce the overall costs of the company. Thus, measures are taken to ensure the availability of production equipment at the same time as good product quality. This article proposes a study in order to optimize the maintenance of a production system and the quality control. A bibliographic research is developed to determine the quality tools that can be used to optimize maintenance. The idea is to determine the best maintenance policy by using information based on quality indicators. A numerical example is also treated on a batch production with opportunistic maintenance applied.

Keywords: Quality control, maintenance policy, optimization, statistical process control.

1. INTRODUCTION

Quality has become a priority for the majority of companies. With technological advances and an increasingly advanced automation, operators no longer have complete control over their production processes. The influx of data (especially on the quality of products) is increasingly important. Unfortunately, these data are not always exploited. In this article, we want to describe quality tools that can be used in the organization of maintenance.

Maintenance and quality are intimately linked. Indeed, poorly maintained equipment will inevitably see the quality of its products degrade compared to a maintained equipment. Moreover, Ollila and Malmipuro (1999) have highlighted the important impact of maintenance on quality. They even conclude a case study by showing that maintenance is one of the three most important causes of quality degradation. The quality control makes it possible to detect drifts. These drifts can act as alarms to trigger maintenance actions. The methodology for determining the best maintenance policy to be applied and the optimal sampling parameters will be discussed.

2. LITERATURE REVIEW

In this section, we will present documents integrating a methodology to use quality control information to manage maintenance. A first interesting article is that of Cassady et al. (2000). In this work, the authors develop a preventive maintenance strategy based on quality control. In fact, a control card controls the production process. When a failure occurs, the process becomes out of control and a jump appears on the control board, allowing corrective maintenance to occur. In order to avoid failures, preventive maintenance is carried out according to a time period p. The article allows optimizing the periodicity of preventive maintenance p and the parameters of the control board (sampling) in order to reduce the costs, from a given process (reliability law). Despite some assumptions, the document provides a solid foundation for integrating quality control into a preventive maintenance strategy for cost-effective optimization.

Another interesting article is that of Linderman et al. (2005). This article advocates "adaptive" maintenance based on quality control. When the process becomes unstable, the maintenance schedule is revised to speed up maintenance. On the other hand, if the process is stable, the time intervals between maintenance will be increased. The optimization is done on the costs generated by the operation of the equipment. Again, it is assumed that the process begins in a in-control state whose law of reliability is known (Weibull distribution). Inspections take place after hours of production to verify that the process has not become out of control. The measured characteristic is reported on a control card. Sometimes, between two samplings (j and $j+1$), a failure occurs and causes a change to an out-of-control state. The process continues and the control card only allows detection of the problem at $j+1$ sampling. The "adaptive" maintenance model is illustrated in Fig. 1. In fact, three different scenarios are proposed. In the first, the out-of-control state is detected and corrective maintenance is organized to restart the process. In the second, the out-of-control state is not detected before scheduled preventive maintenance. Therefore the maintenance operations highlight and repair the failure and allow the system to be brought under control. In the third scenario, the process remains under control (no failure) until a preventive maintenance operation is performed. Despite some assumptions (maintenance AGAN, loss function of Tagushi, ...), the article demonstrates that a model integrating quality control and maintenance can be beneficial.

We can also cite Alsyouf (2007), which has demonstrated the benefits of a maintenance policy on the quality of products (and thus on profitability). This article has proved

