JOINT PRODUCTION, QUALITY CONTROL AND MAINTENANCE POLICIES SUBJECT TO QUALITY-DEPENDENT DEMAND

By

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POLITIQUES CONJOINTES DE PRODUCTION, DE CONTRÔLE DE QUALITÉ ET DE MAINTENANCE SOUMISES À UNE DEMANDE DE QUALITÉ

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RÉSUMÉ

Cette thèse vise à trouver une solution appropriée en utilisant les moyens de contrôle stochastiques optimaux pour un système de production non-fiable avec un contrôle de la qualité du produit et une demande dépendant de la qualité. Le système consiste en une seule machine produisant un seul type de produit (M1P1) sujet à des pannes et à des réparations aléatoires et devant satisfaire un taux de demande client non constant, qui répond à la qualité des pièces reçues. Étant donné que la machine produit avec un taux de produits non conformes, une inspection des produits est effectuée afin de réduire le nombre de pièces défectueuses pouvant être livrées au client. Cela se fait en continu et consiste à contrôler une fraction de la production. Les produits approuvés sont remis sur la chaîne de production, tandis que les mauvais produits sont jetés.

L'objectif visé par cette étude est de fournir un contrôle de la qualité et une politique de production optimale, qui maximise le revenu net composé du revenu brut, du coût des stocks, du coût des pénuries, du coût de l'inspection, du coût de la maintenance et du coût des pièces sans qualité. Les principales variables de décision sont le taux d'échantillonnage du système de contrôle de la qualité ainsi que seuil d'inventaire de produit fini. La fonction de demande réagit au niveau de qualité moyen sortant (AOQ) des produits finis. Dans le troisième chapitre de cette étude, les stratégies de maintenance préventive et de tarification dynamique sont ajoutées à la stratégie optimale, citée ci-dessus.

Pour atteindre les points optimaux de la politique, qui maximisent nos revenus de production nets, une approche de simulation est mise en œuvre à titre expérimental et ses résultats sont utilisés dans la méthodologie de la surface de réponse.

Pour mettre en œuvre le plan d'expérience (approche de la simulation) reflétant parfaitement les considérations du modèle, telles que son caractère continu et sa variété, une variable continue a été introduite pour la probabilité de défectuosité, fonctionnant avec l'âge de la machine jusqu'à la prochaine maintenance. Deuxièmement, afin de refléter l'effet du processus de contrôle qualité qui se traduit par une qualité moyenne sortante plutôt que par une simple possibilité de défectuosité, cette fonction (AOQ) a été construite sur la base du comportement instantané de la fonction mentionnée ci-dessus en tant que variable indépendante. Troisièmement, en raison de l'utilisation des hypothèses de la théorie des clients potentiels pour créer une fonction de demande répondant au niveau de défectuosité fournie par le client (AOQ), une fonction continue réactive a été créée pour la demande, réagissant au niveau de qualité du produit en déterminant son taux. Finalement. Pour illustrer la politique de fabrication de la machine basée sur Hedging Point, une variable d'inventaire du produit fini a été introduite dans la conception de l'expérience.

En résumé, nous avons un système de production conçu de manière à ce que, en augmentant son âge (A_t), il soit possible d'accroître les possibilités de défectuosité et de réduire la demande en unités de temps. Cette manière de procéder continue jusqu'à la prochaine action de maintenance du système, ce qui restaure tous les facteurs dans leurs conditions initiales. En utilisant l'approche de simulation d'optimisation, une expérience est conçue et mise en œuvre pour contrôler les variables de décision de la politique et maximiser la fonction objective du revenu net moyen (ANR). Les variables de décision sont statistiquement et pratiquement prises en compte, telles que le niveau d'inventaire (Z), la proportion d'inspection (F) et les seuils de PM (Mk ou Pk).

Mots-clés: Production system, optimal stochastic control, quality control, simulation, experimental design, response surface methodology, quality dependent demand, prospect theory

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ABSTRACT

This thesis is a strive to find a proper solution, using the stochastic optimal control means for an unreliable production system with product quality control and quality-dependent demand. The system consists of a single machine producing a single product type (M1P1) subject to breakdowns and random repairs and must satisfy a non-constant rate of customer demand, which response to the quality of parts received. Since the machine produces with a rate of non-compliant products, an inspection of the products is made to reduce the number of bad parts that would deliver to the customer. It is done continuously and consists of controlling a fraction of the production. Approved products are put back on the production line, while bad products are discarded.

The intended objective of this study is to provide optimal quality control and production policy, which maximize the net revenue consisting of the gross revenue, the cost of inventory, the cost of shortage, the cost of the inspection, the cost of maintenance and the cost of no-quality parts. Main decision variables are the sampling rate of the quality control system as well as the threshold of finished product inventory. The demand function reacts to the average outgoing quality level (AOQ) of finished products. In the third chapter of this study, preventive maintenance and dynamic pricing policies are added up to the optimal policy, cited above.

To achieve the optimal points of the policy, which maximize our net production revenue, a simulation approach is implemented as an experimental design and its results were used in response surface methodology.

To implement the experiment design (simulation approach) which thoroughly reflects model considerations such as its continuous nature and the variety, first, a continuous variable for the probability of defectiveness was introduced, functioning with the age of machine up until its next breakdown maintenance. Second, so as to reflect the effect of quality control process that results in Average Outgoing Quality rather than simple defectiveness possibility, this function (AOQ) was built based on instant behavior of mentioned function above as its independent variable. Third, due to the use of prospect theory assumptions in building a demand function that responds to the level of client delivered defectiveness (AOQ), a responsive continuous function was created for the demand, reacting to the level of product quality by determining it's needed per time amount. Finally. To illustrate the machine's manufacturing policy based on Hedging Point, finished product inventory variable was introduced in the experiment design.

In a nutshell, we have a production system that has been designed in a way that by raising its age (A_t), leads to more possibility of defectiveness and less demand in time units. This manner continuous up until the next maintenance action of the system, which restores all factors to their initial conditions. By use of the simulation approach of optimization an experiment is designed and implemented to control decision variables of the policy and maximize the objective function of average net revenue (ANR). Decision variables are statistically and

practically in the matter of consideration such as finished product inventory threshold (Z), the proportion of inspection (F) and PM thresholds (M_k or P_k).

Keywords: Production system, the simulation approach of optimization, quality control, simulation, experimental design, response surface methodology, quality-dependent demand, prospect theory

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LIST OF THE ABBREVIATIONS

A_t	Age of the system during time
λ	Demand sensitivity metric
C_{nq}	Cost of no quality
C_s	Cost of shortage
C_h	Cost of inventory
C_{insp}	Cost of inspection
C_{rep}	Cost of repair
C_{ret}	Cost of return
x_t	Finished product inventory level
Z	Finished product inventory threshold
F	Proportion of inspection
M_k	PM threshold in produced number of parts
P_k	PM threshold in decreased price
P_{ri}	Price
P_t	Proportion of defectives
P_0	Quality level of system in its “as new” condition
ANR	Average net revenue
U_{max}	Maximum production rate
U_t	Production rate
U_{ins}	Inspection rate
D	Demand rate
D_0	Initial demand rate
MTTF	Mean time to failure
MTTR	Mean time to repair
MTPR	Mean time to repair in preventive maintenance scheme

INTRODUCTION

These days, manufacturing companies are experiencing real changes that have a significant impact on their competitiveness, investment and improved production capacity. In the era of communication and information revolution, social media and other means of technology are making clients more aware of product features, which would result to less loyalty and more responsiveness toward product and service quality. Since the new generation of clients such as baby boomers and generation X are far sensitive than their predecessor, manufacturers are expected to face considerable challenges in quality, managing the production and maintenance of increasingly complex manufacturing systems. In fact, the frequency of breakdowns continues to increase over time, disrupting production activities and thus directly influencing the ability of businesses to respond to customer demand that is not constant anymore.

In order to adapt to the varying demand of consumers, manufacturing companies must be flexible and responsive. In an increasingly competitive economic environment, financial issues are crucial. The selling price of the products, which depends on the cost of manufacture, remains very much influenced by the competition. To remain competitive and above all to guarantee a suitable profit margin on the sale of products, the main objective of manufacturing companies is to maintain their product demand in its feasible level.

The existence of varying and dependent demand for product quality requires the establishment of a good quality control policy. This requires rigorous maintenance of production equipment, proper product quality control and production planning that takes into account hazards and good inventory management. In this work, we will address the issues of production management and quality control by asking the following main question:

In the existence of responsive demand, how could we predict and manage non-quality costs and quality control investments in a way to maximize corporate benefits?

To answer the question above, it is important to consider below sub-questions:

- What quality control policy should be implemented?
- What production control policy should be implemented?
- What repair and maintenance policy should be considered?

All these aspects will be studied in this thesis to maximize the average net revenue.

Given the importance of production planning and quality control for companies, several authors have studied the subject. one of the closest efforts to this study is done by Bouslah, Gharbi et al. (2016) who have developed a new joint approach to production policy, continuous quality control, and a preventive maintenance policy, in order to minimize costs.

The approach used in this thesis for quality control is done by controlling a fraction of the production. In other words, the operator will control each time just a percentage of the parts produced. This approach is suitable for companies that have a continuous production system. The objective will initially be to find a production policy that takes into account outages and that will determine the rate of production depending on the stock, and then find the percentage of products to control.

This thesis is organized into three chapters. The first chapter is a review of literature that introduces some theoretical notions that will be addressed in this thesis and allows us to position our work in relation to others. In the second chapter, we will propose a production and quality control policy with a simulation approach, experimental designs and response surface methodology. In this chapter, we will discuss two cases. In the first case, we will consider a quality control policy with a fraction of continuous sampling and in next two cases, we will verify its efficiency with two other cases, 100% sampling plan, and no sampling plan measurements. The second case is an evolved version of production and quality control policy with a simulation approach, experimental designs and response surface methodology, which considers a delay in demand response based on an average in AOQ. In chapter 3, the system will be studied in the existence of preventive maintenance policy in order to increase the availability of the system and have less amount of costs, resulting from unavailability. In the second case of this chapter, we propose a policy of production, quality control and corrective maintenance for an unreliable production system with a variable price offer to the demand so as to get a more realistic sense of M1P1 supply chain in real-life. Finally, a general discussion of the study along with a conclusion of the thesis and some future work perspectives is provided at the end of the chapter 3.

CHAPTER 1

LITRATURE REVIEW

1.1 Introduction

In this chapter, we will first focus on the structure of production systems by presenting the particular case of unreliable systems. Then we will present the critical threshold policy, statistical quality control techniques, and the simulation-based approach to solve such problems. After explaining some applications of prospect theory in related contexts, we will then carry out a critical review of the literature in relation to our subject and will position our work in relation to previous research. After having presented the research question addressed in our study, we will elucidate the objective of our research work. Finally the selected methodology to solve the problem will be presented before concluding.

1.2 Structure of unreliable production systems

In order to understand the structure of unreliable production systems, it is important to define certain terms and concepts in advance.

1.2.1 Production system components in a supply chain context

The so-called "supply chain" is a supply chain made up of suppliers, manufacturers and distributors whose objective is to allow the flow of information, financial resources and products from the ordering of raw materials to the supplier up to the delivery of finished products to the customer (Nakhla 2006).

Accordingly, studied production system involves three main actors: the supplier, the manufacturer and the client. In the context of our work, we will only focus on last two, which are, the manufacturer and the customer, assuming that the supply of raw material is always available.

1.2.2 Production system concepts

In the manufacturing domain, a production system is a set of material resources (production assets) and human resources (managers, managers, operators) aiming to transform the raw material into finished products that satisfy customer requirements. These resources interact with each other through physical flows (products) and information flows (quantity, quality, production plan) (Benedetti 2002). Several criteria are used to classify manufacturing enterprises according to their mode of operation. We can name three main type of classification of production units, in particular, according to the volume of production, the policy of management of production and the nature of production.

I. Production volume

According to this categorizing criterion, (Hounshell 1985)manufacturing companies are classified into three categories of unit production, batch production and mass production enterprises. (Sethi, Zhang et al. 1997)

II. Production Management Policy

There are three (3) modes of production management (Nodem and Inès 2009) either build to stock production, where the management is in push flows, or on-demand production, where the management is done in pull flows or production of hybrid nature as the third type. In push production, production planning is based on forecasts of customer demand; we produce, even if the client is not clearly identified. The pull management policy has been used in the work of Hajji, Gharbi et al. (2011), Lavoie, Gharbi et al. (2010). In other words, their implemented production management policy has been based on an specific customer demand.

III. Nature of production

According to this criterion, we can distinguish three sorts of production starting with continuous flow production systems (for instance metal production, refinery), batch flow systems where products in the form of separate parts are manufactured (automotive industry) (Elhafsi and Bai 1996). Based on this categorizing logic, there are also hybrid systems where both types of continuous and discrete flows are used simultaneously (Bhattacharya and Coleman 1994) .

1.2.3 Process variation factors affecting production system

According to Benedetti (2002), production events are of two types (External and Internal). External process variations are those that do not depend on the company itself. Among these external process variations, we can consider the variation of delivery times of suppliers, the uncertainty of the quality of raw materials delivered by the supplier, the fluctuation of customer demand.

Internal process variations are those that appear within the company and always manages have no power of avoiding them. Among these internal process variations, we can consider machine failures as well as their repairs, the quality of manufactured products that must have a minimum tolerable threshold before being accepted by the customer. Minimum quality is one of the important constraints that allows retaining the customer of a company in addition to adhering minimum order quantity, the delivery time, the place of delivery and the cost of sale (Benedetti 2002).

1.2.4 System degradation

The modeling of quality and reliability degradation in manufacturing systems is a key element that determines to what extent one can imitate the reality of the complex dynamics of these systems, but also to what extent the policies developed with such modeling could be put into practice. In the literature, almost all production control, quality, and maintenance integration models are based on a number of simplistic and unrealistic assumptions in modeling of manufacturing system degradations. In this section, some important aspects of quality and reliability degradation are discussed that have been demonstrated from several real-life case studies, thought they have been overlooked in the literature.

1.2.4.1 Modeling of quality degradation

Quality degradation is an inherent phenomenon of manufacturing systems. The most widely used mode of quality degradation in the literature is that of describing the production process by two states: the 'under-control' state at the beginning of each new production cycle where all manufactured products conform , and the 'out-of-control' state from the moment the process starts generating nonconforming products. The transition from the 'under-control' state to the 'out-of-control' state is assumed to be random, often following an exponential distribution for reasons of simplification of the modeling(Bouslah, Gharbi et al. 2014).

Rosenblatt and Lee (1986) are among the first researchers to study different forms of quality degradation in production planning. These authors proposed four modes of degradation when the system gets out-of-control, namely:

1. production of a constant proportion of non-compliant products (no degradation)
2. linear degradation of quality over time
3. exponential degradation of quality over time
4. Multi-level degradation of quality with a random transition from one level to another higher level.

This study, which determines the impact of these different modes of quality degradation on the Economic Quantity of Production, has been the subject of several extensions in the literature. Yet most of these extensions are based on Rosenblatt and Lee (1986) first model, which ignores the dynamic aspect of quality degradation. However, there are some exceptions as below:

Khouja and Mehrez (1994) considered that the rate of production is flexible and it can affect the intensity of quality degradation (transition from 'under control' to 'out of control'). In fact, this hypothesis is based on several industrial studies that have shown the acceleration of the production rate increases the degradation of quality. For instance, in the case of robotic assembly systems, Offodile and Ugwu (1991) have shown that increasing the speed of movement of a robot's joining arm results in a decrease in repeatability. Repeatability is defined by the robot's ability to return to the same target point at the beginning of each assembly cycle. This measure is criticized in terms of product quality: Albertson (1983) and Mehrez and Felix Offodile (1994) have shown that degradation of repeatability leads to an increase in the percentage of non-compliant items produced by the robot. The direct effect of the production rate on product quality has also been observed in other industrial contexts such as in the automotive industry and in the machining and cutting processes of metals(Owen and Blumenfeld 2008). Although the effect of the production rate on the intensity of quality degradation has been demonstrated in several industrial studies, the majority of integration models in the literature have completely neglected this type of dependence.

1.2.4.2 Modeling of reliability degradation

In the literature, the reliability degradation a machine is defined to either be dependent on production operations (that is, depending on the use of machine) or time dependent (regardless of the use of machine). Hence, machine breakdowns have often been classified into two categories:

1. Operational breakdowns: Failure of this type can occur only when the machine is operational. The breakdown usually occurs because of machine wear, which depends on the production rate, the production volume during a given cycle or the number of production cycles.
2. Time-dependent breakdowns: Failure of this type can occur even during periods of forced machine shutdown (locked or unpowered machine). The failure rate increases with the advancement of time and is due to phenomena other than wear.

In a thorough industrial study of production line shutdowns in the automotive industry by Buzacott and Hanifin (1978) (Chrysler Corporation case), it is demonstrated that 84% of outages are operation dependent and only 16% of outages are time dependent. Thus, according to the study mentioned above, it is more realistic to use operation-dependent failure models to model the reliability of production systems, since these failures occur much more frequently

in practice than time-dependent failures. Yet, most integrated operations management models in the literature use time-dependent failure models for simplification purposes.
In fact, it is much more complex to model the operational-dependent failures than the time-dependent ones as in the first type of breakdowns, it is necessary to count, in particular, only the times when the machine is operational in the modeling of reliability degradation(Matta and Simone 2016). In a comparative analysis of the two failure models, Mourani, Hennequin et al. (2007) have shown that modeling a machine subject to outages dependent on operations in a production line by a time-dependent failure model can lead to significant underestimation of overall production capacity (up to more than 16% in some cases).

1.2.5 Category of the studied system

This research project considers a pull and batch production system, that is, firms whose production policy is dependent on customer quality dependent demand as shown in Figure 1.1. We have an unreliable production system that is subject to breakdowns and random repairs and produces non-compliant parts. The possibility of defectiveness (non-compliant production) is depended on the age of production system and continuous until next breakdown event. An inspection policy is put in place to reduce the rate of non-compliant products after production.
We also have an inventory used to store finished products before delivery to customers.

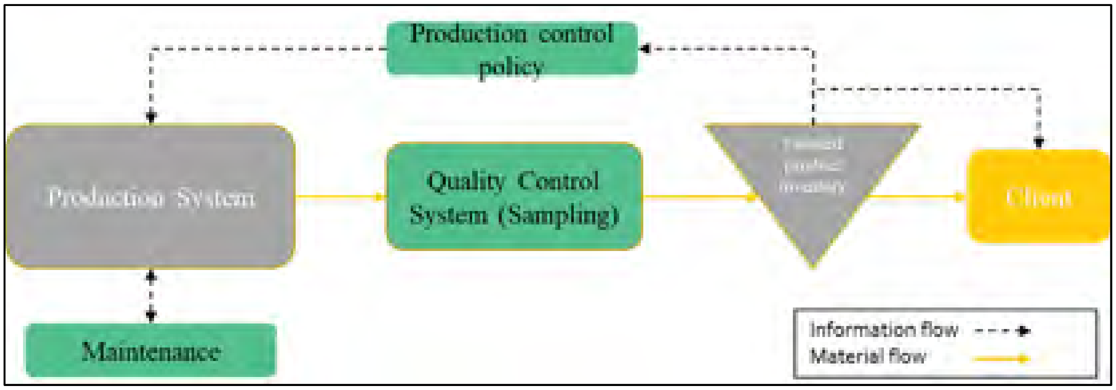

Figure 1.1 Illustration of the manufacturing system under review

The system above proceeds with only one type of finished products. To meet customer demand, the system produces with a variable production rate. The behavior of the system is described by a continuous variable (finished product inventory) and a discrete component (status of machine, on, off).To carry out this work, we will consider the following hypotheses that are commonly used in the literature:

- The machine is subject to breakdowns and random repairs.
- The mean time of malfunction (MTTF) and the average time of repair (MTTR) of the machine are constant and known.
- The different costs are constant and known.
- The demand rate for finished products is quality dependent and decreases from its initial as long as age of machine raises.
- Demand rate restores to its initial value when machine is repaired.
- The maximum production rate of the machine is known.

1.3 Critical threshold control policy

Introduced for the first time by Kimemia and Gershwin (1983), the critical threshold control policy is to maintain a security stock of the finished product inventory at an optimal level called a critical threshold. This stock is maintained during production periods to prevent potential hazards that could occur (production system failure, scheduled shutdown). They modeled the control problem using dynamic and stochastic programming, a heuristic allowed them to approximate the critical threshold that minimizes the total cost of inventory and out of stock. Akella and Kumar (1986) found an analytical solution to the Hamilton-Jacobi-Bellman equations for a control problem of a single machine and a product type, according to breakdowns and random repairs. They have determined the optimal critical threshold which is called hedging point that minimizes the total cost. This control policy has been formulated as follows:

$$u_t = \begin{cases} u^{max} & if\ x_{t<z} \\ D & if\ x_{t=z} \\ 0 & otherwise \end{cases} \tag{1.1}$$

Knowing that u_t is the rate of production depending on the stock and mode of the machine if status variable=1 the machine is in operation, status variable = 0 if the machine is down. For considering preventive maintenance mode of operation, status variable=2. This condition will be studied in chapter 3.

This policy has been confirmed by Bielecki and Kumar (1988). It allows controlling the rate of production according to the instantaneous state of the inventory. When x_t is below the critical threshold z, the rate of production is maximum, when the level of inventory is maintained at the level of the critical threshold it is equal to the rate of the demand. If the level is above the critical threshold, production stops to avoid additional inventory costs.

1.4 Quality control

In order to satisfy the quality demanded by customers, companies are obliged to inspect (control) the products manufactured before delivery to the customer. At the end of the inspection or control, the manufactured products can be qualified as compliant when they meet previously defined specifications, otherwise they are qualified as non-compliant (Baillargeon 1999). In order to guarantee a good quality of products sent to their customers, manufacturing companies have developed several techniques for controlling or inspecting their production. In the literature, there are several types of quality control, 100% control and acceptance sampling plans.

1.4.1 Hybrid continuous sampling plan

Continuous sampling plans were introduced by Dodge (1943) to control product quality for continuous production systems. A continuous production system is a system dedicated to producing a very narrow range of standardized high volume sales products. In some companies with a complex production process, it is difficult to perform batch control, such as companies producing electronic equipment such as computers or vehicles (the process is done in an assembly line). The best-known continuous sampling plan in industry is Plan CSP-1; this inspection method is carried out according to the following three steps:

- Step 1

100% inspect consecutively manufactured products and continue until a number of compliant products are obtained. This number is the number of permissions still called the clearing interval.

- 2nd step

Once a consistent number of compliant products have been obtained, the 100% inspection is halted; only a fraction f of randomly taken production is inspected at 100% ($0 \leq f \leq 1$).

- Step 3

At this stage, when a defective product is detected in a sample, then a 100% inspection is immediately applied (Step 1) (Dodge 1943).

Since in our case, sampled defective products do not return to the production line we only consider having a fraction of randomly taken parts from production line. Therefore, resulted average outgoing quality of this hybrid continuous sampling plan will be as following:

1.4.1.1 Average Outgoing Quality (AOQ)

According to Dodge (1943), he considers that during the inspection, the products are rectified and re-introduced in the production process. The total quantity of products available after production remains unchanged. In our system, we considered that during the inspection, the defective products are not rectified, they are discarded, as it is the case for companies whose rectification is impossible or takes too much time or so cost very expensive.

$$AOQ = \frac{(1-f).p}{1-(f.p)} \qquad (1.2)$$

According to the formula above, by removing sampled defectives from the system, remaining un-sampled defective parts ($(1-f).p$) are divided on total remained manufactured parts in order to calculate a precise percentage of remaining defectiveness which is called AOQ.

1.5 Preventive maintenance policy

In manufacturing context, all equipment under production process will get out of service. These events without any preparation or expectation occur sometimes at their worst possible time. In order to control effects of such undesired moments, companies implement preventive maintenance policies in order to minimize Mean Time Between Failures (MTBF) and maximise Mean Time to Failure (MTTF) (Gross 2002).
Considering only Corrective Maintenance (CM) in order to restore machine status after each break down, in chapter 2 and 3 of this thesis, the time of machine breakdown is submitted to an exponential distribution which is subjected to average age of machine as its mean. When machine breaks down, a corrective maintenance action will be proceeded, restoring machine status to the condition, which is as good as beginning.
However, there is no preventive maintenance action in first two chapters, in order to have a better realistic approach, in chapter 3 machine failures are subjected to the cumulative number of manufactured parts since the latest maintenance. Cumulative number of manufactured parts is referred as `virtual age` of machine in the literature. We account break down of machine follows two-parameter Weibull distribution (EL CADI, Gharbi et al. 2017). By using virtual age as break down estimator, preventive maintenance actions can be determined based on threshold consideration in number of cumulative manufactured parts (virtual age). In this manner, PM actions will occur after passing `MAge` threshold, turning system status to PM mode.

1.6 Prospect theory

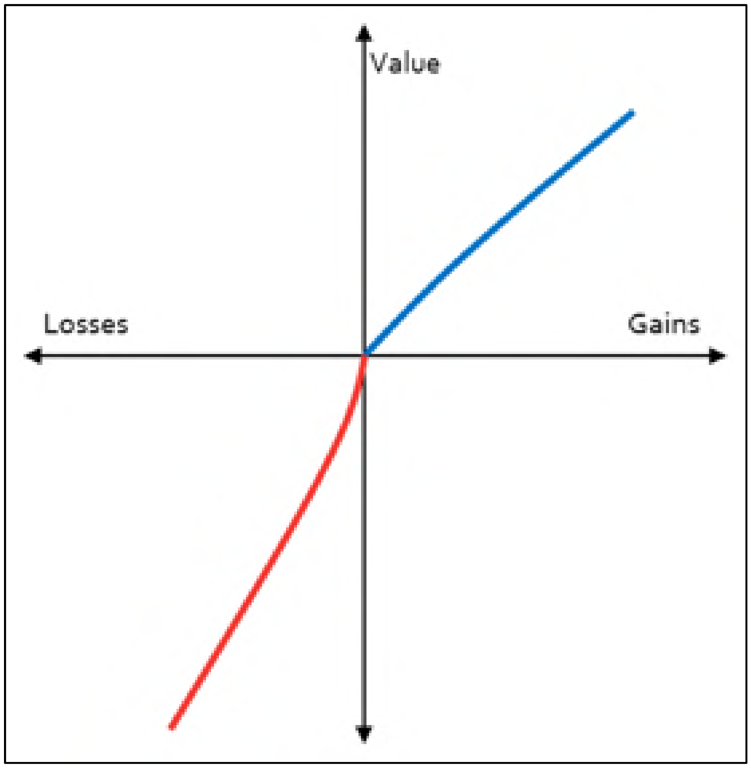

Figure 1.2 A hypothetical value function (Tversky and Kahneman 1992)

Individuals choosing behaviours under risk is not consistently explainable with the assumptions of utility theory in a persuasive manner. In general, people weight outcomes below their exact value that come from probability-outcome compared by outcomes, obtained with 100% certainty. Such type of tendency, which is defined as the certainty effect, leads to risk aversion behaviour in choices with 100% gains to risk seeking behaviour in choices with 100% losses (Kahneman and Tversky 2013). In other words, when people face in gain opportunities, prefer to choose certain options rather than any other probable choice (which may have more gain but equal utility). In reverse, in case of loosing, people try to go for options with more uncertainty to maybe avoid expected losses.

The value function as presented in figure 1.2, has the shape of concave in gain area however, in loss area due to loss averse behaviour explanation, it has became steeper (Tversky and Kahneman 1992). Illustrating that people are afraid of losing far more than joy of winning.

In addition, there is a tendency in this theory called isolation. According to isolation effect, individuals have a tendency toward discarding of some shared components of a prospect under their considerations. Isolation effect will lead individual to have changeable preferences facing with the same choice, presented in other ways (Kahneman and Tversky 2013).

Kahneman (1979) also has illustrated another aspect of individual decision making by a probability scale which is nonlinear and explains its transformation by overweighting small probabilities and moderating/ underweighting high probabilities. In other words, the probability weighting function shows that individuals do not respond to probabilities in a linear manner and this is proven by the study of Gonzalez and Wu (1999).

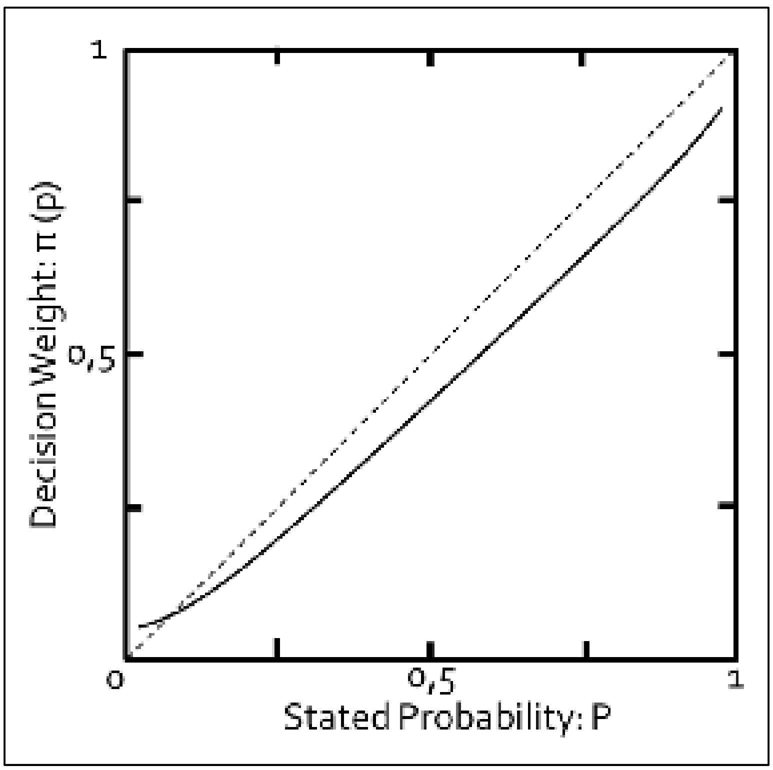

Figure 1.3 The weighting function

The weighting function proposed by Kahneman (1979) was not defined near the end points however it has shown underweighting of large scale probabilities (Gonzalez and Wu 1999) and overweighting of small ones. For instance, according ECONOMIST, there is a very small risk of die in an aircraft crash less than 1 in 5.4 million. Accordingly, this little possibility is big enough for passengers to purchase travel insurance, showing how considerably this risk is overweighed for individuals. This approach is widely used by gambling and insurance industry during centuries (Kahneman and Tversky 2013).

In above figure, the probability weighting function is denoted by π (p), this function maps the interval of 0 and 1 onto itself. Tversky and Kahneman (1992) then developed above weighting function as they believed that changes in probability appear more dramatic in the neighborhood of end points rather than middle. This reversed S shape got later proved by empirical studies (Gonzalez and Wu 1999).

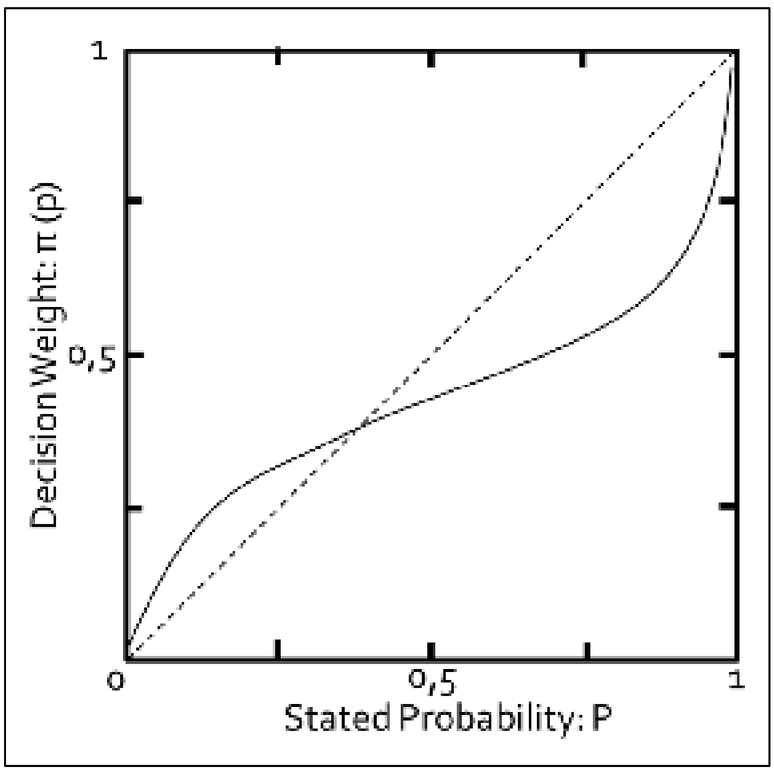

Figure 1.4 Evolved weighting function

According to prospect theory, an alternative theory of choice has ben developing during last 40 years by assigning values to gains and losses rather than simply defined final assets. Decision weights are replaced with probabilities of utility theory to better address behaviour of individuals.

1.6.1 Prospect theory applications

During recent years, applications of standard microeconomics tools in order to have precise assumptions of human behavior which is imported from psychology has begun and vastly developed which according to Rabin (2002), this has shaped `second-wave behavioral economics` (Rosenkranz and Schmitz 2007). In this regard, one of the most prominent economic paradigms, which has helped to comprehend reference-based behavior of people in utility, is prospect theory (Rosenkranz and Schmitz 2007). In general, applications of prospect theory could be segmented in 3 major, general groups as below:

1.6.1.1 Reference points

Based on prospect theory, reference point is a measure of outcome perception by people. People verify utilities by comparing with reference points(Kahneman 1979). It is to say that factors who determine the reference point are not specified in the context (Werner and Zank 2019). This point acts as a boundary to distinguish gains and losses from each other(Tversky and Kahneman 1992).

Among recent publications, reference point is vastly utilized in major subjects such as pricing in the studies of Hsieh and Dye (2017) for optimal dynamic approaches by considering reference price as a basis of comparison for customers deepening on their degree of remembrance. Also in finance, reference point is considered as the risk-free rate and in insurance industry is referred to expectations of future outcomes (Barberis 2013).

1.6.1.2 Risk aversion/seeking

As mentioned in figure above, people has risk aversion attitudes in gain occasions though in loss occasions they prefer to be risk-seeking(Kahneman 1979). This type of behavior has been studied in terms of extend of gains, implying that people tend to take risks of smaller monetary gains rather than big ones (Weber and Chapman 2005) or the fact that risk aversion has a rising tendency between infancy and adulthood (Levin and Hart 2003).

According to Kahneman (1979), individuals are not particularly risk averse or seeking in every situation that incorporate two different functions in mentioned loss and gain areas. This inconstant type of respond has been taken into account in demand studies during recent years. Research in mid 90s illustrates that tolerance of risk changes among different groups of individuals (Sewell 2009). For instance, the cluster of high educated, rich, drinkers, people with no insurance immigrants, Jewish individuals and races such as Asians are risk seekers while the second cluster, comprising of average wealth and source of income, those with health insurance and middle education level plus people who are in their sixties is risk averse (Barsky, Juster et al. 1997).

Accordingly, Hsieh and Dye (2017) has considered three different comportments of customer demand based on prospect theory assumptions. Their aim of study was to propose an optimal dynamic pricing policy for a demand with three different characteristics (following prospect theory assumptions) in relation with stock inventory, selling price and deterioration. According this study, penetration strategy is suitable in the case that reference price is lower than market (case of risk seeking demand type) and skimming strategy best suits for risk averse type of demand behavior.

Assuming risk averse attitudes in times of loss and risk seeking one in comparison with the reference point, Swinyard and Whitlark (1994) has applied customer satisfaction and dissatisfaction in store return intentions. Proving findings of prospect theory, they found that dissatisfaction affects two times more store returns intentions than satisfaction.

Briefly and based on our best of knowledge, risk averse approach in times of loss has generally used in majority of reviewed research.

1.7 Problem Statement

To the best of our knowledge, according to the law of demand, customer demand of certain commodity has always been assumed to be directly affected by price, in the context of demand and supply (Marshall 1892). This sort of inverse relationship between price and demand can be affected by other factors such as quality improvement or degradation, considering shift of demand curve. In other words, accordingly, demand curve shifts may be caused by a variety

of reasons such as income raise of customers, unexpected changes in product's quality, its substitutes or complements (Marshall 1892). On the other hand, utility is another factor that deals with levels of demand. Utility is the degree of satisfaction in costumers by committing an actions in decision making, individuals tend to increase their utilities (Kapteyn 1985). Higher levels of utility curves imply better provided satisfaction for customers, however these are not clearly explainable without consumer behavior theories(Kapteyn 1985).
Since better quality in product could be referred to better satisfaction and higher utilities, there is no specific function introduced in economics and marketing literature to estimate demand degree of response to improvement/degradation in quality. Even by assuming the fact that the non-quality amounts affects the demand in a negative way, the extend of this response needs to be well- addressed in a way to conform to known demand dynamics. This study is a strive to find a proper direct deal between quality measurements in quality dependent demand with the use of prospect theory for demand response measurement. In this work, the amount of demand response to any non-quality will be determined and an integrated policy for a production system with quality and reliability degradation needs to be defined, optimizing its average net revenue.

1.8 Research objectives

The main objective of this research is to implement a proper production control, maintenance and pricing policy while there is responsive demand comportment toward non-quality output of the system. Therefore, to reach the main objective above, following sub-objectives are considered as well:

1. To maximize total profit function rather than minimizing total cost of production regarding to the context of study in demand area.
2. To adequately model the complex dynamics of product quality degradation and machine reliability like real manufacturing systems. This involves modeling dependency relationships between quality and reliability degradation, machine aging, and production rate.

3. To develop a new approach to design sampling plans in the context of integration with production and preventive maintenance policies.

The objectives above are based on five main assumptions to be validated as part of this study, below:

1. It is possible to use sampling plans for production systems with a degradation of quality by ensuring the fulfillment of imposed requirements on after-control quality(Bouslah, Gharbi et al. 2018).
2. The level of final quality after-control is the result of the configuration of all the parameters of production control, quality and maintenance of the manufacturing system. In other words, the level of quality, perceived by client does not depend only on the quality control parameters(Lavoie, Gharbi et al. 2010).
3. Demand of client reacts to the level of perceived level of final quality after control and this behavior is considered to be loss-averse according to prospect theory.
4. There is no rectification plan estimated in quality control part of system. All inspected defectives items get out of the production process(Hajji, Gharbi et al. 2011).
5. Any delivered defectives items to clients will be collected and taken out of production system with no rectification (EL CADI, Gharbi et al. 2017).

1.9 Thesis’s structure

The research work carried out as part of this thesis in the form of two scientific articles. These two articles are presented in chapters 2 and 3.

In article one, which is presented in chapter 2, responsive demand comportment in the existence of quality and production control systems is taken into consideration. This article has contributed to two types of responsive demand behavior, instant and delayed when degradation and maintenance policies are implemented based on real-time units and exponential distribution for the reliability of the production system.

The second article is about the intervention of preventive maintenance policies into the relationship of responsive demand and production system, considered in article one. The approach is to increase net corporate revenue in the existence of operation caused failures of the production system based on an accumulated number of production. Later, this article considers pricing policies in the context of competition to reflect a better image of reality by use of prospect theory assumptions, this time in price, quality and demand relationship.

1.10 Research methodology

The adopted approach in this study has been about modeling and solving problems of joint design and optimization of some integrated models, proposed in two articles. These steps are summarized by the following methodology:

1. Definition of the objective and assumptions of the problem under study: This step consists of understanding the problematics and objectives of the study and modeling of determined assumptions.
2. Mathematical formulation of the problem under study: This step is about identifying decision variables and formulating the objective function along with the constraints of the problem.
3. Using a simulation-based optimization approach: This step consists of two sub-steps: The first is to develop and validate a simulation model with the ARENA software, based on the analytical modeling of the problem. Next, to use simulation-based optimization techniques, such as Response Surface Methodology, meta-heuristics, and gradient-based search methods to determine the optimal solution.

CHAPTER 2

The policy of joint quality and production control for an unreliable manufacturing system subject to quality-dependent demand

2.1 Abstract

In this chapter, a joint production control policy comprising of quality and production decision variables has been developed for unreliable production units with an age-based quality degradation and a quality-dependent demand, which responds to the quality levels of delivered products. Using hedging point policy that uses a certain amount of stock in the finished product inventory, the production rate of the machine gets controlled to avoid the excessive cost of shortages during the stop time of production such as maintenance and breakdown and change in demand amounts. The principal objective of this study is to maximize the total profit of the manufacturing system by setting a certain amount of safety stock quantity and a fraction of production output as the sampling of the quality control. By using response surface methodology based on gathered results of the simulation, a simulation-optimization approach for the developed stochastic mathematical model is developed. Results of the study clearly show some very strong ties between safety stock levels and percentage of sampling as the decision variables. This confirms the need for jointly and simultaneously application of policies in this integrated model. Altogether, a joint production and quality control policy in the presence of quality-dependent demand is proposed. Moreover, it is illustrated that setting periods during the machine’s available times for computing average outgoing quality and getting demand reactions, will result in more total profits, comparing with the initial assumption.

2.2 Introduction

In today's world, enterprises are paying more and more attention to their product's quality through their supply chain to increase their customer satisfaction which literally results into higher demand (Modak, Panda et al. 2015). Except for quality consideration, demand satisfaction in today's modern world really matters and the consequences of unsatisfied demand such as losing market share, brand and reputation damage, loss of sales and service level reduction are really significant (Jabbarzadeh, Fahimnia et al. 2017). Although demand and quality are getting closer, over past years of manufacturing and quality studies there have been three approaches towards demand.

2.2.1 Constant demand approach

In the first group, it is assumed to have a constant rate of demand under certain circumstances. For instance, Hlioui, Gharbi et al. (2015) have considered the demand rate stable and constant factor and they proposed a hybrid policy which always outperforms the 100% screening or discarding policies. In another work by Hlioui, Gharbi et al. (2017) in the same context of manufacturing and quality control, a dynamic supplier selection policy has been proposed, assuming the demand rate is unchanged in all time. Again, This assumption has been used in the work of Bouslah, Gharbi et al. (2018) in the case of finding a policy, covering production, quality, and maintenance control in a set of two machines which the reliability of the second machine is affected by the output of the first machine. The quality management system has been generally considered as an element of motivating and penalizing suppliers in the study of Starbird (2001) in an inspection policy to deliver better products based on determined quality targets of customer. However, in this study demand is deterministic and remains unchanged. To the best of our knowledge, in such simultaneous production and quality control policy design during recent years, there has not been any other demand assumption but constant and continuous.