2405-8963
Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2018.09.643

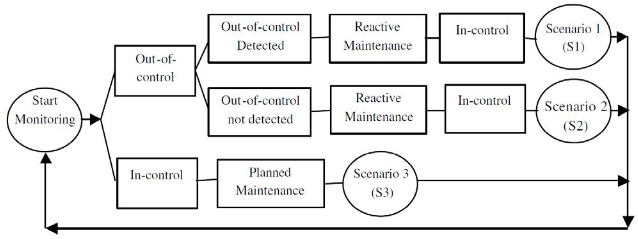

Fig. 1. Simulation principle in Linderman et al. (2005)

that the implementation of an effective maintenance policy reduces failures, operating costs and improves product quality. The advantage of this article is that it provides an industrial study case (a Swedish stationery). However, this article is not based on statistical monitoring of the process. Rather, it is an application of TPM based on the collection of various data (expected operating time, planned production rate, planned and unplanned downtime, poor quality products, etc.). The work of Ben-Daya and Duffuaa (1995) also makes an important contribution to the maintenance-quality approach. In this work, the authors identify links between quality and maintenance. In fact, they propose two approaches: one is based on the imperfect maintenance concept and the other uses Tagushi's approach to quality and maintenance (Rahim and Ben-Daya (2001)).

In the work of Lu et al. (2016), the authors propose a model where the improvement of the quality of the products intervenes in the decision-making of preventive maintenance. In fact, economic losses due to poor quality products are included in the total cost, which is minimized to get the best planning for preventive maintenance operations. A case study then shows that the model achieves better economic performance than traditional preventive maintenance. In this paper, the problem concerns a single machine subjected to a degradation reducing the quality of the products and increasing the rate of failure. When a failure occurs, a corrective maintenance operation restores the machine to the state before failure (ABAO). Preventive maintenance takes place when the failure rate reaches a threshold. This maintenance reduces the failure rate and improves the quality of the products. This is an imperfect maintenance (between AGAN and ABAO). In the model, it is considered that product quality degradation is a random process that can be modeled by a Gamma process (variable X (t)). Regarding the reliability of the machine, the authors use Weibull's law. They thus obtain the analytical form of the failure rate. Then, for optimization, a total cost is calculated (maintenances and quality). For quality, the cost generated is based on the loss function of Tagushi but the cost is adapted by integrating the variable X (t) generated by the Gamma process. By minimizing the total cost, it is possible to determine the threshold of the failure rate to be applied for preventive maintenance.

In the paper of Rivera-Gomez et al. (2016), the authors are also interested in an economic optimization of a manufacturing system subject to degradation. This degradation causes defects (non-quality) in the products. Revisions make it possible to mitigate the effects of deterioration. The aim here is to determine the frequency at which revisions are to be performed. This is a general model in which the costs incurred include repairs, revisions, arrears of production, defects, production costs and subcontracting costs. Here, when the production machine is no longer able to supply the product to the customer (due to failure or bad products), a second machine is used for manufacturing (subcontracting). This second machine, however, has a higher cost than the first one and so it is avoided to use it too frequently. The economic optimization aims at determining the best maintenance policy (revision) and the best use of the subcontracting option (second machine). The production system evolves according to a semi-Markovian process, returns in ABAO condition after a corrective maintenance (repair) and becomes AGAN after a preventive maintenance. The authors also use a correlation between the degradation of product quality and the age of the machine. The rate of defective parts is directly related to the age of the machine. A numerical example is treated to conclude the article.

In the paper of Gouiaa-Mtibaa et al. (2016), models integrating the effects of non-quality and of preventive maintenance are developed. The objective is to determine an optimal maintenance and quality control strategy taking into account a rate of quality loss and the impact of the recovery activities of the wrong products. Two different strategies are proposed. In the first, the batches of products are sold at a reduced price because of the progressive loss of quality due to the degradation of the machine. The objective is to determine the optimum number of batches to be produced (N_1) before each preventive maintenance operation by maximizing the total benefit per unit of time (PT_1). The second strategy proposes to rework all the products of poor quality in order to sell them at the maximum price P_{max}. Here, it is desired to determine the number of batches produced and reworked (N_2) before each preventive maintenance operation in order to maximize the total profit per unit time (PT_2). If a fault occurs between preventive maintenance, a corrective maintenance operation is performed. The advantage of this work is that it links directly the preventive maintenance action to the degradation of the quality of a product (batch of products). The approach is original but does not use statistical control of product quality. Rather, it is based on a rate of loss of quality (taken constant in the numerical example treated).