2.2.2 Demand uncertainty approach

In the second approach, which is generally popular in the supply chain network, demand uncertainty is due to the existence of some factors. Callarman and Hamrin (1984) have examined tree different lot sizing rules in the presence of stochastic demand. Another study which considers market demand as a random variable and a probability density function (PDF) for this is done by Mukhopadhyay and Ma (2009) to address quality and demand uncertainties in production and procurement decision making. Generally, a stochastic behavior has been taken into account this behavior as Van Donselaar, Van Den Nieuwenhof et al. (2000) used a uniform distribution in a simulation-based experiment design to verify how wrong demand assumptions could affect supply chain planning. This study has analyzed the case of a truck manufacturer in the Netherlands and used its historical demand data. One year later, Caridi and Cigolini (2001) have proposed a buffering strategy to control uncertainty of market demand, using safety stock. Their main objective was to make corporate able to monitor in real-time the amount of demands however, this study does not support any mathematical model for demand behavior.

2.2.3 Dependent demand approach

In the third approach, despite the assumptions of mentioned production and quality based works, nowadays, customers are engaged with those products, offering better quality at a reasonable price and business demand which is derived from individual demand is, even more, fluctuating (Armstrong, Adam et al. 2014). Gurnani and Erkoc (2008) have taken into account a decentralized distribution channel of manufacturer and retailer, considering a level of quality that is chosen by the manufacturer and particularly, this quality level determines the product demand along with selling efforts that are chosen by retailer. Supposing that quality and price specifications delivered by suppliers directly affect potential market demand. Yu and Ma (2013) have studied demand behavior affected by the pricing of the manufacturer and direct delivered quality of the suppliers in an optimal decision sequence with three different scenarios. In this study, all three decisions models with separated decision sequences are implemented to maximize the profit of each player (manufacturer, supplier). In a closed-loop supply chain framework, Maiti and Giri (2015) have assumed to have a quality and price dependent demand for two completely different manufacturing and remanufacturing process lines. The supply chain in this study includes a manufacturer, retailer and third party for remanufacturing process. In other contexts rather than above, quality responsive demand has been studied enough. In the study of Modak, Panda et al. (2015), the demand of retailer is related to three factors of quality, selling price and warranty by considering profit function optimization for both manufacturer and retailer in the context of two layers supply chain. According to this interactive relationship which is modeled using Stackelberg game, the retailer is focused on maximizing its margin based on provided price, quality and warranty while the wholesale price of goods of the manufacturer is depended to its produced level of quality, however, demand and quality factors are assumed to be following stochastic behavior. Swinyard and Whitlark (1994) have used prospect theory with the idea that dissatisfaction of customers results more in their store return intentions than their satisfaction. Accordingly, customers who were dissatisfied tended to not be back two times less than those satisfied customers who were willing to be back.

Following prospect theory application in demand area, some studies have worked on framing effect as a tendency to avoid any risk when people face with positive options with exact gain and to be risk seeker when a negative option is presented beside exact loss (Kahneman 1979). In other words, Tversky and Kahneman (1981) have explained that the attractiveness of choices to choose, changes when the decision problem gets framed in other manners. According to this, Wu and Cheng (2011) have verified the impact of framing bias on decision-making attitude of internet buyers to see how information presentation stimulate demand of online customers with different product knowledge. In a nutshell, the current study has aimed the third approach, using prospect theory applications to well address demand responses in the context of manufacturing and quality consideration which is the case of first explained approach.

2.3 Problem statement

Considering an imperfect production unit, illustrated in figure 2.1, operating under a stochastic type of failures and repairs throughout its operation. This unavailability usually leads to having interruptions during the production process, resulting in shortages in satisfying demand rate and lost sales. Failure incidents will be repaired by implementing corrective maintenance measurements and bring back the system status to its initial condition (as good as new) with minimum defectiveness possibility since such actions normally are about replacements of broken components in a real context (Bouslah, Gharbi et al. 2018). The amount of time spent on corrective maintenance follows a random distribution. In addition, the production system is subject to aging which results in degradation of the quality in the percentage of manufactured products. As long as the machine is not broken and its age is raising, degradation of quality increases in the proportion of defectiveness until a predefined maximum limit, set to prevent having negative values of demand in responding to the quality level. Quality and reliability degradation of the intended production system is not dependent to its operation scale however, this manufacturing system produces with a flexible rate between 0 and maximum production capacity. Such production line feeds a quality-dependent demand, which decreases its rate upon receiving defective items by measuring the proportion of delivered no quality products. Because of mentioned demand dynamics dealing with quality, a quality control policy is designed to conduct a continuous checking over a portion of production output $\{0 \ll f \ll 1\}$ and remove out of range items as scrap. Production line does not rectify non-conforming parts, after quality control inspection. Unsatisfied demands in terms of quantity will not be back-ordered and all remaining no-quality items, passed to the customer will be returned and scraped with a rejection cost. Raw material stream in this study is considered to be constant and infinite to satisfy the production unit. The objective is to maximize the total net revenue function, comprising of average gross revenue, the average cost of inventory and shortage, the average cost of inspections, the average cost of CM and the average cost of no-quality product returns.

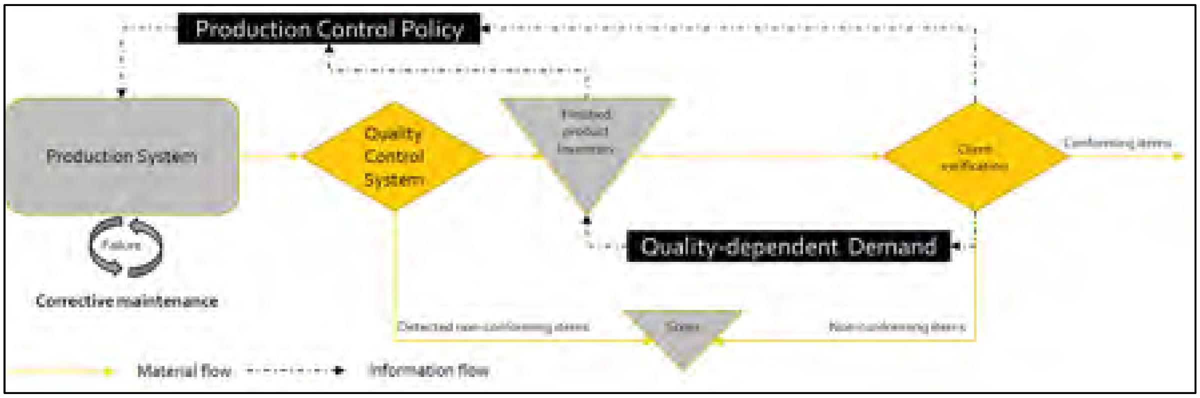

Figure 2.1 Manufacturing system subject to degradation and quality-dependent demand

2.3.1 Degradation model

The production unit status is described by two different variables. The first variable is a discrete-state for showing the operational condition of the production unit at time t. This discrete variable ($s(t)$) takes only two values $\{0,1\}$. In other words, if $s(t) = 0$ it means that the system is out of order and under corrective maintenance. If $s(t) = 1$ the system is under operation. The second descriptive variable records systems age from the last corrective maintenance until time t. This variable ($A(t)$) will determine the age of the production system such that in time of being out of service will keep its latest amount and not increase, following 2.1 equation:

$$\frac{\partial A(t)}{\partial t} = 0 \tag{2.1}$$

It is considered that the state variable follows an exponential distribution. Therefore, failure of the production system is not dependent on the extent of the operation and no preventive maintenance is taken into account. Although the reliability of the system has no tie with the scope of operations, quality degradation of the system augments during system's available time ($s(t) = 1$). Hence, degradation of quality is defined as increase in the proportion of defectiveness in intended production system. This is calculated, using 2.2 equation:

$$\mathrm{p}(\mathrm{A}) = \mathrm{p}_0 + \eta\left(1 - \mathrm{e}^{-\lambda . A_t{}^{\gamma q}}\right) \tag{2.2}$$

Above equation represents the possibility of defectiveness in the production rate. This percentage is dependent on the age of the system. Hence, in order to show degradation, as time goes on, defective percentage augments. P_0 is defined as the quality level of the system in its "as new" condition. It is a very small percentage of defectives items produced by the manufacturing system at its initial state. The sum $P0 + \eta$ determines the peak percentage of defectives items.

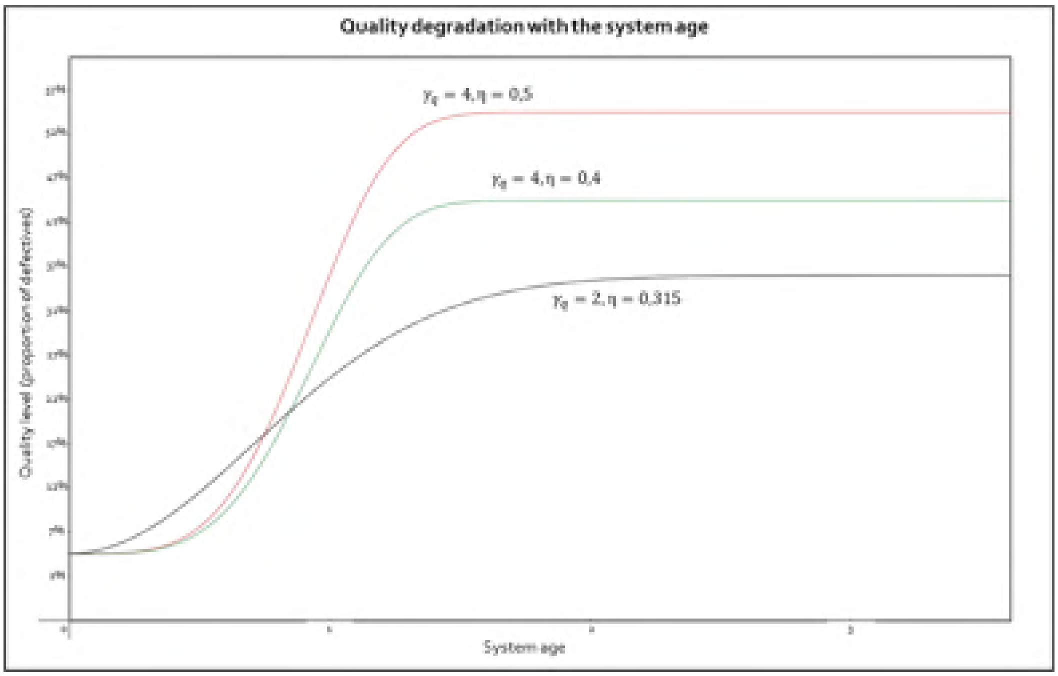

Figure 2.2 Quality degradation over time in correlation with the system age

Because demands amounts might face huge drops such as zero or negative without having any control on this factor, the degradation factor is designed in a way that takes a constant amount toward infinity. Figure 2.2 clearly illustrates the effects of changing factors on the shape of drawn functions. It is also assumed that coming raw material into the system is defect-free.

2.3.2 Quality-dependent demand nature

In this study, the possibility of defectiveness has been interpreted as a perceived loss of a customer who treats according to a loss-averse behavior in prospect theory. Based on Tversky and Kahneman (1992) findings, there are two different functions that describe customer responses. Function f(x) for the explanation of perceived gains and function g(x) for the loss area.

$$\mathrm{f(x)} = \begin{cases} x^{\alpha} & if\ \alpha > 0 \\ \log(x) & if\ \alpha = 0 \\ 1-(1+x)^{\alpha} & if\ \alpha < 0 \end{cases} \tag{2.3}$$

$$\mathrm{g(x)} = \begin{cases} -(-x)^{\beta} & if\ \beta > 0 \\ -\log(-x) & if\ \beta = 0 \\ (1-x)^{\beta}-1 & if\ \beta < 0 \end{cases} \tag{2.4}$$

As mentioned, the possibility of defectiveness is accounted for a loss for people. Therefore, following findings of Tversky and Kahneman (1992), function g(x) will build the response of demand to such existing imperfection. To have precise values of β, the empirical results of Tversky and Kahneman (1992) are used as our benchmark the quality-dependent demand is built in equation 2.5 as below:

$$D = D_0(1 - (\lambda * AOQ^{\beta})) \tag{2.5}$$

Where β is benchmarked as 0.88 and λ is equal to 2.25 that show customer sensitivity and scale of response to any received percentage of defectiveness that refers to average outgoing quality (AOQ) explained in section 1.4.1.1.

Briefly, the above demand function determines the extent of the customer response to any detected level of defects, delivered to the customer as average outgoing quality. Upon having AOQ level, demand function decreases its initial rate of $D_0$to a less rate, affected by the power of β and multiplied byλ.

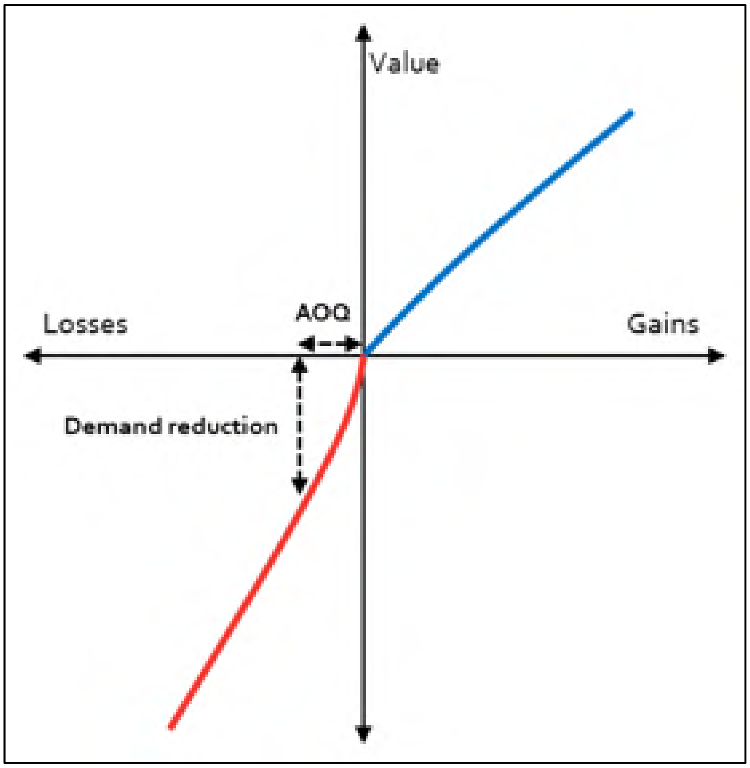

Figure 2.3 Demand function

In other words, demand function penalizes any scale of non-quality by reducing its determined rate even more than the exact amount of defects.

2.3.3 Production policies

The efficient mean of performing production policy is known as the production rate ($u(A)$) of this unreliable manufacturing system which is constrained between its zero and maximum capacity ($0 \leq u(A) \leq U_{max}$). As one of the most well-known production policies for continuous flow and unreliable systems is presented by Akella and Kumar (1986), we use this hedging point policy (HPP) in order to reach to an efficient rate of production subject to system availability and inventory levels.

$$u_t = \begin{cases} u^{max} & if\ x_t < z \quad and\ s(t) = 1 \\ D & if\ x_t = z \quad and\ s(t) = 1 \\ 0 & otherwise \end{cases} \tag{2.6}$$

The dynamic of mentioned HPP policy is illustrated in equation 2.6 such that it sets production rate on its maximum (u^{max}) when finished product inventory level is less than HPP's threshold, named z. In case of reaching finished-product inventory level to threshold level of z, the system tries to keep its maximum value of z in inventory levels by choosing to produce as much as the demand rate. According to HPP, the system stops its production in case of having excessive amounts in its finished-product inventory or failure. Due to the presented HPP policy, there are three system phases: the first phase leads the system to produce in its maximum rate to build its safety stock of z. However, such safety stock building is not linear and it depends on the proportion of defectives items, detected by the inspection and failure of the machine which affects such increase toward reaching to maximum z threshold. In the second HPP phase, the system production rate is adjusted to the demand rate in order to keep maximum amounts of safety stock z. It is to say that sometimes second phase doesn't occur if system faces any failure in phase one because it takes time again to provide the maximum finished-product inventory of z and as system failure comportment is exponential, production policy will take place between phase one and three. In the last phase (three), the system is under reparation due to corrective maintenance. In this period of operation, the system rate is null, facing finished product inventory drop with the rate of demand.

2.3.4 Quality control policies

Explained quality-dependent demand reacts to the fraction of received defective items by reducing its rate. Therefore, it is crucial to avoid facing high percentage of non-quality in delivered orders by verifying an optimized fraction of production as the quality control. Otherwise, high percentage of non-quality in the system this will result in a very low rate of demand.

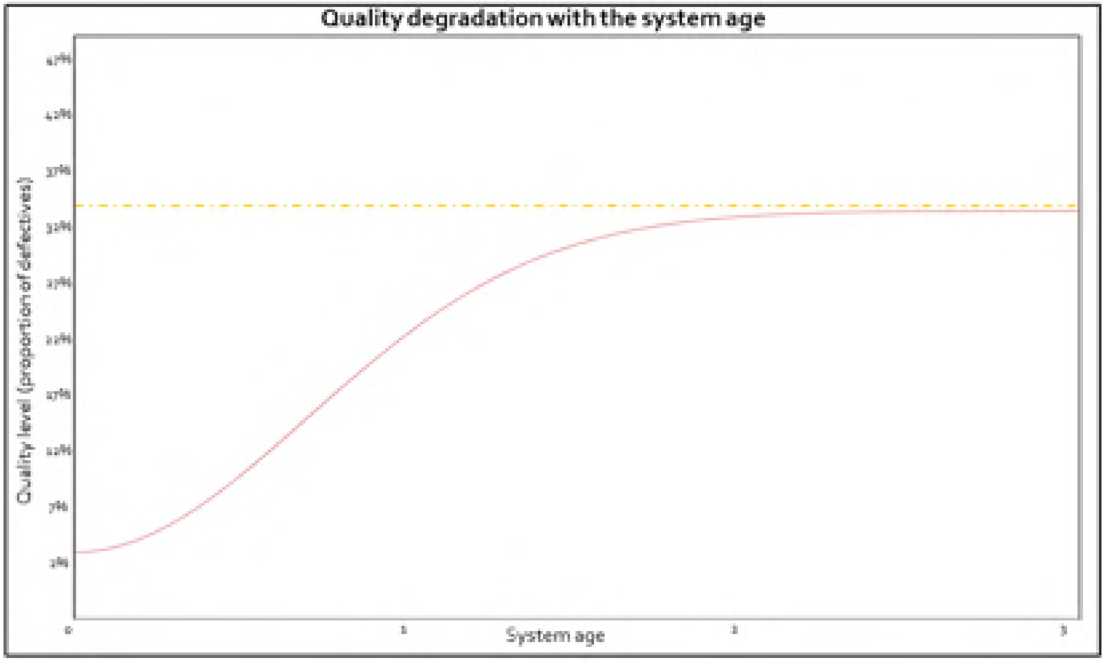

Figure 2.4 Quality degradation behaviour in correlation with the system age

Figure 2.2 is a sample of the degradation behavior of the system as fully presented in section 2.3.1. When the system is reset to its as good as new condition, the possibility of defectives is small and around 2.5%. According to the figure 2.4, as long as the system continues to produce and its age increases, quality degradation starts increasing. The rate of defects reaches its peak of around 34% when age reaches around 2. At this time, the degradation will grow very slightly and stops later. Further, the main objective of quality control policy is to reduce mentioned proportion of defectives by a dynamic and unceasing sampling unit, which takes a fraction of production output and puts any detected non-conforming part out of the system. Hence, the new rate of the defect will be less because of the operations by the quality control unit, modeled in equation 2.7:

$$AOQ = \frac{(1-f).p}{1-(f.p)} \tag{2.7}$$

It is to say that f value in equation 2.7 is free to take any fraction of the production output in the interval of $\{0,1\}$. Since one of the main two decision variables of this study is factor f, putting values around 1 will result in 100% inspection of all producing materials with high expected cost and process time. On the other hand, taking 0 or very low value of f will not be helpful in quality improvement and results as it makes the AOQ metric close to the rate of defects. Therefore, it is crucial to proceed with an optimum fraction of production output for inspection. Therefore, such a fraction of production inspection will be set to become optimal, based on the state of the production system in terms of degradation scale, failure dynamics and demand response to defectives items.

2.4 Resolution approach

The formulated problem for optimization is highly stochastic because of its failure comportment based on statistical distributions that makes nonlinear relationships of factors. For instance, CM and PM actions follow general distributions, facing random occurrences for a body of events. Also, computing a total number for approaching costs such as those of inventory and quality in an analytical approach is so challenging that makes impossible to overcome their complexity. Furthermore, it is not possible to derive the closed form analytical expressions. Thus, classical mathematical programing methods cannot be used. Therefore, an experimental approach is adopted to solve the problem by defining a simulation-based approach of optimization, which comprises a simulation model, experimental design and the response surface methodology.

2.4.1 Simulation-based approach of optimization

The simulation based approach of optimization has been widely used in the literature of manufacturing systems in recent years, combining mathematical formulation, simulation, experimental design and statistical analysis such as regression and response surface methodology. This optimal strategy is used in the work of Gharbi and Kenné (2000) and Bouslah, Gharbi et al. (2018) which are highly related to the context of this study. Mentioned approached is consist of below steps to proceed:

- Step 1- Problem formulation: The optimal solution is introduced by two factors: the finished product level Z to maintain and the fraction of unceasing production inspection

F. In order to develop this optimal strategy and maximizing average net revenue (ANR), following optimization problem is solved with its objective and constraints:

$$Maximize \qquad ANR\ (Z,F) \tag{2.8}$$

$$ANR= \quad \frac{\int_0^T (pri.D)}{T} \left\{ \left[C_{inv} * \frac{\int_0^T (U_t - D)}{T} if\ u_t > D \right] + \left[C_s * \frac{\int_0^T (D-U_t)}{T} if\ u_t < D \right] + \left[C_{ret} * \frac{\int_0^T (AOQ*D)}{T} \right] + \left[C_{isnp} * \frac{\int_0^T (U_{insp})}{T} + \left[C_{nq} * \frac{\int_0^T (p*u_{insp})}{T} \right] + \left[C_{rep} * \frac{\sum B}{T} \right] \right] \right\}$$

$$Subject\ to: \qquad 0 \leq F \leq 1$$

- Step 2- Simulation modeling: A combination of a discrete and continuous simulation model is built and modeled, using ARENA Simulation software that utilizes SIMAN simulation language along with Visual Basic for Applications (VBA). In this simulation experiment, continuous aging of the production system, increase of the defectives proportion and inspection quality control policy which results in AOQ metric are implemented beside failure of the system and its corrective maintenance actions, finished product inventory control policy and responsive demand nature. In this step, inputs of the system are considered as finished product inventory threshold (Z) and a fraction of unceasing inspection in quality control (F) which result in gross revenue as the output of the simulation model.

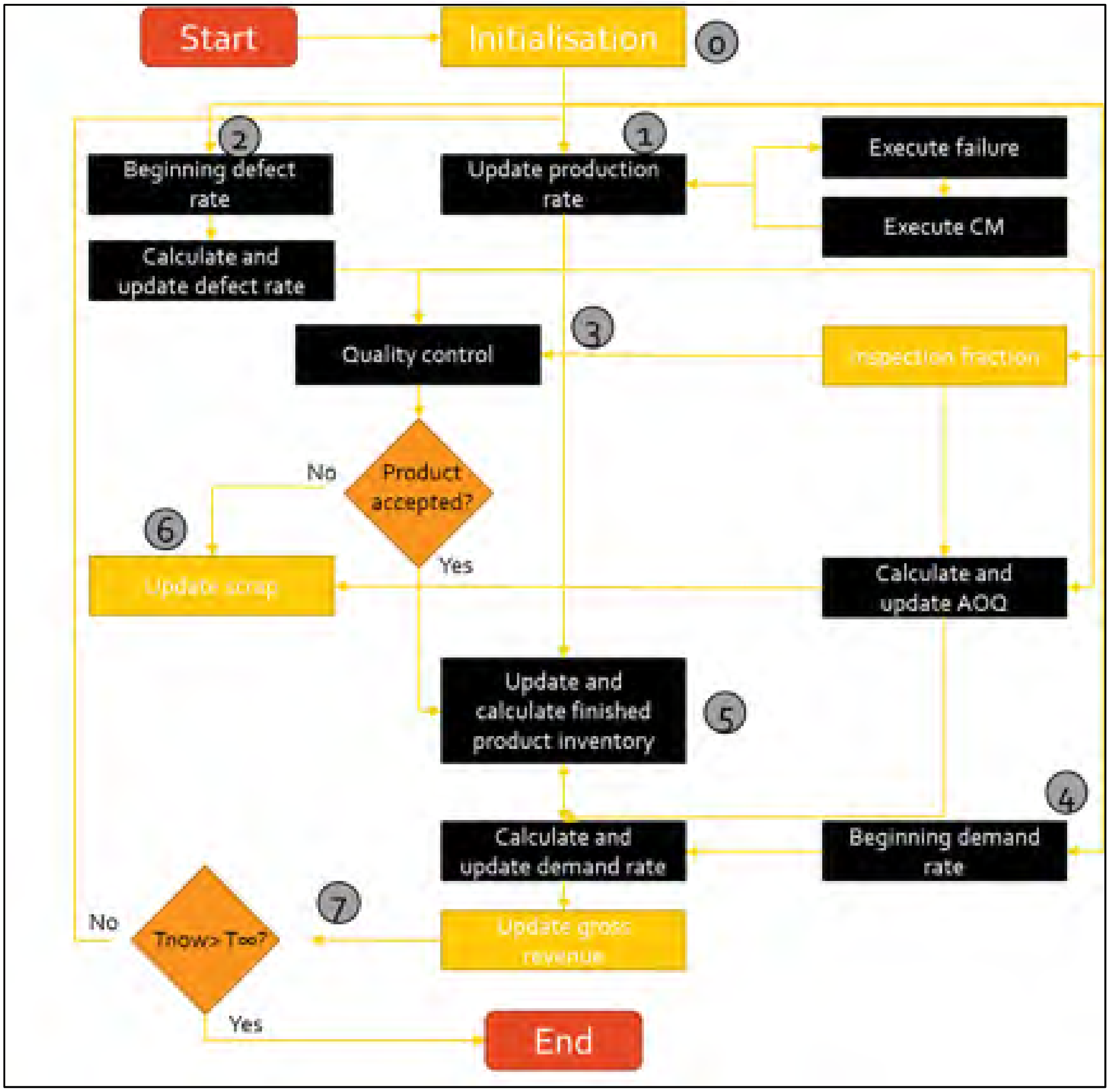

Figure 2.5 Implementation logic chart of the joint control policy of production and quality

Figure 2.5 illustrates all steps of the simulation model in terms of implementation. In block 0, It allows initializing all the variables of the model such as decision variables (Z, F), demand rate, maximum production rate (Umax), average times of breakdowns/repairs (MTTF, MTTR). This step sets progress over time for the integration of cumulative variables. In block 1, the production rate of the system is getting control, considering failure and corrective maintenance actions of the system. Further, this block communicates with block 5 to completely receive needed information about HPP and the optimized rate of production. Block 2, proceeds for calculation of quality degradation with regard to the age of the production system. The proportion of defects is the output of this block which communicates with block 3. By taking a fraction of production rate to verify, block 3 updates AOQ value. In this block, verified parts get separated into finished product inventory or become scrap. The output of this module in the number of scraps will be used for calculating net revenue function. Block 4, uses the updated value of AOQ from previous module and proceeds for generating next demand rate according to received quality level of the client. This block determines all dynamics of responsive demand and sends its output (revised demand rate) to finished product inventory (block 5). The main task in block 5 is calculating a real-time inventory level of the finished product, regarding demand rate, production rate and incoming stream of good products from block 3. Scrap module in block 6 receives all rejected parts from customer according to AOQ and also those of non-conforming parts from quality control section (block 3). The output of this block will be used in net revenue calculations in the main function. Finally, block 7 does run-time control of the simulation by verifying predefined run-time of the system (T_{∞}) with current simulation time (T_{now}).

- Step 3- Optimization: In this step, using STATGRAPHICS software, first the scale of experiment gets defined which is consist of experimental space of independent variables (Z, F) and the number of total experiments to execute. Next, obtained results of the dependent variable (net revenue) will be verified with defined values of independent variables as inputs of the experiment, using analysis of variance (ANOVA) and Response Surface Methodology. Accordingly, effects and quadratic effects of main factors will be examined by ANOVA to see if they have significant interactions with the main function (dependent variable) and later, response surface methodology determines the relationship of main significant factors on total net revenue. In such way, optimal values of the design factors and optimal net revenue will be estimated with pre-defined percentage of uncertainty.

2.4.2 Simulation model validation

In order to confirm that the defined simulation model portraits precisely the system under study, dynamics of production, quality and responsive demand are graphically in figure 2.6 to find out if simulation runs correctly coincide according to designed equations of demand, Hedging Point Policy, quality degradation and Average Outgoing Quality (AOQ).
The first part of the figure above represents tracking of the evolution of the system quality degradation in relationship with the system age. As long as the system is on, its possibility of defectives heads up and this remains constant in correction maintenance periods. As soon as repairing the system, defect rate is reset to its initial value, which confirms as good as new assumption of CM actions in terms of maintenance. By tracking system quality degradation, the demand rate keeps lowering its rate in order to penalize production system for mentioned degradation. Note that demand amounts stay unchanged during CM actions and reset to its initial value as soon as the system is repaired. As it is illustrated in the figure, the production rate is changing following HPP assumptions. Since the finished product inventory has reached its threshold, the production rate follows demand values and adjusts itself by some minor reductions in a periodic review manner. Mentioned minor production drops are pointed on the graphic. Also, the production rate is well following breakdowns by turning to zero and this immediately reacts to system repairs and available time by setting maximum capacity of the system on production as finished product inventory has dropped from the Z level.

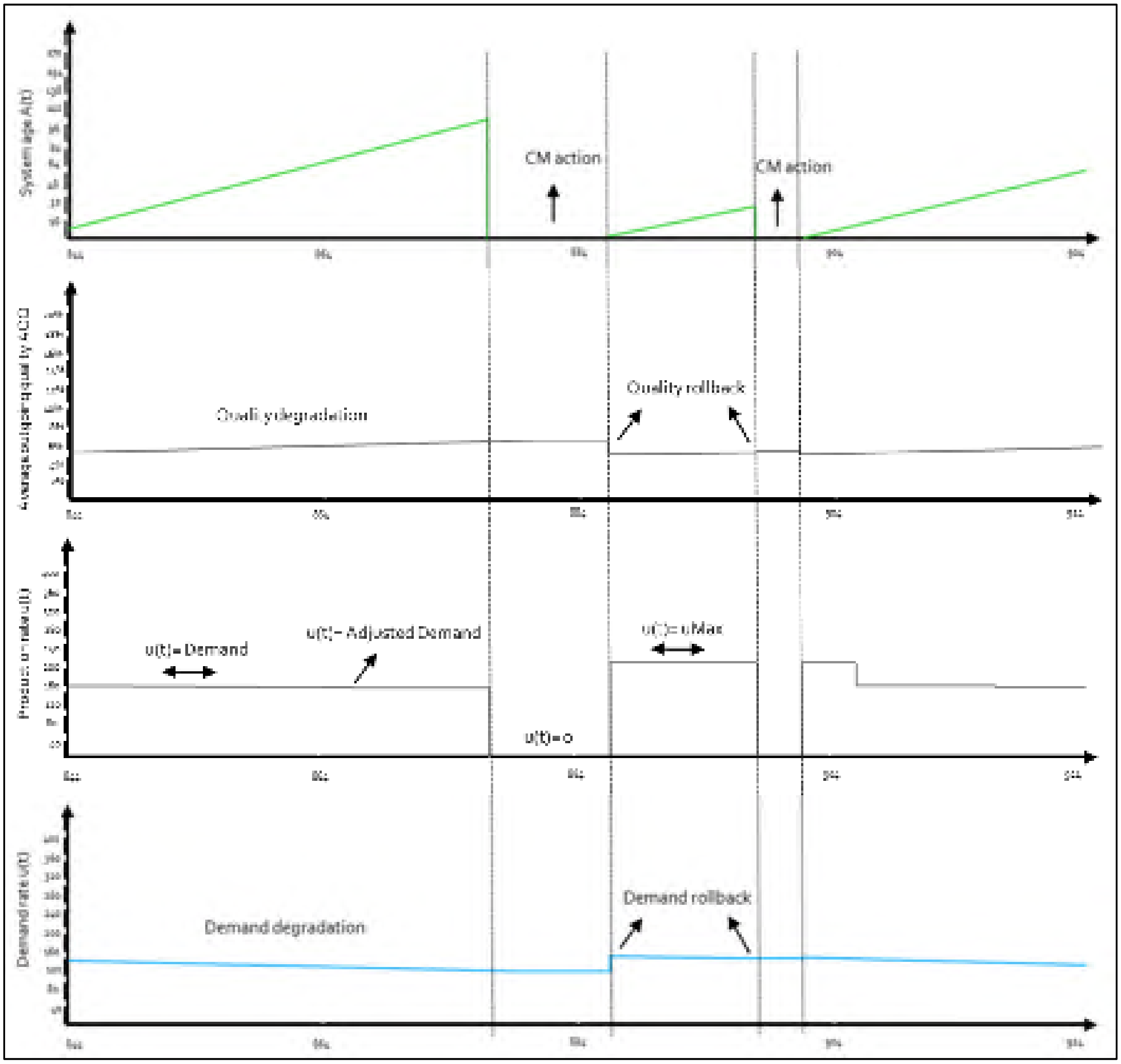

Figure 2.6 Evolution of system age, AOQ, production rate and demand rate during the simulation run

2.5 Experimental Design and Response Surface methodology

In order to illustrate how the designed resolution approach functions with data, a numerical example is presented in this section. Furthermore, a sensitivity analysis is done to give better insights into the dynamics of optimal production and quality control policies, dealing with the responsive nature of demand.

2.5.1 Response surface methodology and numerical example

We have performed experiments for different possible combinations of decision variables (Z, F) and the observed behavior of the response, which is the total net revenue, has been verified. In order to consider interactions of variables, two decision factors are varied at three levels each. Therefore, for a complete experiment, this has led to performing 3^2, or 9 tests. For better accuracy and ensuring that the steady-state is reached in the simulation run, 4 replications are performed, leading to a total of 36 tests of 240 000 time units of time (hour) each that are simulated with Arena simulation software. Note that the order of the experiments is entirely random. The inputs used to calculate the total net revenue and parameters of the simulation are shown in the table 2.1 as below.

Table 2.1 Numerical example of the experiment

U^{max}	D_0	P_0	Pr	MTTF	MTTR	C_{inv}	C_s	C_{ins}	C_{rej}	C_{nq}	C_{cm}
190	150	0.075	100	30	10	2	50	10	5	400	1000
				Exponential							

Responsive demand function is tailored with $P_{0}=$ 0.075, γ_q= 2.0, λ_q=2*10^{-2} and $\eta = 0.315$. Therefore, the defect proportion is implemented in a way that produces the minimum possibility of defectives (7.5%) when the machine is repaired or new. Further, according to below, without any fraction of quality inspection (if F, as a decision variable is equal to zero) this proportion will reach no more than 39% when the machine is aging, making sure demand function has always positive amounts.

$$\lim_{t\to\infty}\left(0.075 + 0.315\left(1 - e^{-t^2}\right)\right) = 0.39 \qquad (2.9)$$

By using exponential failure behavior in this study, we have disregarded any relationship between operations and quality/reliability of the system. Different levels of the decision factors (F, Z) used in the experiment design are presented in the table 2.2 as below:

Table 2.2 Levels of decision factors in the experiment

Factor	Low	Middle	High
Factor_A (F)	0,05	0.1	0,15
Factor_B (Z)	250,0	375,0	500,0

According to the ANOVA analysis of fitting models for all acceptance number, the linear and quadratic effects of the factors (F, Z) and their interactions with each other are significant for the response variable at a 0.05 level of significance. As below, figure 2.7 illustrates the Pareto chart of standardized effects when the acceptance number is equal to 2.

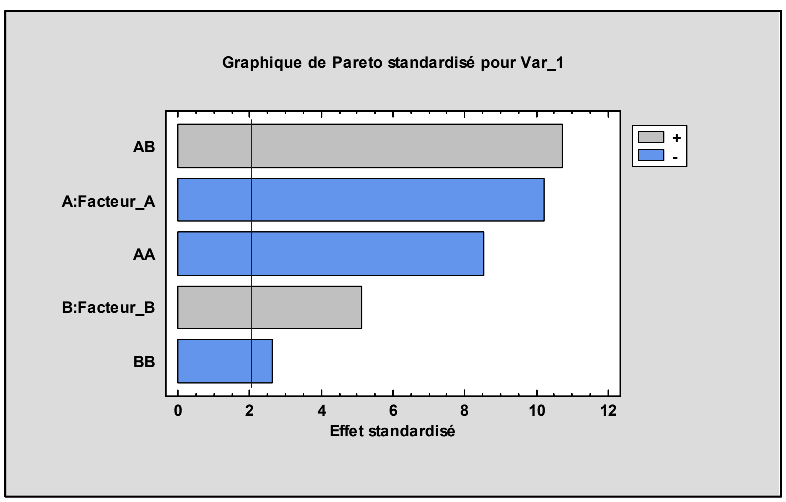

Figure 2.7 Pareto chart of standardized effects

As a statistical measure of determining estimation power, R-squared of this experiment is equal to 98.64 percent with Standard error of estimate = 173,063 and Average absolute error = 131,736. In addition, referring to the output of STATGRAPHICS software, and in order to find out optimal net revenue of the experiment as our main objective, respond surface function is equal to below:

NetRevenue = 7560,24 + 16046,5*F - 1,06708*Z - 209152, *F^2 + 92,7959*F*Z-0,0160131*Z^2

Accordingly, the response surface equivalent to this function is shown in the figure 2.8:

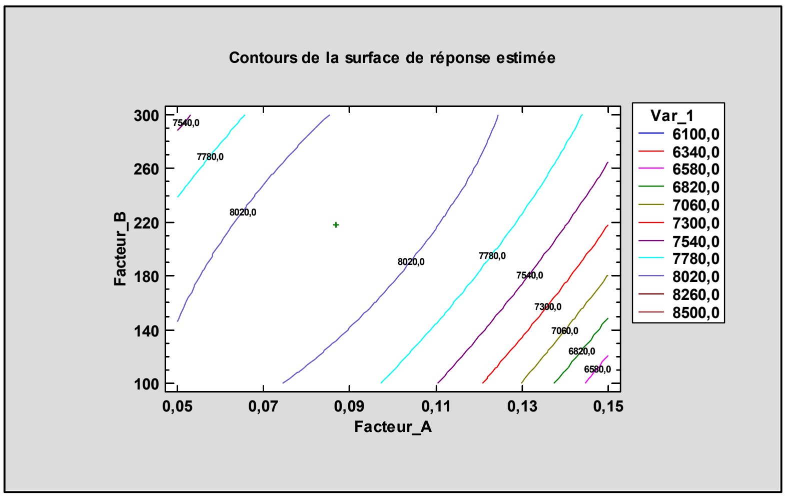

Figure 2.8 Estimated respond surface contours

The total maximum net revenue obtained from the above quadratic function is equal to \$ 8139.57 with the optimal production parameters of F=8.66% and Z=217.57. In other words, the production system has to consider an inspection plan with a complete verification in 8.66% of its output and holding 217.57 of its finished product stock as HPP threshold to be able to reach an average 8139.57\$ per time unit. As it is traceable on the figure above, there are several local maximums around the global optimum point.

2.5.2 Sensitivity analysis

In this section, sensitivity analysis by modifying the parameters of the model (Sensitivity of demand, cost of no-quality, cost of shortage, cost of inventory and cost of inventory) is conducted to verify how such changes affect two principal decision variables of the model (F, Z) that determine production and quality policies. Therefore, seven series of experiments are done to find out how the optimal control parameters (F*, Z*) react to newly defined conditions of the model parameters. In other words, this sort of sensitivity analysis also shows the functionality of the proposed resolution approach in case of having different system parameters.

Table 2.3 Sensitivity analysis of parameters

Sets	Z	U_{max}	F %	D	P	MTTF	P_{ri}	C_{ins}	C_{inv}	C_s	C_{nq}	λ	ANR
Basic	**247,27**	19	**11,95 %**	150	7,5 %	30	100	10	2	50	400	2.25	**8110,53**
	290,59	19	18,03 %	150	7,5 %	30	100	10	2	50	400	**4**	7615,02
2	198,29	19	6,25 %	150	7,5 %	30	100	10	2	50	400	**0,5**	8888,37
3	286,64	19	16,4 %	150	7,5 %	30	100	10	2	50	**430**	2,25	7875,05
4	210,63	19	7,82 %	150	7,5 %	30	100	10	2	50	**370**	2,25	8354,24
5	294,86	19	7,51 %	150	7,5 %	30	100	10	2	**55**	400	2,25	8118,74
6	209,73	19	17,58 %	150	7,5 %	30	100	10	2	**45**	400	2,25	7766,75
7	136,71	19	1,5 %	150	7,5 %	30	100	10	**3**	50	400	2,25	7824,92
8	290,09	19	17,15 %	150	7,5 %	30	100	10	**1**	50	400	2,25	7986,21
9	155,84	19	1,61 %	150	7,5 %	30	100	**15**	2	50	400	2,25	7924,92
10	297,98	19	17,9 %	150	7,5 %	30	100	**5**	2	50	400	2,25	8386,21
11	25,66	19	**0%**	150	7,5 %	30	100	10	2	50	400	2,25	6360,17
12	714,78	19	**100%**	150	7,5 %	30	100	-10	2	50	400	2,25	4583,79

All results are brought in Table 2.3 in a way that the responses of the optimal decision variables (F*, Z*) and the optimal expected average net revenue (ANR) can be traceable in relationship with modified, highlighted model parameters. Any reaction of decision and dependent variables is highlighted by green and red which refers to increase or decrease in order.