The work of Azadeh et al. (2016) aims to determine the best maintenance policy to minimize the average of the total cost per unit of time (maintenance costs and quality costs). Here, the authors consider the use of buffer stocks to meet demand despite breakdowns or preventive maintenance. The system under study is illustrated in Fig. 2. This is a series of production machines separated by buffer stocks to ensure continuous operation. Each machine produces a certain rate of non-conforming products. The size of intermediate stocks may vary. A simulation is performed and the values of buffer stocks and nonconformity thresholds are determined to obtain the minimum average total cost using the Tagushi method. Here, preventive maintenance operations are carried out when the rate of non-conforming products reaches a certain threshold and the corrective maintenance operations are carried out when the rate of non-conforming products exceeds another threshold. The size of the buffer stocks also intervenes because the storage costs depend on the

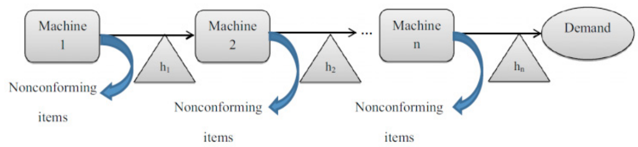

Fig. 2. Production line in Azadeh et al. (2016)

number of items present in the stock. It is assumed that the rate of non-compliant items increases in a random manner according to an established relationship. A case study is then developed on two production machines.

In Chen (2013) paper, the author develops a model integrating maintenance and product quality. The originality is to take into account the existence of errors in preventive maintenance and the possibility of reworking a certain percentage of the products of poor quality. Here, preventive maintenance is applied when the system is under control. Effective preventive maintenance results in a reduced failure rate for the machine. On the other hand, there is a certain probability that this maintenance operation is inappropriate and causes the system to change to an out-of-control condition. Inspections are carried out to determine the state of the production system and the quality of the products. However, these inspections have a cost and one of the objectives of the model is to optimize the planning of the inspections. Economic optimization involves minimizing the total cost. The latter includes the cost of installation, the cost of storage, the cost of recoveries of non-conforming products, the cost of inspections and preventive maintenance, and finally a cost of late deliveries.

The Tambe and Kulkarni (2015) paper describes a model integrating maintenance and quality applied to batch production. In fact, this model studies the production of a set of parts manufactured by die casting. Here, quality control is performed to determine whether the parts produced are compliant or non-compliant. The system produces a P_1 rate of conforming parts when it is under control and a P_2 rate when it is out of control. Switching from in-control to out-of-control occurs when there is a failure in one of the components of the machine. Corrective maintenance is performed when a fault is detected. However, when changing the type of part produced (mold change), the authors take the opportunity to apply preventive maintenance if necessary. Optimization leads to the determination of the best parameters for quality control and the best maintenance strategies to be applied to the components of the production system. The model developed is very interesting in the context of optimization of quality control and opportunistic maintenance.

To synthesize this literature review, we present in this paragraph the advantages and disadvantages of the models proposed in the articles presented. Many articles combine corrective maintenance and preventive maintenance on a single-component machine (Cassady et al. (2000), Linderman et al. (2005), Ben-Daya and Duffuaa (1995), Lu et al. (2016), etc.). However, in these models, preventive maintenance has time periods which are varied to find the optimal value. In reality, time periods of preventive maintenance can be fixed by external events (tool changes, production stoppage, ...) The term opportunistic maintenance is used to describe this situation. We wanted to study this particular situation and we based ourselves on this Tambe and Kulkarni (2015) document to develop our first model. However, in this paper, the authors rely on a genetic algorithm and on simulated annealing. Here, we will instead perform the simulation using the Monte Carlo method. In fact, in the Tambe and Kulkarni (2015) article, preventive maintenance (conducted at an opportunity) is carried out based on the actual age of the components. Here, we will test different strategies of preventive maintenance (by random drawing) and we will compare them to determine the best. We will also rely on the quality control elements performed in the work of Cassady et al. (2000) and Linderman et al. (2005)].