- Variation of demand sensitivity (λ): By increasing λ factor in demand function, its sensitivity to the proportion of delivered nonconforming parts raises and demand penalizes the production system more by dropping its next orders. In this case, the system has tried to increase its inspection around 7% to produce less non-conforming parts and backlog inventory is increased in a way to compensate delays of inspection to avoid shortages. On the contrary, the system finds less restrictive demand behavior and tries to decrease its inspection measurements along with reducing backlog levels in order to slash the cost of inspection and inventory. As a result, average net revenue has increased.
- Variation of cost of non-quality (Cnq): When production system faces with more cost of non-quality, related to return and scrap of non-conforming, delivered parts it tries to invest more on inspection to avoid these excessive penalties. Since such action spends more process time and may face shortages in finished product inventory, the system tries to increase its backlog stock of Z. In a more convenient state, in terms of non-quality costs, the system reduces its investment in quality control and inventory to bring more net revenue through costs savings. As a result, average net revenue is bringing more profits than the basic set.
- Variation of cost of shortage (Cs): When the cost of shortage is higher than normal, the system tries to bring more stock in its inventory to avoid expected shortages. Consequently, with the aim of bringing more products into the inventory, the system reduces its inspection plan. However interactions of F and Z is positive in Pareto chart and this has been positive in other sensitivity analysis cases, in this set, the negative effect of the factor A which has the second strong effect is needed, leading the system to maintain its net revenue level. In contrary, as the system intends to reduce its backlog investments and find it possible to have more restricted quality actions. In consequence and according to Pareto chart, the increase in F measurements has caused negative effects on net revenue.
- Variation of cost of inventory (C_{inv}): When the inventory cost increases, the system tries to reduce its inventory levels by decreasing its Z and the optimal sampling plan becomes reduced in order to avoid shortages. On the other hand, the system looks for

more inventory levels and finds possible to have better quality investments as inventory levels would compensate shortages.

- No inspection plan (F=0): In order to better understand the effect of responsive demand on the net revenue function, in this case, control policy is omitted. Consequently, the system has dropped its backlog inventory as it finds no major shortages. Also, the increase in cumulated no-quality costs due to having no quality control has caused a complete net revenue drop in this case.
- 100% inspection plan (F=100): In contrast with the above case, the effect of a complete 100% inspection is examined. In this situation, inspection delays have made production system to have a massive buffer of Z to be able to control shortages. Results in terms of net revenue are even worse than the previous set. This implies the effect of shortages in lost sales.

2.6 Comparative Study with periodic time bases

In previous parts, it was assumed that demand instantly reacts to any amount of defectives by decreasing its order rate. This assumption does not seem to reflect real-life cases because there is always a delay for non-conforming part verifications and reacting to that. Therefore, in this part a delay in demand response is considered such that demand reacts to the average of received non-conformation in periodic time bases (***ΔT***) as below:

$$AAOQ = \frac{\int_0^{A_p} AOQ}{\Delta T} \qquad (2.10)$$

Accordingly, demand function will react to such new level of defectives in equation 2.11 as below:

$$D = D_0(1 - (\lambda * AAOQ^{\beta})) \qquad (2.11)$$

The dynamic of such periodic functionality in the simulation plan is presented in the figure 2.9. According to this, demand will react based on the average value of AOQ in every period of ΔT and determines its next order as a fixed rate for the next period. In this way, expected real-life demand delays in terms of reactions to the quality are considered by watching levels of average outgoing quality in fixed periods of time. It is to note that the efficiency of this approach in terms of net revenue improvements should be studied during system available time. If determined periods violate availability of the system, the random number of breakdowns will affect any conclusion about the efficiency of this case. Therefore:

$$\Delta T \leq MTTF \tag{2.12}$$

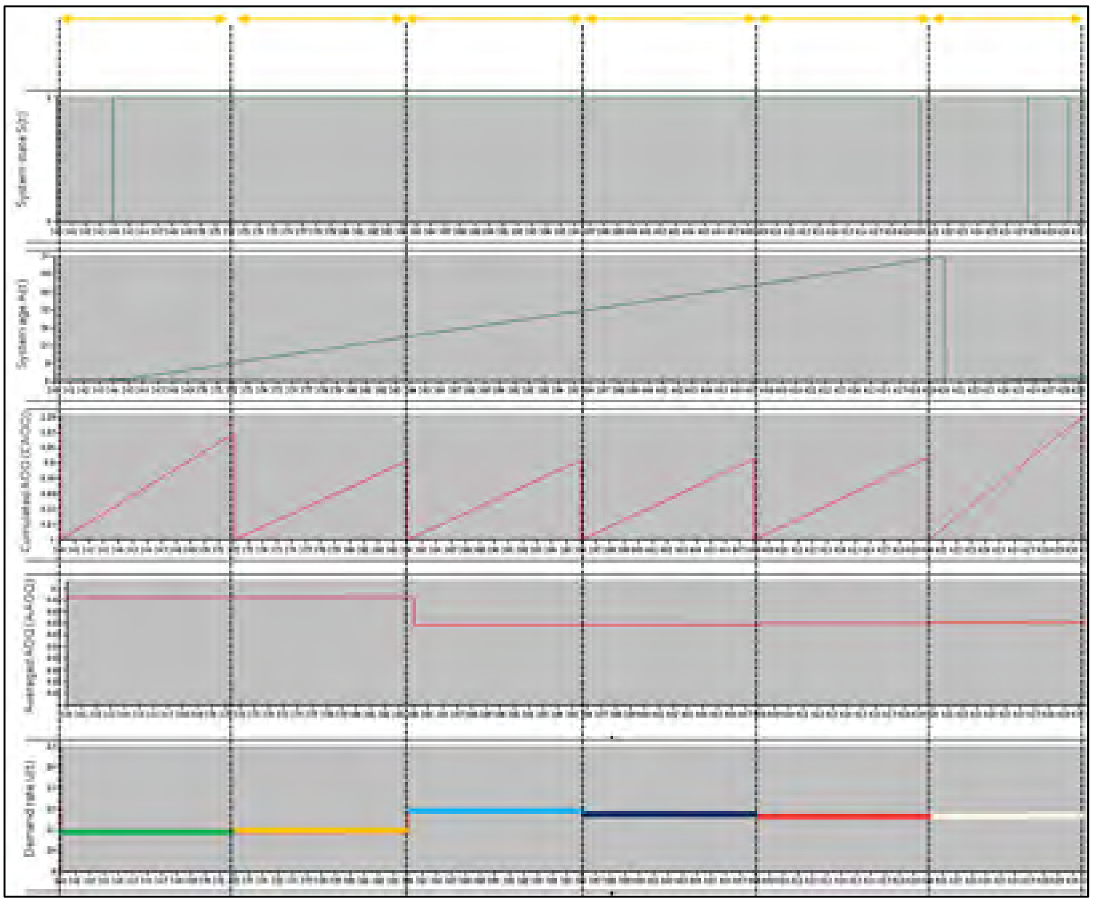

Figure 2.9 Evolution of the simulation run in periodic time bases

An experiment design is conducted, considering all assumptions of section 2.5. Hence, numerical data is presented in table 2.4:

Table 2.4 Numerical example in the periodic review case

U^{max}	D_0	P_0	Pr	MTTF	MTTR	C_{inv}	C_s	C_{ins}	C_{rej}	C_{nq}	C_{cm}
190	150	0.075	100	30	10	2	50	10	5	400	1000

Quality-dependent demand function is tailored with $P_0 = 0.075$, $\gamma_q = 2.0$, $\lambda_q = 2*10^{-2}$ and $\eta = 0.315$. To reflect real-life situation, ΔT is considered to be 6, 12 and 18 hours.

By implementing the experiment design on STATGRAPHICS software for three cases with differentΔT, optimal values are obtained. It is to mention that in order to keep the experiment comparable, the level of this experiment in terms of factors has remained intact as below.

Table 2.5 Different levels of the decision factors

Factor	Low	Middle	High
Factor_A (F)	0,05	0.1	0,15
Factor_B (Z)	100,0	175,0	250,0

Obtained results are compared with the instant case, discussed before to find the effect of considering time bases.

Table 2.6 Comparative analysisi of ANR response in correlation with ΔT increase

Sets	Z	U_{max}	F %	D	P %	MTTF	ΔT	P_{ri}	C_{ins}	C_{inv}	C_s	C_{nq}	λ	ANR
Basic	171,2	190	7,11	150	7,5	30	**6**	100	5	2	500	400	2.25	**8170,04**
1	179,9	190	7,27	150	7,5	30	**12**	100	5	2	500	400	2.25	**8289,34**
2	203,37	190	9,63	150	7,5	30	**18**	100	5	2	500	400	2.25	**8568,4**
3	247,2	190	11,9	150	7,5	30	**Instant**	100	5	2	500	400	2.25	**8110,5**

As it is illustrated in the table 2.6, augmenting periods of time will provide more time to respond to demand, making the system to bring more parts to sell in every period of time. In this way, as long as time base raises, system inspects more and keeps more amount of buffer in its inventory. Hence, the mentioned increase in F and Z influence the net revenue function in a positive way as it is illustrated in below Pareto chart. Comparing time base units with discussed instant case proves mentioned interpretation in a better way.

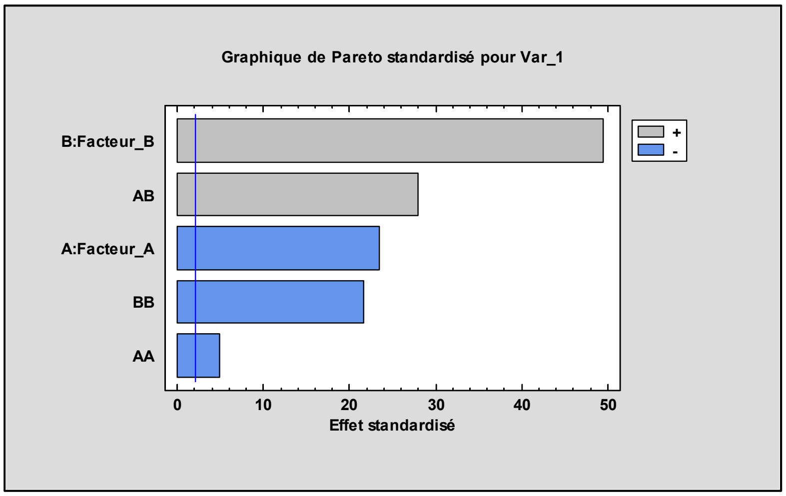

Figure 2.10 Pareto chart of the second case on standardized effects

2.7 Conclusion

The joint policies of production control and statistical quality control measurements have not been enough studied in the presence of quality-dependent demand, which is the essence of customer and vendor relationship. Hence, this study contributes to research on the joint design of production and quality control in unreliable manufacturing systems, where the production control policy comprises of a modified hedging point policy and quality control is performed by unceasing inspection plan. A mathematical model has been developed to explain the dynamic of production, inventory, quality control, degradation and demand, and system constraints were defined to calculate the overall incurred cost. Because the optimal solution cannot be reached due to the stochastic complexity of the model, a resolution approach based on experimental Design with simulation and Response Surface methodology is proposed to optimize hedging point level and inspection fraction. By performing experiments and through sensitivity analysis, an important impact of integrated inventory levels and inspection fractions on average net revenue function in the existence of quality-responsive demand and its penalty function has been proved. An interesting outcome of this study, when customer's demand faces delays, it leads to more net revenue due to the functionality of the system in response to average outgoing quality. Future research could be undertaken to investigate the studied context in the presence of operation-dependent degradation and preventive maintenance actions. Another area for future consideration is how to deal with dependent demand to other factors such as price and deterioration.

CHAPTER 3

The policy of integrated preventive maintenance, quality and production, Subject to quality-dependent demand and dynamic pricing

3.1 Abstract

With the aim of slashing unavailability costs of production in the presence of quality-dependent demand, this chapter addresses the problem of preventive maintenance policy, integrated with quality and production control policies. Further, since real-life production systems may be subjected to more complex failure consequences, particularly caused by their operation procedures, we considered the system's reliability and quality degradation as an operation-dependent factor. In other words, we deal with of an unreliable production unit with quality degradation caused by its operation duties and a quality-dependent demand, which responds to the delivered quality of finished products. In addition, different levels of quality in the real-life will make manufacturers or retailers to have discounts and promotions on their inventories, persuading clients to keep buying and not losing corporate market shares. Therefore, in order to reflect such dynamic of pricing that deals with levels of quality, pricing policy is built based on prospect theory assumptions in individual's behavior. Applying hedging point policy that maintains a certain level of the finished product in the inventory, will make an under control production rate. This results in less cost of shortages during the stop time of production such as maintenance and breakdown and fluctuation in demand rates. The principal objective of this study is to maximize the total profit of the manufacturing system by determining a proper point to activate preventive maintenance and setting a certain amount of safety stock and a fraction of production output, for quality control. By applying response surface methodology based on extracted simulation data, a simulation-optimization approach for the developed stochastic mathematical model is designed. This study is developed in two different cases, in the first one, the effect of preventive maintenance policy on production availability improvement is

practiced while in the second case, the preventive maintenance interactions on quality and dynamic pricing are taken into account. Results of the study clearly show a significant difference in preventive maintenance application in terms of average net revenue, compared with the non-applied case. Furthermore, it is shown that the use of preventive maintenance policy can play an important role in the reduction of quality control resources in both two different scenarios.

3.2 Introduction

The integration of production planning and preventive maintenance with quality control using control charts has been widely studied in the past. Ben-Daya and Makhdoum (1998) have studied the effect of a variety of preventive policies in a joint optimization scheme, comprising of economic production quantity and control charts. As a result, PM actions reduced out of control status rate of the system. A year after, Daya (1999) developed the model by adding a general probability distribution in the context of increasing hazard rate and in 2000, the work has been extended by considering that preventive maintenance is able to affect the increasing hazard rate, previously introduced (Ben-Daya and Rahim 2000). Yeung, Cassady et al. (2007) brought an age-based preventive policy along with an initial control chart idea. With the goal of getting maintenance management and statistical process control closer to each other, Zhou and Zhu (2008) have worked on the integration of these two concepts by use of cost analysis and grid search approaches for optimizing. In another study done by Chen (2011) and with the aim of considering a multi-state Markov chain which is time-dependent for probability transitions and aging of the system, the maintenance policy is not state-dependent. By relaxing multiple failures among system degradation, Liu, Li et al. (2013) developed a condition-based maintenance policy, specified for systems with stochastic degradation process. This work aimed to find the optimum maintenance threshold, maximizing production system availability. By developing ten scenarios for the production process, Yin, Zhang et al. (2015) have built an integrated model with the regard of statistical process control and maintenance decision making by taking delayed monitoring policy into account. After reviewing all related literature, it comes to light that there are very little models in this context that simultaneously integrate production, preventive maintenance, and quality control with sampling plans. It is important to mention that this lack of research is in contrast with the reality of industry since sampling plans have been widely used there for a long time to reduce excessive costs of 100% control (Montgomery 2007). Note that Sampling plans have very specific statistical properties (Schilling and Neubauer 2009). These kinds of statistical properties directly affect the overall performance of manufacturing companies such as level of perceived quality by customers, which is referred as an average outgoing quality, in hand inventory, cost of quality and productivity (Cao and Subramaniam 2013). One of the attempts in this area of research is done by Bouslah, Gharbi et al. (2016) to fill the literature gap by assuming a deteriorating production process which despite regularly considered production systems is not statistically in-control and therefore it is not possible to apply control charts over that. This article has compared two different CSP-1 sampling plans in the existence of preventive maintenance for an unreliable production system with quality degradation. In another article, by the same author Bouslah, Gharbi et al. (2016) have again supposed all three major aspects of preventive maintenance, production, and a sampling-based quality control system in the context of degradation of the manufacturing system. In this study, CSP-1 is replaced with an acceptance sampling plan and a constraint for average outgoing quality is considered to reflect better essence of customer and manufacturer relationship. The result of this study has illustrated a 20% reduction in cost due to the proposed integrated model.

Considering vast markets that are full of products and rivals with narrow product differences and very close pricing patterns, companies have to gain competitive advantages to attract customers. In this context, manufacturers of products and services must comprehend to have marketing plans that can provide more value to their customers who are exposed to other competitors (Armstrong, Adam et al. 2014). In this intensive and complex competition era, customers are in touch with product quality and price very repeatedly which leads them to have a reference process of each product. This will be explained as internal standards that are made based on previous prices and user experience of customers to evaluate new pricing schemes (Kalyanaram and Winer 1995). In other words, customers have an expectation of products of each company such as quality and price. A psychological trade-off for customers is defined as perceived value. This back-and-forth happens in the mind of customers between what they could gain (quality) and whatever they lose (price) or sacrifice in any purchase (Monroe and Chapman 1987, Monroe 2002). According to Levy, Weitz et al. (1998), every customer considers its merchandise purchasing condition as an equation that value=quality/price. Therefore, decision-makers are able to affect this equation with the aim of raising customer perceptions by increasing quality and keeping the same price. Porter and Helm (2008) have tried to evaluate such an equation by reducing price and keeping the same quality. For instance, IKEA has taken the advantage of this novelty in its advertising brochure by claiming “new lower prices, same great quality” to keep quality and drop the price or claiming “improved sound quality, same price”(Callarman and Hamrin 1984). In a comprehensive research, conducted by Yoon, Oh et al. (2014) to verify which of above-mentioned means are more useful, five particular works are taken into account. The first study has illustrated that perceptions about the reputation of brand influence such preference among price and quality as the promotion type. The second study has found that the level of value perception by customers is effective in this balance. In the third one, the brand image of the retailer about reflecting luxury and prestigious (case of Nordstrom .co) or being cost-saving and thrifty (case of Walmart) are significant. Level of price perception by the customer is considered in fourth work and the last study implies the quality level has an independent moderating effect on store image rather than perceived value. This paper concludes however enterprises tend to increase customer value perception through both price and quality means, all five research results are suggesting that customers are better affected by price promotions rather than high qualities (Yoon, Oh et al. 2014).

According to the fact of customer reference points, retailers widely use price promotions in different ways and for a variety of objectives and among them, the most fundamental reason is to provide more profits for companies (Greenleaf 1995). By defining price promotion strategies based on prospect theory applications in customer reactions patterns, Greenleaf (1995) has examined a series of interacting factors in order to maximize corporate profit.

To the best of our knowledge, in all previous research involving PM, quality and production integration, the demand rate is considered to be constant despite the fact that product quality and price affect its demand (Banker, Khosla et al. 1998). Maiti and Giri (2015) have approached price and quality dependent demand with no PM action in a closed-loop supply chain where demand varies with market price and quality output of the system. In another study, done by Xie, Yue et al. (2011) however the demand is not responsive to quality and price, it is assumed to have it uncertain and risk-averse based on suggested behaviors of prospect theory. This study has extended assumptions of Banker, Khosla et al. (1998) about demand, depending on quality and price. Based on prospect theory assumptions by (Kahneman 1979) people have loss aversion attitude. In other words, they are more afraid of losing values rather than the joy of gaining the same value. A similar problem formulation is applied in the work of Hsieh and Dye (2017) in order to build a price-dependent demand function for an optimal dynamic pricing model which considers deterioration. In this study, reference prices are considered as adaption levels, which are relative to a neutral reference point in the mind of customers. Any change in prices toward more or less than reference prices are accounted as perceived gain and loss that results in intentions of more or less purchase. Further, following three different customer demand scenarios of risk-averse, risk-neutral and loss seeking, responding to difference in current and reference price, Hsieh and Dye (2017) established a dynamic pricing strategy. This approach has applied prospect theory assumptions in terms of the way individuals convince loss.

3.3 Problem statement

In this study, as it is illustrated in figure 3.1, an imperfect production unit is subject to aging that leads the system to augmentation of both defectiveness percentage (quality degradation) up to a level and failure rate (reliability degradation). There is a constant and infinite flow of raw material as the input of the production and system will never face a lack of raw material during its operation. As clock time age is not a realistic consideration of production systems in real-life contexts because it does not reflect the extent of production system usage differing between its maximum capacity and idle time, age of this manufacturing unit is a continuous variable depending on its operation, representing the cumulative number of produced items (Cassady and Kutanoglu 2005). This production unit has a discrete state cycle in terms of its status (status variable) in each time, taking values of $\{0,1,2\}$. Briefly, if the system is out of order and under corrective maintenance, the status variable is equal to 0. In times of being under preventive maintenance, the status variable is equal to 2 and the value of 1 is when the machine is available for production. Intended production line supplies a quality-dependent demand, which has a maximum demand rate in case of having a perfect production without defectiveness. The demand responds to the level of defectiveness by decreasing its value rate upon verifying average outgoing quality (AOQ) metric which is the overall quality output of the system after affecting quality control policies. Due to the existence of the quality-dependent demand in this model, the production line cannot satisfy its demand rate except having control activities of quality. To keep the quality level of production output ensure a high rate of demand, a quality control unit with a continuous sampling scheme is taken into account. This section verifies a fraction of the system output $0 \ll f \ll 1$ and proceeds to decrease defectiveness possibility by removing observed defectives from the system without rectification process. The customer will examine all delivered items and non-complaints will be returned and discarded from the system according to AOQ metric and without rectification. Unsatisfied demand in a time of corrective or preventive maintenance will be considered as a lost sale. The objective is to maximize the total net revenue function, including average gross revenue, the average cost of inventory and shortage, the average cost of inspections, the average cost of PM and CM and the average cost of no-quality product returns.

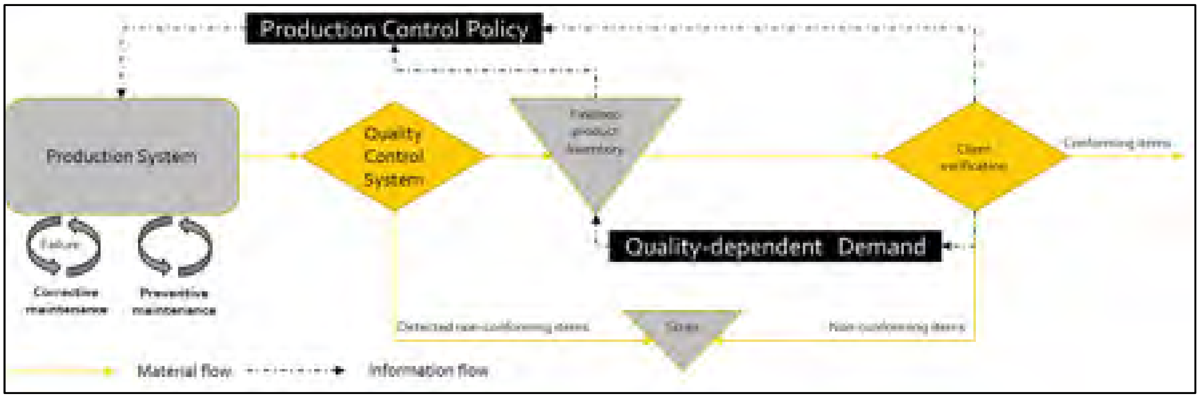

Figure 3.1 Manufacturing system subject to degradation, responsive demand and prevantive maintenance

3.4 Quality-dependent demand

In the present paper, we have used fundamentals of prospect theory by Kahneman (1979) to generate a penalizing function in the presence of defectiveness in quality of finished-products. Risk-averse attitude says that people think in terms of expected utility relative to a reference point (e.g. current wealth) rather than absolute outcomes. Therefore, if customers have loss aversion attitude (according to prospect theory assumptions) and find out the current quality is less than its reference-quality or any expected level, it would result to decrease their purchase more than the time they increase their purchase when they find the price less than their in-mind reference price as equation 3.1 suggests:

$$D = D_0(1 - (\lambda * AOQ^{\beta})) \tag{3.1}$$

Effectively, presented demand function simulates risk-averse respond of the customer by watching levels of average outgoing quality as the delivered rate of defects from the production system to customer. By a continuous AOQ level verification, demand function reduces the initial rate of D_0 to some lower levels, considering β and λ values. Mentioned values are benchmarked from empirical work of Tversky and Kahneman (1981).

Furthermore, reliability of the production system has a direct effect on amounts of demand since after each maintenance action either it is corrective or maintenance, state of the system rolls back to its as good as new condition and because such state has better quality output, it results to a higher amount of demand rates. Hence, in every reparation, system quality level, and demand rate return to their initial values (p_0, D_0) and due to the degradation, the demand rate decreases with explained dynamic.

3.5 Demand-dependent price

In the real-life, retailers set different price based on a variety of product qualities they have, called price lining. The same context is implemented for products with low moving in terms of shelf life, making price promotions inevitable in order to keep market share and get customers used to mentioned products (Armstrong, Adam et al. 2014). In the second part of this work, as much as demand drops in terms of quality degradation, the manufacturer tries to keep selling and saving its customer by reducing its price, assuming customer behavior is risk-averse. In other words, the manufacturer is considering interactive market factors such as competitors, price and quality and trying to provide a price-lining policy for its continuous quality fluctuations.

$$Pr = Pr_0(1 - \left(\lambda * \left(\frac{D_0 - D}{D_0}\right)^{\beta}\right)) \tag{3.2}$$

Regarding the above equation, price dynamics is depended to demand changes. Since this behavior reflects a risk-averse attitude, any change in demand will result more on price. In other words, the customer is persuaded to keep its relationship if the manufacturer gives more discount percentage, comparing with the occurred percentage of the shift in quality. Hence, in general, a system is assumed with quality degradation, resulting to demand reductions and price drop. In such a case, quality control measurements and PM actions play a crucial role in terms of providing an optimum operation estate, maximizing net profit. In this case, the system will continue producing until a reasonable level of price and demand.

3.6 Degradation model

By reviewing related literature in terms of degradation model, it becomes known that the quality and system availability dependency on time is repeatedly and highly overused during past years. This general assumption is not effectively reflecting real-life cases because the way of system operates in terms of production rate or its duration of idle times does not result in constant degradation rates (Van Horenbeek, Scarf et al. 2013). In manufacturing systems operations directly affect quality degradation of the system (Bouslah, Gharbi et al. 2018). It is to mention that many authors have studied the effect of operations on quality. For instance, repeatability and accuracy of robots as their significant quality deterioration element have been studied in assembly lines by Khouja, Rabinowitz et al. (1995). Also, Owen and Blumenfeld (2008) have studied this context in relation with operations pace of metal cutting procedures and surface milling. In our study, quality degradation is dependent on the age of the system. Bouslah, Gharbi et al. (2018) have used quality degradation approach in relation to an accumulative number of manufactured pieces as systems age variable. Hence, production rate better reflects how the machine is operated as it does change by any difference in the state of production systems such as speed and stops while the time-dependent assumption does not. By increasing the production rate, in most the manufacturing systems, failure possibility of machines increase and quality degradation accelerates which seems to be more realistic. Therefore, in this article, an operation-dependent approach is assumed to shape quality and reliability imperfection of the system under study. Instead of having a clock time, the age of the machine is a function of its yielded pieces. Therefore, any modification in system operation such as idle times, speed and downtimes will be taken into account of degradation.

The state of the production system unit is described by a discrete-state stochastic variable, displaying its operational situation at time t.

$$s(t) = \begin{cases} 1 & system\ available \\ 2 & prevantive\ maintenance \\ 0 & corrective\ maintenance \end{cases} \tag{3.3}$$

This discrete variable ($s(t)$) gets values of collection$\{0,1,2\}$. If $s(t) = 0$, the system is broken and corrective maintenance is set to renew its initial state status. $s(t) = 2$ refers to preventive maintenance mode, resulting in the same initial condition of the production and $s(t) = 1$ demonstrate an available system during production and degradation progress. The second variable records system`s age from the last corrective maintenance until time t, however, this age is not clock time and is referred as the cumulative number of produced parts from the last maintenance either it is CM or PM:

$$A(t) = \int_{T_m}^{t} u_t \tag{3.4}$$

Equation 3.4 calculates the age of production system between the current time and latest maintenance action time (T_m). For this reason, failure consequence of the production system will be tied to the extent of the operation, which let us proceed for preventive maintenance measurements. In this study, the reliability of the system can be described by the following Weibull distribution function:

$$\mathrm{F(A(t))} = \left(1 - \mathrm{e}^{-(\frac{A_t}{\lambda})^k}\right) \tag{3.5}$$

Above parameters of Weibull distributions in equation 3.5 could be derived from real-life data, shaping the cumulative possibility of system failure in each time unit. Applying operation dependent age function, quality degradation of the system raises during its available time ($s(t) = 1$).

$$\mathrm{p(A(t))} = \mathrm{p_0} + \eta\left(1 - \mathrm{e}^{-\lambda.A_t{}^{\gamma q}}\right) \tag{3.6}$$

Equation 3.6 represents the possibility of defectiveness in the production rate. The resulted percentage depends on the operation scale of the system, which is referred to its age ($\mathrm{A(t)}$). As the production starts and the system is in its initial condition, it has a very small proportion of defective, shown as P0. $\mathrm{P0} + \eta$ determines the peak defective proportion during the system`s on-time. This peak can be calculated as below limit sequence:

Following the formula in equation 3.6, the possibility of defectives will be bounded between P_0 and the maximum amount of the same function toward positive infinity as below:

$$\lim_{t\to\infty}\left(\mathrm{p_0} + \eta\left(1 - \mathrm{e}^{-\lambda.a_t{}^{\gamma q}}\right)\right) = P_0 + \eta_k \tag{3.7}$$

Therefore: $\mathrm{p_0} \le \mathrm{p(a)} \le \lim_{t\to\infty}\left(\mathrm{p_0} + \eta\left(1 - \mathrm{e}^{-\lambda.a_t{}^{\gamma q}}\right)\right)$

It has to be taken into account that in real-life, operations affects the possibility of machine failure that is called operation-dependent failure (Buzacott and Hanifin 1978).

The reason for choosing such degradation function with peak point is to make sure excessive proportion of defectiveness resulted from any long periods of system availability or weak quality control do not result in huge demand drops. Demand drops Such as zero or negative values does not make any sense in a responsive demand context. That is to say with no quality control policy or by experiencing longer available times of productions system, the proportion of defectives will not reach from a determined level and it is aimed in a way to have constant amounts of defectiveness in terms of percentage, after a while since the system starts its operations. Further, since this study has considered demand dynamics of a production system, dealing with manufacturing and finished-product quality control policies coming raw material of the system is assumed defect-free just to have better concentration and provide less complexity into the system.

3.7 Production policy

The production rate of such continuous flow system $(0 \leq u(A) \leq U_{max})$ is controlled by hedging point policy (HPP), presented by Akella and Kumar (1986). This policy is known as a very efficient mean of performing production control in unreliable manufacturing systems, subjected to quality degradation. HPP regulates the production rate between its zero and maximum capacity with regard to finished product inventory levels and the availability of the system. Its dynamic is summarized by the following equation:

$$u_t = \begin{cases} u^{max} & if\ x_t < z \quad and\ s(t) = 1 \\ D & if\ x_t = z \quad and\ s(t) = 1 \\ 0 & otherwise \end{cases} \tag{3.8}$$

HPP sets production rate on its maximum (u^{max}) capacity when finished product inventory level is less than HPP`s threshold, named z. By reaching the finished-product inventory level to the threshold, the system produces equal to demand rate with regard to its responsive nature to the quality and tries to keep its maximum value of z in inventory levels. It is important to mention that a variety of studies have set production rate on $\frac{D}{1-f(A)*p(a)}$ or $\frac{D}{1-AOQ}$ when inventory level reaches to z. The reason is to feed an exact amount of conforming items to the client which in this case (quality responsive demand) is not necessarily the case. The system stops its production upon passing the HPP threshold or conducting CM or PM actions.

3.8 Quality policy

As stated in the nature of quality degradation in the model under study, the proportion of the defective starts from a very small level, augments slightly and continues in an upper level until next CM or PM action arrives. For this reason and because of having a continuous degradation in quality, an unceasing quality inspection is considered to verify between 0 to 100% of production output ($0 \ll f \ll 1$). It is to mention that 100% inspection is expensive and sometimes impossible to proceed in production systems due to the nature of products such as explosive military equipment or products line constraints. Moreover, no quality inspection in the presence of responsive demand does not make any sense with the objective of such models. Therefore, implemented quality control policy in this work has to reduce the proportion of defectives by verifying a part of production output and posing any non-conforming part out of the system. According to this, a new rate of the defect will be calculated by the below equation:

$$AOQ = \frac{(1-f).p}{1-(f.p)} \tag{3.9}$$

The fraction of production inspection (f) in equation 3.9 is free to take between the intervals of $\{0,1\}$.

3.9 Maintenance policy (case one)

In the first case, the production system is subjected to an operation-based (aged based) preventive policy. According to this PM policy, the system is maintained upon break down or by getting through a determined age (cumulative number of produced parts). According to this maintenance policy, both PM and CM (corrective maintenance) roll back the system to its initial condition which is considered as good as new state. A threshold in terms of system's age conducts PM policy, denoted by m_k. Therefore, the discrete-state stochastic variable of PM can be defined in equation 3.10 az below:

$$PM = \begin{cases} No & if\ A_t < m_k \\ Yes & if\ A_t = m_k \end{cases} \tag{3.10}$$

According to the above function, the passing threshold will make the system to conduct PM policy. For the age of less than m_k, the system would experience CM actions, denoted by 0 or availability, denoted by 1.

3.9.1 Resolution approach (case one)

The formulated problem of this study is highly stochastic, dealing with statistically distributed failures of the production system and along with quality and reliability degradation, which makes nonlinear relationships of decision and dependent variables. Hence, an experimental design approach is set to answer the problem by bounding a simulation-based approach to optimization. This problem-solving methodology is comprising of a simulation model, experimental design and the response surface methodology.

3.9.1.1 Simulation-based approach of optimization

Over recent years, Simulation-based approach of optimization has been extensively employed in the literature of manufacturing systems. This methodology combines mathematical formulation and simulation in experimental design and takes advantage of statistical analysis such as regression and response surface methodology. Mentioned resolution strategy is used in the work of Gharbi and Kenné (2000) , Hlioui, Gharbi et al. (2015) Bouslah, Gharbi et al. (2018) which have strong ties with the context of the current study. Stated approached pursues below measures in order to reach to the optimized outcome:

- Step 1- Problem formulation: For the purpose of establishing an optimal strategy, the following optimization problem is formulated and solved with below objective and constraints:

$$\begin{aligned} &Maximize \qquad Net\ Revenue\ (Z, F, M\ ) \\ &Subject\ to: \qquad 0 \leq F \leq 1 \end{aligned} \tag{3.11}$$

The optimal solution is introduced by three factors: the finished product level Z to maintain, the fraction of unceasing production inspection F and the maintenance threshold expressed as age (cumulative number of produced parts) of production system when it is available.

- Step 2- Simulation modeling: A combination of the discrete and continuous simulation model is structured. In this fashion, two programming languages of SIMAN simulation and Visual basic Applications are developed on ARENA Simulation software. In this simulation experiment, aging of the production system, augmentation of the defectives proportion and inspection quality control policy which results in AOQ metric are implemented beside failure of the system and its corrective/ preventive maintenance procedures. Further, finished product inventory control policy and demand-responsive nature are considered as well. In this step, inputs of the system are considered as finished product inventory threshold (Z), the fraction of unceasing inspection in quality control (F) and the threshold of preventive maintenance (Mk) which result in gross revenue as the output of the simulation model.

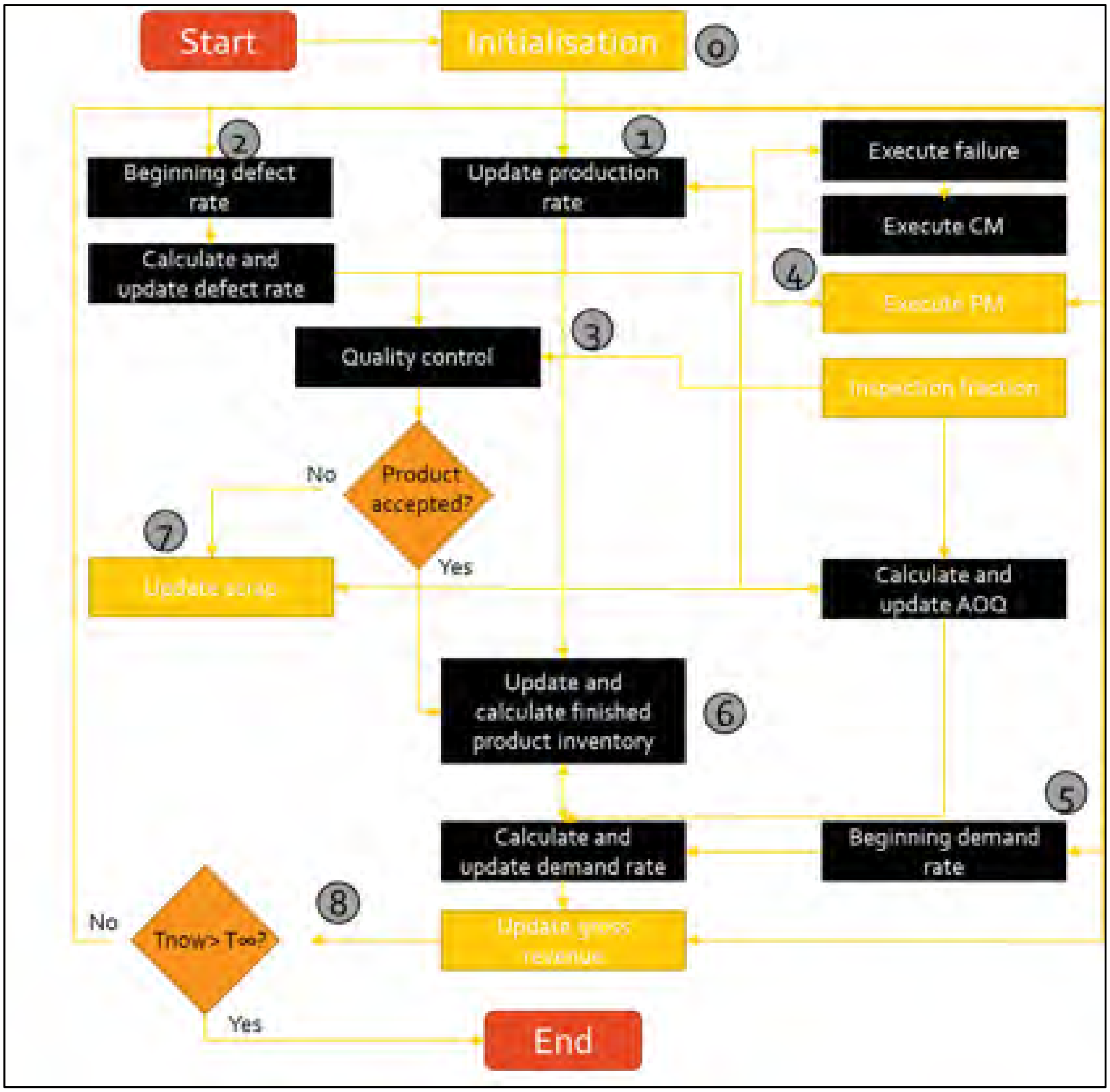

Figure 3.2 Implementation logic chart of the integrated control policy in case one.

Figure 3.2 demonstrates all followed measures of the simulation model. In block 0, It defines all the variables of the model such as decision variables (Z, F, M_k), demand rate, maximum production rate (Umax), average times of breakdowns/repairs (MTTF, MTTR). Step zero sets progress over time for the integration of cumulative variables. In block 1, the system controls production rate through communication with block 4 and block 5 to have updates of downtimes and demand rate. In this way, the system has complete data of corrective and preventive maintenance along with demand progress. Block 2, conducts quality degradation of the system with regard to the age of production system which is the cumulative number of produced parts since the last breakdown. It is to add that the proportion of defects is considered as the output of this block which makes a way to block 3 for quality examination. Block 3 proceeds for updating AOQ value by considering the F value as one of three decision variables. Considering a process capability of inspection as a maximum value, verified parts split up into either finished product inventory or scrap, as a waste. In block 4, the cumulative number of produced parts with regard to the latest production stop (downtime) get calculated. This cumulative value is considered as the age of the system. Block 4 stops the production after reaching to a determined threshold of the system (M_k) to proceed for preventive maintenance action. Block 5, uses the updated value of AOQ from the previous module and proceeds for calculating an instant demand rate according to the received quality level of the client. All aspects of responsive demand behavior, modeled above, get generated in this block. Revised demand rate goes as an output to block 6, calculating the finished product inventory. The major duty of block 6 is about calculating a real-time inventory level of the finished product, regarding demand rate, production rate and incoming stream of good products from block 3. Scrap module in block 7 receives all rejected parts from customer according to AOQ and also those of non-conforming parts from quality control section (block 3). The output of this block will be used in net revenue calculations in main function. Finally, block 8 does run-time control of the simulation by verifying predefined run-time of the system (T_∞) with the current simulation time (T_{now}).

- Step 3- Optimization: In this measure, using the STATGRAPHICS software, first of all, the scale of the experiment is defined. This first step leads to having the experimental space of independent variables (Z, F, and M_k) and the number of total experiments to carry out. Afterward, obtained values of the dependent variable (net revenue) which is the result of the simulation will be verified with the beginning, defined values of independent variables (inputs of the simulation). This progress is done, using analysis of variance (ANOVA) and Response Surface Methodology. As a result, effects and quadratic effects of the main factors are examined by ANOVA to find out if they have significant interactions with the main function (dependent variable). Subsequently, the response surface methodology defines the relationship of main significant factors on total net revenue. In such a way, optimal values of the design factors and optimal net revenue will be estimated with a pre-defined percentage of uncertainty.

3.9.1.2 Validation of the simulation

To validate that the outlined simulation model is able to describe the system under study, the dynamics of production, quality, and responsive demand are illustrated graphically as shown in figure 17. This figure verifies the total functionality of the system in a traceable manner. The aim is to find out if the simulation is functioning correctly based on all assumed conditions of responsive demand and quality degradation. In essence, it will be shown that assumptions about Hedging Point Policy, dealing with corrective and preventive maintenance measurements are working in their predetermined manner.