3. MODEL DEFINITION

The goal of the model is to determine the best maintenance policy and the best quality control parameters for batch production. For the maintenance, the more maintenance actions are performed, the less failures there will be (so less non-compliant products). On the other hand, maintenance costs will increase. There is therefore an optimum to determine. For quality control, the more frequent will be the sampling, the sooner the failures will be detected and therefore, there will be fewer non-compliant products. In addition, taking large samples (Ns large) increases the accuracy of the detections (the risk of not detecting a failure decreases when Ns increases). Again, an optimum is to be determined for the quality control parameters.

The realized model applies to a batch production where m different products are produced on the same machine. This machine itself consists of n different components. A model is used to determine the best preventive maintenance policy and the best quality control parameters for a given production sequence.

3.1 Parameters

Here are the parameters used in the model (Table 1).

3.2 Methodology

The methodology is shown in Fig. 3. After choosing the data, the first step is to propose a preventive maintenance strategy. For this, we randomly draw a maintenance strategy. By component, we fix a replacement during the production of m lots and as many repairs as we want. However, a repair can not occur when a replacement is planned. The definition of the maintenance strategy concerns the n components of the machine. At the end of the production of a batch, this strategy informs us of the maintenance operation that will be performed on the components: replacement, repair or no operation. This maintenance strategy is presented as an n x m matrix. For example, for a 2-component machine that makes 3 different batches, a typical M maintenance strategy is given in Eq.1.

$$M = \begin{bmatrix} 0 & 2 & 1 \\ 1 & 0 & 2 \end{bmatrix} \quad (1)$$

Table 1. Parameters of the model

Parameters	Definition
n	Number of components of the machine
m	Number of batches
T_{job}	Batch production time (h)
MTTRA	Replacement time (h)
MTTrA	Repair time (h)
ρ	Maintenance efficiency
β	Shape parameter of the Weibull distribution
η	Scale parameter of the Weibull distribution (h)
PR	Production rate (products/h)
CLP	Cost of losses of production (€/products)
CLM	Cost of labor in maintenance (€/h)
CP	Cost of a product (h)
CC	Cost of component (new) (€)
CSP	Cost of spare part (€)
μ_1	Mean of the quality indicator in normal conditions
σ	Standard deviation of the quality indicator
μ_2	Mean of the quality indicator in case of failure
δ	Maximum deviation for quality acceptance
H_s	Sampling period (h)
N_s	Sample size
C_s	Sample cost (€/element)
T_{ins}	Inspection time (h)

In this matrix, the digit 0 indicates that no maintenance operation is performed. The number 1 indicates that a repair is planned. Finally, the number 2 indicates that a replacement is planned. Thus, in the matrix M presented above, the component 1 of the machine (first line) will be replaced at the end of the second job and repaired at the end of the third job. On the other hand, the second component of the machine will be repaired at the end of the first job and replaced at the end of the third job. When the maintenance strategy is defined, the batch production is started. During batch production, a failure may occur. This leads to a repair of the failed component. At the end of batch production, the maintenance strategy is applied to the machine. Then the production of the next batch begins and so on until the end of the jobs. At the end of the jobs, the total cost of batch production is calculated (production, maintenance and quality control).