Figure 17 represents first the status of the system its simulation time. As it coincides with status variable (s (t)) and has taken values of 2 in PM times. This value turns to 1 when the production system is not ceased however it gets 0 values when it is in CM mode. Further, as the quality degradation of the production system is dependent on the system age, in second and third graphs this evolution over time is represented. Briefly, when the system is not available due to CM or PM modes, its age stays unchanged. The same dynamic is programmed for its defective proportion and this remains on each value at the time when the system is stopped. The possibility of defectives continuous to raise and stays around its maximum over time when the system status is equal to one. As soon as the system gets repaired, defect and demand rates step down and return to their initial value. This behavior is pointed out on the figure and confirms as good as the new assumption for both CM and PM actions with regard to maintenance. Following quality degradation in respect of the proportion of defectives, the demand rate reacts to perceived no-quality rates by lowering its rate to penalize the production system for such quality degradation. It should be pointed out that demand amounts stay unchanged during production interruptions (CM or PM) measures.

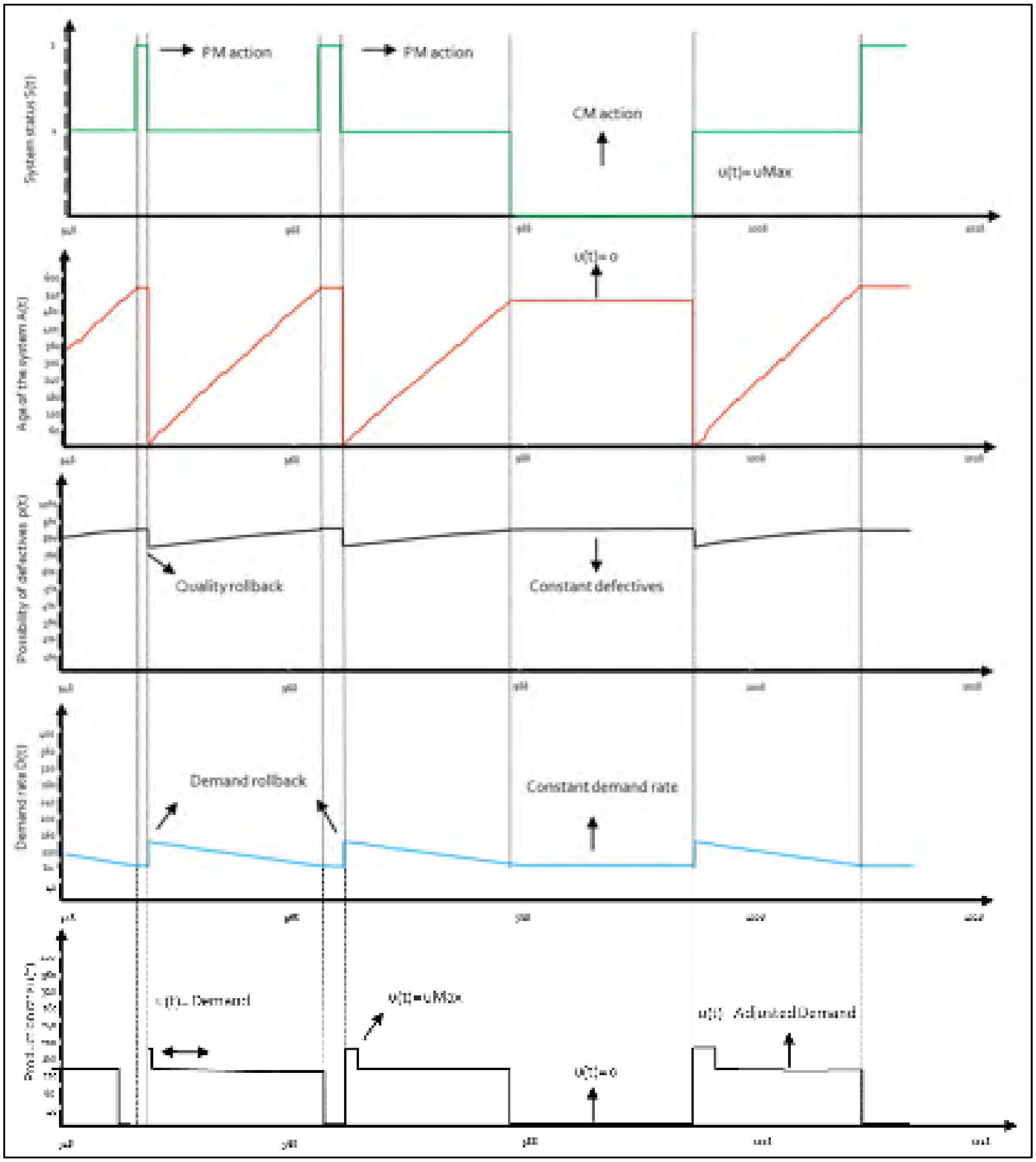

Figure 3.3 Evolution of system during simulation run in case one

As it is illustrated in figure 3.3, the production rate is changing based on HPP assumptions. Since the finished product inventory is not reached to its threshold after PM action, the production rate hits the system's maximum capacity. By compensating whatever has been consumed in the finished product inventory during the maintenance period and having the level of Z in the inventory, the system starts to produce as much as demand values. Production system adjusts itself by some minor reductions in a periodic review manner. Mentioned minor production drops are pointed on the graphic as Adjusted Demand. In addition, the production rate is well-chasing breakdowns by turning to zero. It immediately reacts to the system's unavailability, and available time by setting maximum capacity of the system on production as finished product inventory has dropped from the Z level.

3.9.1.3 Experimental Design and Response Surface methodology

With the intention of showing how the designed resolution approach functions with real data, a numerical example is presented in this section. Furthermore, this numerical example is compared with the case of no preventive maintenance manufacturing to distinguish its contributions in a better way. Mentioned comparison has measured the reaction of the production system in terms of its average net revenue and likewise, its extent of reaction in Z and F metrics.

3.9.1.4 Response surface methodology and numerical example

In the present part, the experiments for various possible combinations of decision variables (Z, F, M_k) are performed and the observed behavior of the response, which is the total net revenue, has been verified. With the aim of examining the interactions of decision variables, three decision factors are varied at three levels each. Therefore, for a complete experiment, this has led to performing 3^3, or 27 tests.

To have better accuracy and secure that the steady-state of the experiment is reached in the simulation run, 2 replications are performed, leading to a total of 54 tests of 240 000 units of time (hour) each simulated by with Arena software of simulation. It is important to point out that the order of the experiments is executed in an absolute random manner. The inputs used to calculate the total net revenue and parameters of the simulation are shown in the table 3.1.

Table 3.1 Numerical example of the experiment for the case one

U^{max}	D_0	P_0	Pr	MTTF	MTTR	MTPR	C_{inv}	C_s	C_{ins}	C_{rej}	C_{nq}	C_{cm}	C_{pm}
190	150	7.5%	100	96	10	5	2	50	10	5	400	1000	900
				Weibull	Exponential								

The quality degradation function is tailored with $P_0 = 0.075$, $\gamma_q = 2.0$, $\lambda_q = 2*10^{-2}$ and $\eta = 0.315$. Therefore, while the production system is now or repaired by CM or PM actions, the defect proportion is implemented in a way that produces a minimum 7.5 % possibility of defectives. Further, according to equation 3.11, without any fraction of quality inspection (In the case of having F, as a decision variable, equal to zero) this proportion will reach no more than 39% when the machine is aging, making sure demand function has always positive amounts.

$$\lim_{t\to\infty}\left(0.075 + 0.315\left(1 - e^{-t^2}\right)\right) = 0.39 \tag{3.12}$$

With the aim of displaying the relationship between operations and quality/ reliability of the system in this study, Weibull distribution is utilized to describe failures of the production system. According to Bouslah, Gharbi et al. (2018), mentioned distribution is among the most compatible statistical models for fitting nonlinear patterns. Therefore, the Weibull distribution is tailored with the scale parameter (λ) of 160000 to have less concentration and the shape parameter (k) of 2, resulting in the mean of 96. In other words, the production system faces breakdowns (MTTF) with an average of every 96 time units (hours in this case).
Different levels of the decision factors (F, Z, M_k) used in the experimental design are presented in the table 3.2 as below:

Table 3.2 Levels of decision factors in the experiment of case one

Factor	**Low**	**Middle**	**High**
Factor_A (F)	0,08	0.19	0,3
Factor_B (Z)	100,0	150,0	200,0
Factor_C (M_k)	500,0	750,0	1000,0

In the analysis step and by considering a 5% level of significance, the analysis of variance (ANOVA) is conducted and for all acceptance number, the linear and quadratic effects of the decision variables (F, Z, M_k) and their interactions for the response variable (Average net revenue).

Table 3.3 Analysis of variance for the PM condition in case one

Source	Sum of squares	DDL	Quadratic mean	F Report	Proba.
A:Facteur_F	3,16746E7	1	3,16746E7	542,57	0,0000
B:Facteur_Z	4,11385E7	1	4,11385E7	704,68	0,0000
C:Facteur_ M_k	342007,	1	342007,	5,86	0,0198
AA	1,04862E7	1	1,04862E7	179,62	0,0000
AB	3,06079E7	1	3,06079E7	524,30	0,0000
AC	395539,	1	395539,	6,78	0,0126
BB	6,34239E6	1	6,34239E6	108,64	0,0000
BC	227517,	1	227517,	3,90	0,0478
CC	4035,04	1	4035,04	0,07	0,7939
blocs	3563,22	1	3563,22	0,06	0,8060
Total error	2,51031E6	43	58379,2		

Figure 3.4 illustrates the Pareto chart of standardized effects when the acceptance number is equal to 2. Considering quadratic factors, 8 factors out of 9 are statistically significant among with all 3 main decision variables.

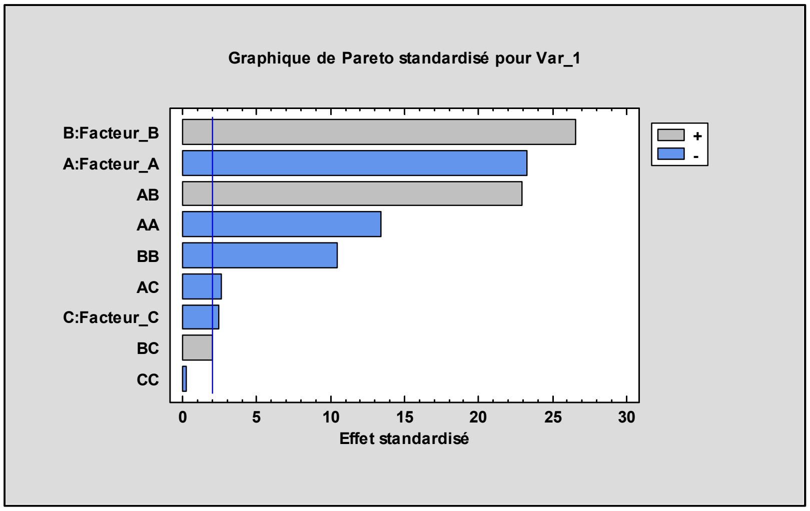

Figure 3.4 Standardized Pareto chart for Average net revenue

As a statistical measure of determining estimation power, R-squared of this experiment is equal to 97.97 percent with Standard error of estimate = 241,618 and Average absolute error = 187,29. In addition, referring to the output of STATGRAPHICS software, and in order to find out optimal net revenue of the experiment as our main objective, respond surface function is equal to below:

NetRevenue = $7234,42+13961,6*F+2,96376*Z\ 0,543817*M_k -77256,1*F^2+ 103,18*F*Z - 4,66827*F*M_k - 0,0734327*Z^2 + 0,00391415*Z*M_k - 0,000293396*M_k^2$

Accordingly, the response surface equivalent to this function is shown in the figure 3.5.

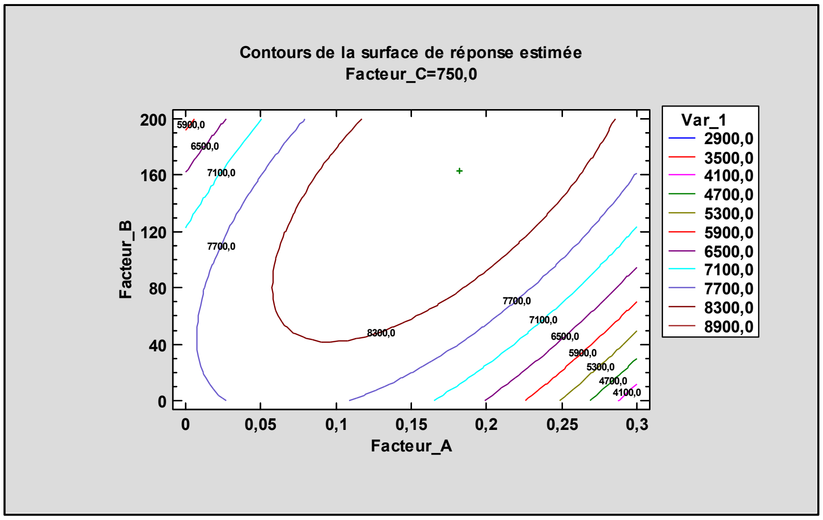

Figure 3.5 Contours of the estimated response area

The total maximum net revenue obtained from the above quadratic function is equal to $ 963.486 with the optimal production parameters of F=12.58%, Z=163.39, and M=565,622. that is to say, the production system has to execute an inspection plan with a complete verification in 12.58% of its manufacturing output and holding 163.39 of its finished product stock based on HPP threshold as well as doing a preventive maintenance job every 565.622 produced parts to be able to reach an average 8903.4$ per hours. It is to mention that based on the figure above, there are some other local maximum points around the global optimum point.

3.9.2 Comparative Study with no preventive maintenance execution (case one)

In the previous section, it was assumed that PM policy is set to execute in periodic time bases to control operation dependent degradation of quality and reliability, taking place in the production system. Preventive maintenance maintains the initial system status based on determined stop periods to help the system acquire more in terms of revenue by slashing its costs. Mentioned costs are caused by excessive amounts of finished product inventory and fraction of the production output to inspect as both F and Z metrics attempt to control system unavailability and quality deterioration. That is to say that preventive maintenance has to demonstrate its effectiveness when compared with the case that it doesn't exist. Thus an experiment with the same assumptions but no M factor to execute PM policy is run to compare results as below:

In order to be able to compare results, an experiment with 36 tests of 240000-time for 2 decision variables (Z, F) is designed and executed with all significantly accepted factors both decision variables and their quadratic and other interacted factors. Compared results with the basic scenario are presented in table 3.4 as below:

Table 3.4 Compared study summaries of case one

Scenario	Z	U^{max}	F	D	P_0	MTTF	P_r	PM?	C_{ins}	M	C_{inv}	C_s	C_{nq}	ANR
Base	163,3	190	12,58 %	150	7.5%	96	100	Yes	10	565,6	2	50	400	8903,4
1	551,7	190	18,23 %	150	7.5%	96	100	No	10	-	2	50	400	7643,8

Just to make sure the results are significantly different in terms of average net revenue (dependent variable of the experiments) a t-test for difference of means is conducted for a sample of 30 for each scenario and H_0 refused, indicating that obtained results are distinct. Thus, as the table clearly illustrates, by implementing PM policy, system invests less on keeping excessive stocks in finished product inventory. More interestingly, it consumes less amount of time and endeavor in inspection because PM actions make system condition better in terms of output quality. Furthermore, as the system faces less time of unavailability by dint of age-dependent PM audits, which take less time, the Z threshold is slashed dramatically. In summary, the above-obtained results have well justified the necessitate of having PM policies in such production systems which are subjected to quality and reliability degradation.

3.10 Extended maintenance policy with respect to demand-responsive price (case two)

On the contrary to the production system, discussed in the first case, preventive maintenance in the second case is subjected to a demand-dependent price function. According to this PM policy, the system is maintained upon getting through a determined price threshold. The price function keeps reducing the price as much as demand drops in terms of quality degradation. According to this maintenance policy, both PM and CM (corrective maintenance) roll back the system to its initial condition which is considered as good as new state. A threshold in terms of system`s price conducts PM policy, denoted by p_k. Therefore, the discrete-state stochastic variable of PM can be defined in the equation 3.13 as below:

$$PM = \begin{cases} No & if\ p_{ri} < p_k \\ yes & if\ P_{ri} = p_k \end{cases} \tag{3.13}$$

According to the above function, the passing threshold will make the system to conduct PM policy. For the prices less than p_k, the system would experience CM actions, denoted by 0 or being available which is denoted by 1 in system status variable.

3.10.1 Resolution approach

Following the approach utilized in case one, current problem-solving methodology comprises a simulation model, experimental design and the response surface methodology as well.

3.10.1.1 Simulation based approach of optimization

Likewise to all three chased steps of the case one, the approach of optimization starts with problem formulation as below:

$$\begin{aligned} &Maximize \quad Net\ Revenue\ (Z, F, P_k\ ) \\ &Subject\ to\colon \quad 0 \le F \le 1 \end{aligned} \tag{3.14}$$

Thereby, the optimal solution is reached with three factors of the finished product inventory to hold, the percentage of non-stop inspection and finally the price threshold for PM execution. As the second step, simulation modeling is presented as below figure to distinguish minor differences of the current discrete-continuous model with the one explained in case one. Since both cases carry out preventive maintenance approaches with two different regards toward the system age and the system dynamic pricing, block 4 in the current case (figure 3.6) has been modified to well address dynamic pricing matter by updating its value in block 4 and ordering for the next PM when it attains to P_k threshold. However, quality and reliability degradation are still dependent on the cumulated number of produced parts since the latest breakdown. Consequently, such assumptions are remained intact in blocks 1, 2 and 5. It should be emphasized that either HPP or uneased inspection policies are functioning the same way case one does in blocks 3 and 6, making sure the only difference between the functionality of systems is about their PM comportment.

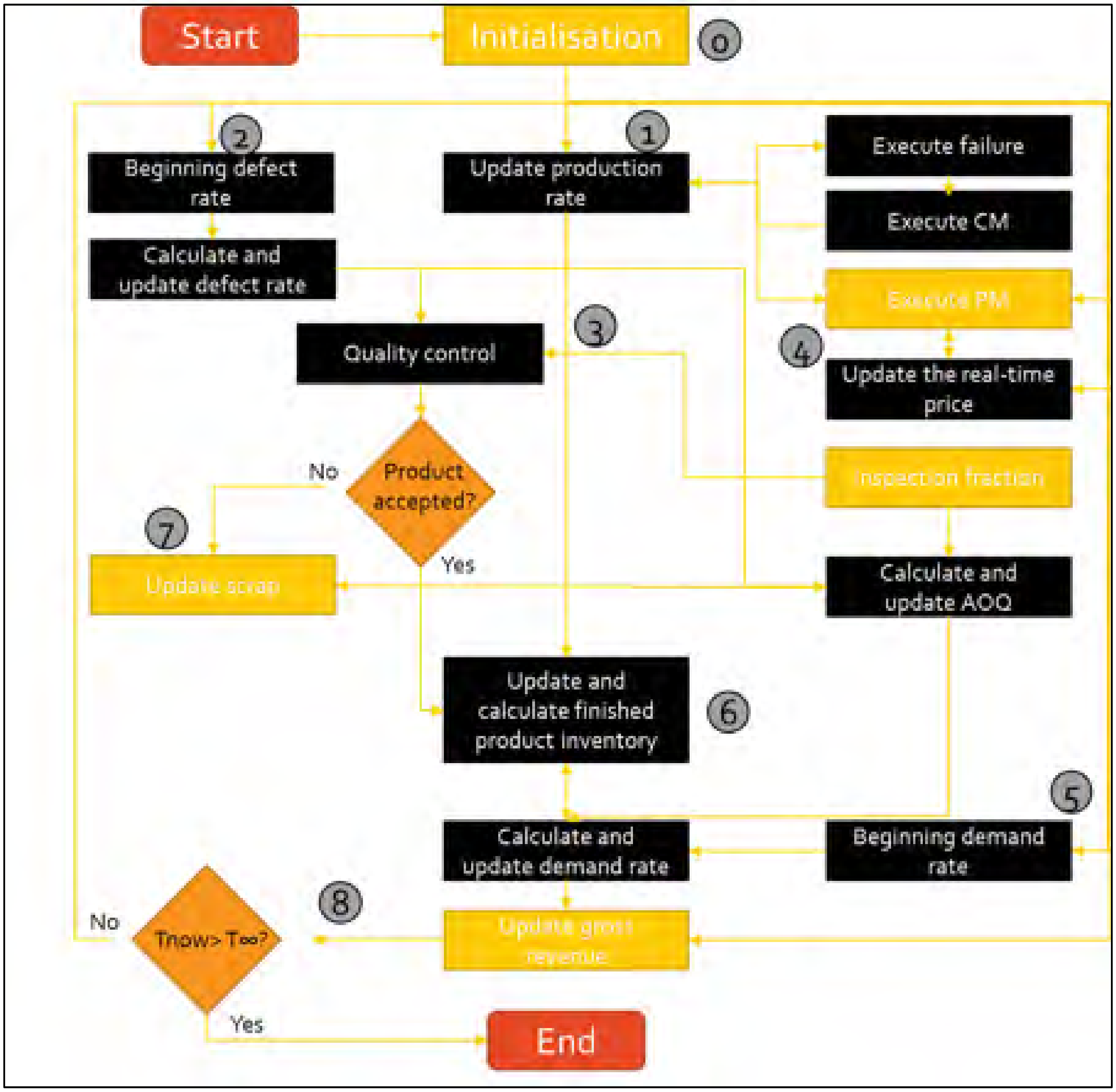

Figure 3.6 Implementation logic chart of the integrated control policy in case two

For the purpose of adhering step 3 in so far explained simulation-based approach of optimization, optimization is accomplished by launching Response surface methodology. Through this way, first decision variables were defined in STATGRAPHICS software along with the total number of experiments and later, the designed experiment of variables was evaluated with the main function to see if they have any significant interactions or not.