We still need to know how to detect failures. Indeed, their detection is important because these failures lead to an increase in the rate of non-compliant products and need a repair action that brings back the system under control. This detection is carried out through the quality control. The principle used for the simulation is shown in Fig.4. The quality control parameters are first fixed (Ns, Hs, Cs, ...). Then, a Monte Carlo simulation is performed: the failure times of each of the n components are determined. For this simulation, we use the Weibull reliability law whose expression is recalled in Eq.2.

$$R(t) = e^{-(\frac{t-\gamma}{\eta})^{\beta}} \qquad (2)$$

It is assumed that the quality indicator follows a normal distribution and that the occurrence of a failure moves the mean of the normal distribution from μ_1 to μ_2. The control chart used is an mean Shewhart chart. The production simulation then begins. During batch production, a quality control is carried out. In fact, we take Ns products (samples) at time interval Hs (sampling period). This sampling is made by random drawing on the above-mentioned normal laws. If the value obtained has a greater difference than δ compared with μ_1, an inspection is started to determine if a problem has occurred. If a failure has occurred, a repair is performed. The purpose of quality control is to detect failures and thus avoid prolonged production of non-compliant products. Indeed, the appearance of a failure causes the increase in the rate of non-compliant products

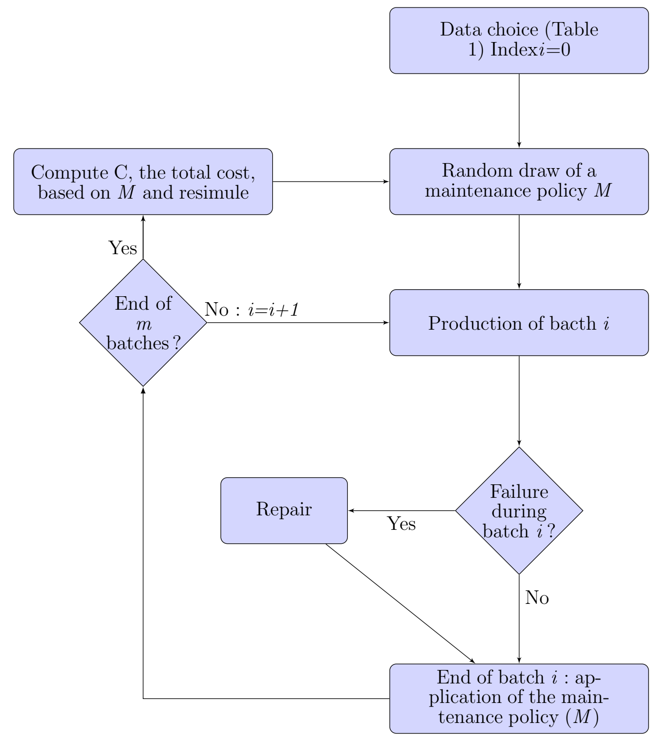

Fig. 3. Methodology used

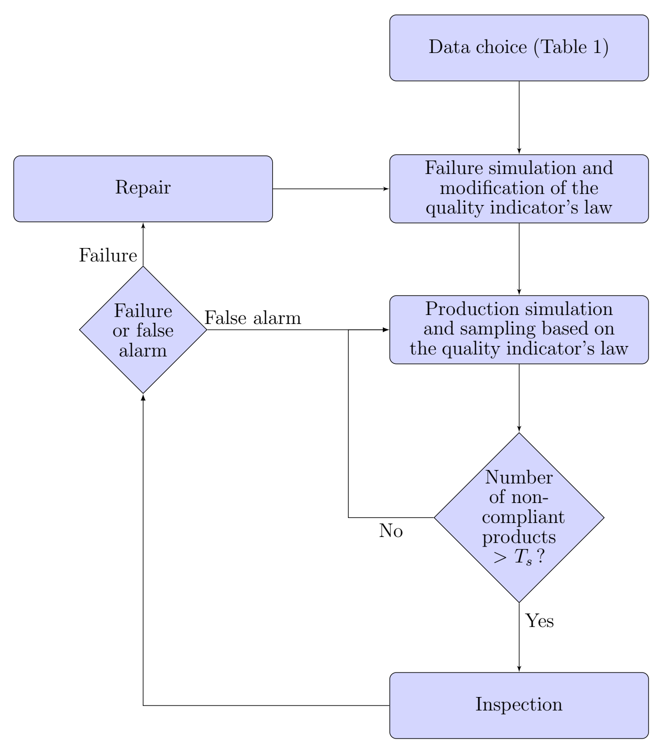

Fig. 4. Quality control (simulation principle)

manufactured and therefore, the increase in costs related to non-quality.

4. NUMERICAL EXAMPLE

In this section, an example similar to that proposed in the Tambe and Kulkarni (2015) article is treated. It is a die casting machine. It manufactures a series of identical products and then the mold is modified and the machine then produces other parts. We will limit ourselves here to one component. The component selected is the one which failures lead to many quality defects in the parts produced. This component is a piston.

4.1 Parameters definition

We need to define a series of parameters (see Table 2).For the component and the products, we give the values of the parameters defined previously.

Table 2. Parameters for the example

Parameters	Values
n	1
m	5
T_{job}	[105 189 304 345 400]
MTTRA	6
MTTrA	5
ρ	0.7
β	2.69
η	3744
PR	150
CLP	150
CLM	30
CP	100
CC	120000
CSP	50000
μ_1	20
σ	0.1
μ_2	20.1
δ	0.15
H_s	50
N_s	10 (maximum value)
C_s	10
T_{ins}	0.2

The maintenance efficiency ρ will be used during repairs to find the effective age of the component (imperfect maintenance, Eq.3).

$$v_2 = v + \rho T \tag{3}$$

In equation 3, v_2 symbolizes the age after the repair and v represents the age before the production period T. We also need to define other parameters for the products. These parameters will be used to determine the total cost generated by a given strategy. We will consider here that the machine manufactures 5 different products ($m = 5$) but whose characteristics are the same. The only difference between products is the batch production time (that is the reason why T_{job} is a vector).

4.2 Hypotheses

Some hypotheses have been taken to realize the model:

(1) Given its average lifespan (compared with job completion times), the component can fail only once during the realization of the m jobs
(2) Detecting a failure causes a repair of the affected component
(3) When the system is under control, the quality indicator follows a normal distribution with mean μ_1 and standard deviation σ.
(4) When the system is under control, the quality indicator follows a normal distribution with mean μ_2 and standard deviation σ.
(5) Resources needed for maintenance actions are always available
(6) The maintenance efficiency ρ is known for the component studied.

4.3 Developments

Here we develop the method for the numerical example. The first step is to randomly draw a maintenance strategy. The maintenance strategy is therefore presented here in the form of a 1 x 5 matrix. Each column corresponds to the maintenance action performed at the end of the batches. Then the Monte Carlo simulation is performed. Thanks to this simulation, the failure time of the component is known. The successive realization of the 5 jobs begins, that is to say that the production of the 5 products is launched. During the manufacture of a product, we look at whether a failure occurs. To find out, we need to compare the failure time to the end time of the job. In fact, quality control will enable us to detect failures. In fact, the failure causes a change in the quality indicator. Therefore, samples of *Ns* produced are taken at time interval *Hs*. When the number of defective products among those taken exceeds *Ts* (acceptance limit), an inspection is started to check if the machine is in a normal state. If a failure has occurred, it will be detected through the inspection. A repair is then performed.

Finally, at the end of a job, the preventive maintenance strategy is applied. To average the results of the chosen strategy, the Monte Carlo simulation is repeated a large number of times (10000 for example). The operation is repeated on several different strategies in order to find the best strategy.

4.4 Results

In this section, we decided to vary N_s between 1 and 10. For each value of N_s, we compared 20 different maintenance policies (Matrix M). Then we simulated each configuration (N_s-M) 1000 times (1000 simulations). For each configuration, T_s was varying between 0 and the maximal value of N_s. In the figures 6 and 5, we present the results.

The best maintenance policy is given in Eq.4 and the best N_s value is given in Eq.5. The acceptance limit T_s is given in Eq.6. This maintenance policy and these quality control parameters lead to the total cost given in Eq.7.

$$M = [0\ 0\ 0\ 2\ 0] \tag{4}$$

$$N_s = 4 \tag{5}$$

$$T_s = 0 \tag{6}$$

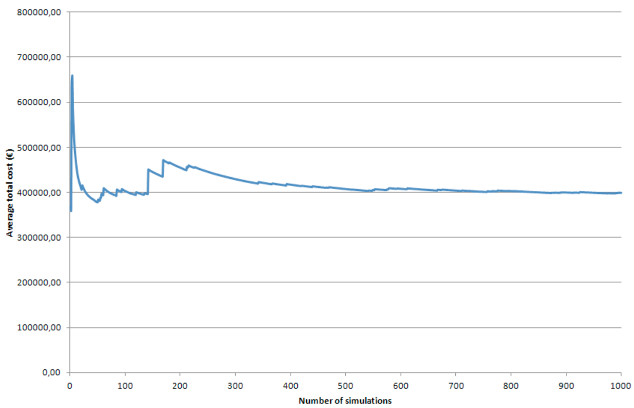

Fig. 5. Total cost in function of the number of simulation
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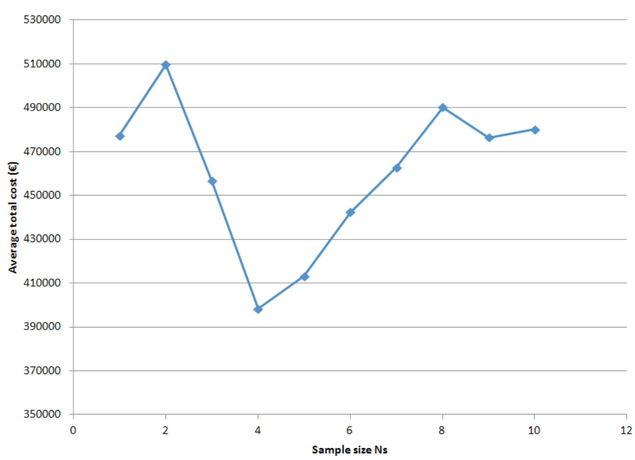

Fig. 6. Total cost in function of the sample size N_s

$$C_{tot} = 398441, 87 \quad (7)$$

That means that the best maintenance policy is to peform a replacement at the end of the fourth batch and to do no repair. The quality control consist of taking 4 products every 50h. If, within this 4 products, there is at least one product outside the quality acceptance interval, a inspection is launched to know if a repair action is needed.

In the figures 6 and 5, we present the results. The number of Monte Carlo simulations has a great impact on the accuracy for the total cost. By doing 1000 simulations, we see in Fig.5 that convergence is ensured. In Fig.6, we see that the total cost is minimized for a N_s value of 4.

5. CONCLUSION

A literature review was carried out to report on existing techniques and models on the integration of quality control and maintenance policies. Based on the article of Tambe and Kulkarni (2015), we realized a first model integrating production, maintenance and quality control. This first model makes it possible to define the best maintenance policy and the best quality control to be applied to a machine that produces batches of products. This model can be applied to a real system with a history of failure times is available (which allows an estimation of reliability laws) and when the effect of failures on quality is known (jump in the average indicator for example). The interest is real since the model gives the best maintenance strategy to apply. In addition, it provides a control plan (H_s, N_s, inspection initiated if detection of non-compliance). On the actual system, it remains to define the defect (dimension out of tolerance, visual defect, ..) and the method of measurement. This model already has a certain complexity since it integrates many parameters (imperfect maintenance, control card, various costs, ...). However, the model can still be improved. Indeed, here we have assumed that maintenance resources are always available. However, this is not always the case in reality and must be taken into account. There are also many variables that affect the total cost (H_s, reliability law, control limits, cost paramaters,...). Further works are needed to find their best values in order to minimize the total cost. Then, there are many different control charts (Shewhart, CUSUM, ...), we could worry about the best control card to apply for quality control.

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