3.10.2 Simulation validation in case two

A sample of some important simulation run metrics are brought in the figure below to ensure all intended functionalities in terms of quality and reliability degradation, quality-responsive demand, demand-dependent sort of dynamic pricing, HPP and maintenance policies are running in a proper way.

According to figure 3.7, the system status is well following what has assumed previously. It has taken 0 values in a time of CM breakdowns and 2 while the system is under PM maintenance measurements. At the same time, the production rate in the last graph is well responding to the system status with regard to demand and inventory positions during the time. Production rate gets demand values and adjusts itself to its decreasing rate when Z is reached in finished product inventory and at some points compensates any amount below Z by producing in maximum capacity for short time units (it is shown by u(t)= uMax). Additionally, as the quality degradation of the system is operation dependent, the evolution of AOQ as the final quality output of the system is well traced. This metric gets increased as long as system status is 1 (on time) and rolls back to its minimum (depending on F value) after each CM/PM action. For this reason, demand dynamic responds in a real-time way to AOQ amounts, decreasing its rate over time. Finally, by tracking demand degradation in respect of the proportion of defectives, the price function reacts to perceived demand reductions and lowers its price in a dynamic way to penalize the production system for such demand shortage, resulted from its quality degradation. Moreover, as such a way of price drops should guarantee the feasibility of production, the system just continuous until a determined threshold of price with the aim of recovering the system into its initial quality state. In other words, the system decides to choose between price reduction and preventive maintenance investments by determining its P_k threshold and then it commands for PM actions as they are well illustrated in the first graph. For CM actions, it could be interpreted that however system price is not reached to its minimum threshold, the system has faced breakdowns.

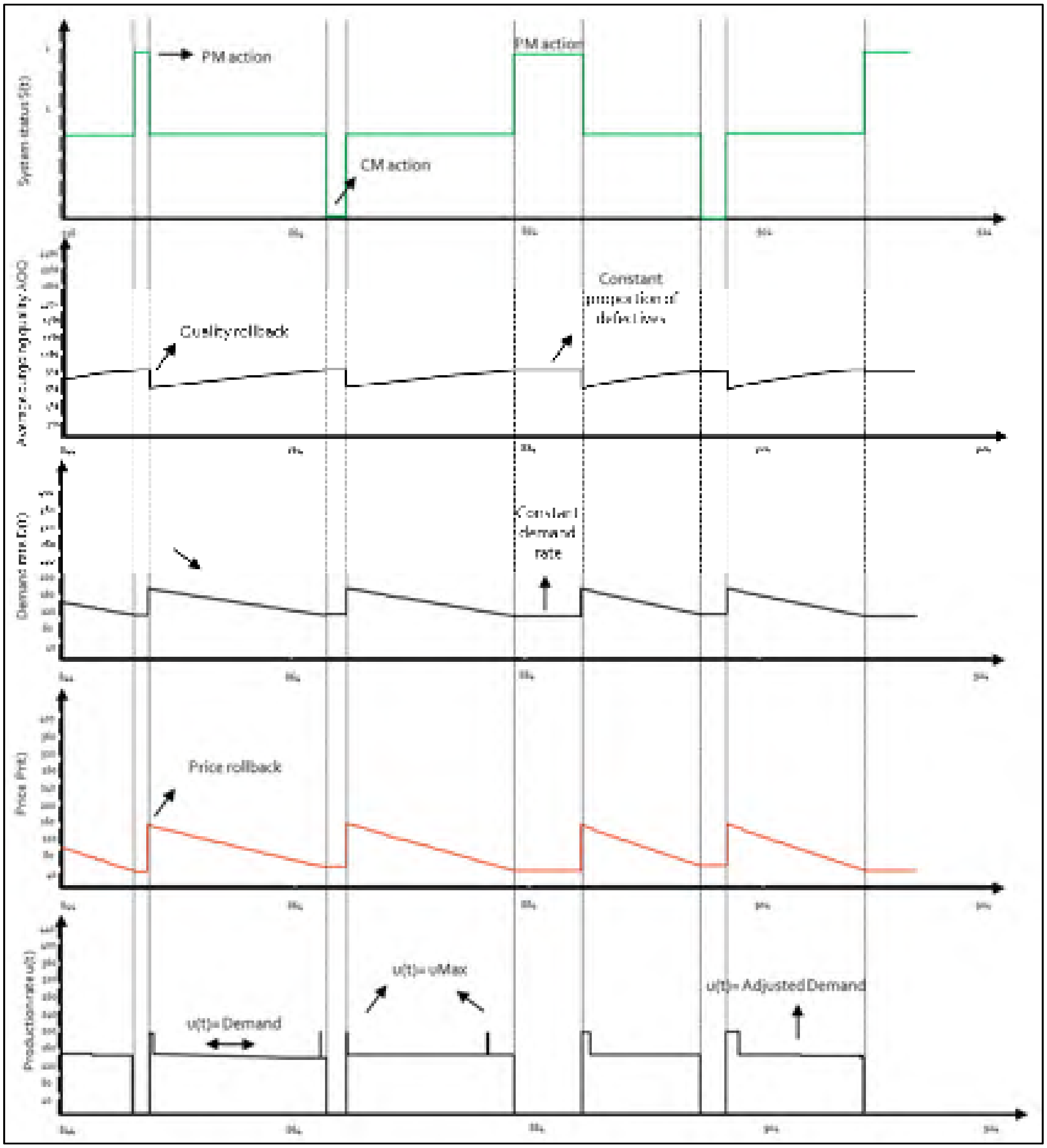

Figure 3.7 Evolution of factors during simulation run in case two

3.10.3 Experimental Design and Response Surface methodology

The functionality of resolution approached is examined, in this part, in order to well reveal how this approach deals with real data. Following the stated way in case one, a numerical example is conducted for various possible combinations of decision variables (Z, F, P_k) and then the observed behavior of the response, which is the total net revenue, has been audited. To achieve what mentioned above, three decision variables are varied at three levels each. Therefore, for having a thorough experiment, this has led to performing 3^3, or 27 tests.

Also, with the aim of having better accuracy and to make sure that the steady-state of the experiment is reached in the simulation run, 2 replications are performed, making a total number of 54 tests that each one has 240 000-time units (hour). All designed tests then got simulated by Arena software of simulation. The order of the experiments is conducted in an absolute random way. Below are the parameters of simulation tests:

Table 3.5 Numerical example of the experiment for the case two

U^{max}	D_0	P_0	Pr	MTTF	MTTR	MTPR	C_{inv}	C_s	C_{ins}	C_{rej}	C_{nq}	C_{cm}	C_{pm}
190	150	7.5%	100	96	10	2	2	50	10	5	400	1000	500
				Weibull	Exponential								

For responding functions of demand and price below, parameters are customized:

Table 3.6 Sensivity metrics of the demand and price functions

Kind	λ	β
Demand Function	2.25	0.88
Price Function	1.1	0.99

The quality degradation function is tailored with $P_0 = 0.075$, $\gamma_q = 2.0$, $\lambda_q = 2*10^{-2}$ and $\eta = 0.315$. Therefore, the proportion of defectives will reach no more than 39% when the machine is aging, making sure demand function has always positive amounts. The proof is as below:

$$\lim_{t \to \infty} \left(0.075 + 0.315\left(1 - e^{-t^2}\right)\right) = 0.39 \tag{3.15}$$

Identical to the first case, Weibull distribution is utilized to describe failures of the production system. This distribution is tailored with the scale parameter (λ) of 160000 to have less concentration and the shape parameter (k) of 2, resulting in the mean of 96.

Three different levels of the decision factors (F, Z, M_k) used in the experiment are brought in the table 3.7:

Table 3.7 Levels of decision factors in the experiment of case two

Factor	**Low**	**Middle**	**High**
Factor_A (F)	0,01	0.08	0,15
Factor_B (Z)	100,0	350,0	600,0
Factor_C (P_k)	50,0	64,5	79,0

For determining which decision variables are significant to the response variable (average net revenue) of the experiment, an ANOVA is conducted by considering a 5% level of significance. The intended analysis is conducted for all acceptance number, the linear and quadratic effects of the decision variables (F, Z, P_k) and their interactions.

Table 3.8 Analysis of variance for the PM condition in case two

Source	Sum of squares	DDL	Quadratic mean	F Report	Proba.
A:Facteur_F	2,27725E7	1	2,27725E7	51,34	0,0000
B:Facteur_Z	9,55865E7	1	9,55865E7	215,51	0,0000
C:Facteur_ P_k	1,88242E6	1	1,88242E6	4,24	0,0455
AA	9,81541E6	1	9,81541E6	22,13	0,0000
AB	1,07029E8	1	1,07029E8	241,31	0,0000
AC	1,56714E6	1	1,56714E6	3,53	0,0669
BB	3,30541E7	1	3,30541E7	74,52	0,0000
BC	39316,6	1	39316,6	0,09	0,7673
CC	1,7724E6	1	1,7724E6	4,00	0,0493
blocs	77,1373	1	77,1373	0,00	0,9895
Total error	1,90719E7	43	443532,		

The figure 3.8 exhibits the Pareto chart of standardized effects for the Box-Behnken design. The acceptance number is equal to 2. Taking into consideration the quadratic factors, 7 factors out of 9 are statistically significant among with all 3 main decision variables. This is also traceable in the ANOVA table above with demonstrated probability columns.

To statistically measure how strong our estimation is determining the response variable, the R-squared of this experiment is calculated and is equal to 93.48 %.

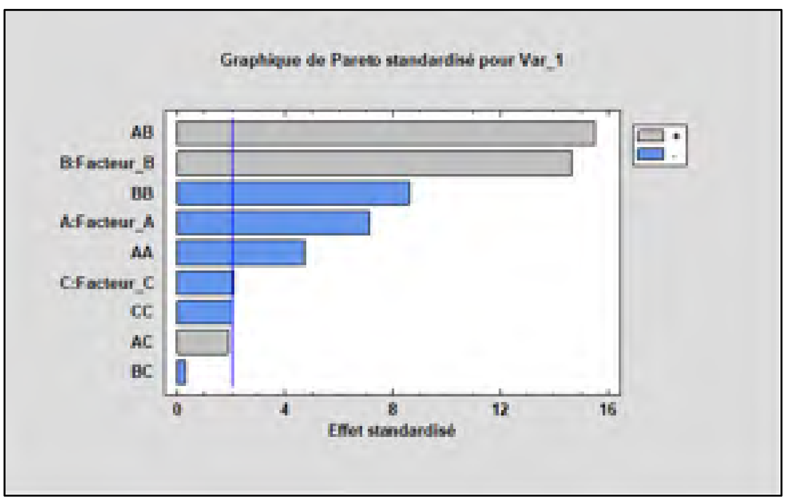

Figure 3.8 Standardized Pareto chart for Average net revenue in case two

Besides, in reference to the analysis performed by STATGRAPHICS software, predicted response surface function is equal to below:

NetRevenue = -1554,52 - 28337,6*F + 9,10348*Z + 202,69* P_k - 184573,*F^2 +100,728*F*Z + 251,757*F*P_k - 0,0185024*Z^2 - 0,00932004*F* P_k - 1,82791* $P_k{}^2$

Above function is able to estimate the optimal maximum point for the response variable by putting the optimized value of decision variables. As a consequence, the respond surface equivalent to this function is shown in the figure 3.9 as below:

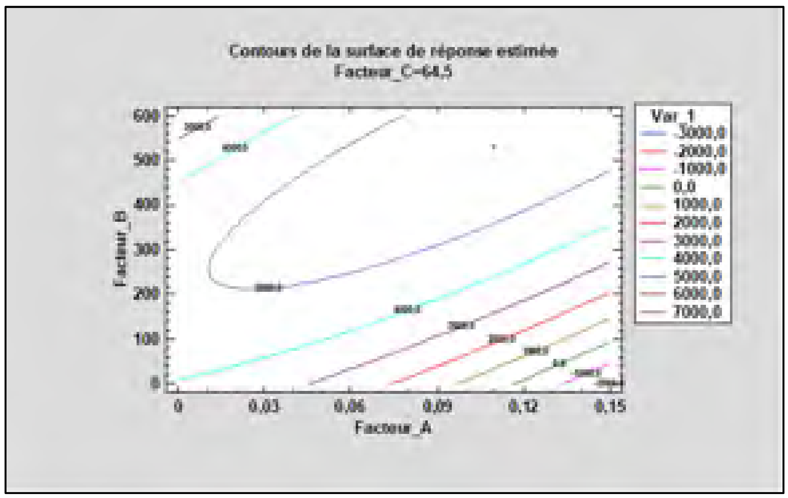

Figure 3.9 Contours of the estimated response area in case-two

It is apparent that the total maximum net revenue attained, is equal to \$ 5546.23 with the optimal parameters of F=10.9%, Z=528,43 , and M=61,63. Put another way, the production system has to run an inspection plan with 12.58% complete verification of what produces and retain 528.43 of its finished product inventory as well as performing a periodic preventive maintenance job after meeting the dropped price of 61.63\$. The explained policy is able to provide an average net revenue of 5546.23\$ per hours. Above figure has demonstrated global optimal point and other local optimums in its vicinity.

3.10.4 Comparative Study with no preventive maintenance implementation (case two)

In this part, with the aim of evaluating estimated contributions of case two, a PM excluded case with identical input and functionality is examined to find out if discussed resolution approach and especially PM actions are statistically able to make any sense in terms of contribution or not. To carry out this comparison, an experiment with 36 tests of 240 000-time for 2 decision variables (Z, F) in three different levels is designed and executed. Accordingly, this experiment is conducted with the explained simulation based approach of optimization. It is to note that all factors (decision variables and their quadratic and other interacted factors) have been statistically significant, resulting to a policy with Z=591.1 and f=14.41% as a case with the demand-responsive function of pricing but no PM measurements. Compared results with the basic scenario are presented in the table 3.9 as below:

Table 3.9 Compared study summaries of case one

Scenario	Z	U_{max}	F	D	P_0	MTTF	P_r	PM?	C_{ins}	M	C_{inv}	C_s	C_{nq}	ANR
Base	528,4	190	10,9 %	150	7.5%	96	100	Yes	10	61,63	2	50	400	5546,2
1	591,1	190	14,47 %	150	7.5%	96	100	No	10	-	2	50	400	4786,7

To do so, a t-test for difference of means is conducted for a sample of 30 for each scenario and H_0 refused, indicating that obtained results are distinct in terms of average net revenue. According to summarized information in the table above, implementing PM policy in the system results in less maintaining of excessive stocks in finished product inventory. More interestingly, by executing PM actions, the system consumes less amount of time and endeavor in inspection because PM actions bring systems as good as new condition, sooner. Further, as the system faces less time of unavailability by dint of price-dependent PM audits, which take less time Z threshold is slashed dramatically. Finally, the difference in average net revenue can be interpreted with the nature of the price threshold as it blocks any sales less than P_k during run times. However, it is possible to go below P_k in no PM case. In summary, the above-obtained results have well justified the necessitate of having PM policies in demand-dependent pricing schemes.

3.11 Conclusion

The joint policies, concerning production-inventory control and preventive maintenance measurements, have not been enough studied in the presence of quality-dependent demand and dynamic pricing, which are absolutely essential in today`s customer and vendor relations. Hence, this study has contributed on relaxing constant demand and age based quality and reliability degradation assumptions by introducing a quality dependent demand dynamic and operation dependent degradation. In other words it is a study on the joint design of two separate cases in production, quality control and preventive maintenance in unreliable manufacturing systems subject to operation-dependent degradation, where the production control policy comprises of a modified hedging point policy and quality control is performed by a fraction of the production output. Two mathematical models have been developed to explain the dynamic of production, inventory, quality control, degradation, demand, and pricing. System constraints were defined to calculate the overall incurred cost. Because the optimal solution cannot be reached due to the stochastic complexity of the model, a resolution approach based on experimental design with simulation and Response Surface methodology is proposed to optimize hedging point level and inspection fraction. By presenting two numerical examples and comparing them with an excluded condition, important impact of developed integrated policies in production, quality, and PM on average net revenue function illustrated. Demand-dependent nature of pricing as a promotional mean of gaining customer in a competitive market extended in the second case, along with quality-dependent demand. As an interesting result, conducting PM actions leads to more net revenue due to the functionality of the system in response to resulting in less inspection and stock holding investments. Future research could be undertaken to investigate the studied context in the presence of absolute finished product inventory values. Another area for future consideration is about depending demand to more affecting factors such as deterioration in the context of lot-sizing and rectification actions.

CONCLUSION

This research work made it possible to deal with the problem of control of unreliable production systems with quality-dependent demand. The main contribution of this study could be about introducing one of the very rare research studies in the context of manufacturing, concerning the dynamics of quality dependent demand in the existence of quality and reliability degradation in production systems. The objective was to find an optimal production policy which makes it possible to maximize the average net revenue (ANR) consisting of the gross revenue, the cost of holding inventory, the cost of shortage, the cost of inspection, the cost of no-quality and the cost of parts returned by the customer. This system consists of a single machine producing a single type of product with a rejection rate, subject to breakdowns and random repairs and a continuous quality control station where a fraction of production is controlled.

The first chapter, devoted to a literature review, made it possible to situate our work in relation to others. In this chapter, we also discussed production systems and quality control techniques in general and presented the prospect theory fundamentals that was the focus of our study in the demand and price behaviour. We presented the problem statement, the research objectives and the adopted methodology which are a combination of the research approach.

In Chapter 2, the production unit consists of a single machine producing a single type of part. No preventive maintenance action was considered in this chapter and the system was subject to the quality degradation and a quality-dependent demand which reacts to it.

The mathematical model has been developed considering finished product inventory threshold (Z) and inspection proportion (F) rates and must satisfy a quality-dependent demand rate. We have shown that the optimal solution is of the critical threshold type, after having solved numerically the simulation-based approach of optimization. A sensitivity analysis validated these results. Also, considering delays in demand response, leaded the system obtain more in terms of the average net revenue.

In the final chapter, we first implemented a mathematical model, considering preventive maintenance actions which deal with the quality-dependent demand behaviour. Then we used a simulation approach combined with experimental designs, variance analysis and response surface methodology, to obtain the significant values that maximize the average net revenue. In the second case of this chapter, the production system is subject to preventive maintenance actions based on a dynamic price, effecting from the demand dynamics. In both mentioned cases, using PM policies resulted in less finished product inventory holding and quality control measurements.

This research work has made it possible to deal with the production and quality control of unreliable production systems with the quality-dependent demand. We have also shown the importance of different PM policies on decreasing the quality and inventory investments. However, the field is open to extending this research work for example by considering a variable supply rate for the raw materials, using non constant levels of finished product threshold (Z), having rectification procedures, considering product deterioration integrating or adding series of two machines for one or two products.

ANNEXE I

SIMULATION MODEL OF A PRODUCTION SYSTEM, CASE OF CHAPTER 1 WITH QUALITY RESPONSIVE DEMAND AND NO PREVANTIVE MAINTENANCE MEASUREMENTS

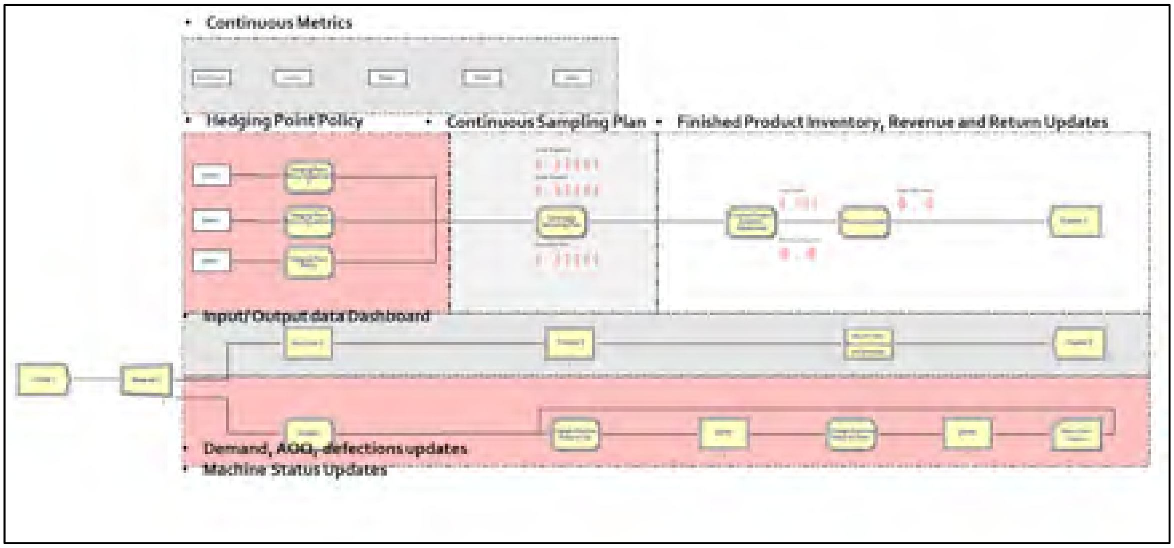

Figure-A I.1 Simulation model with no preventive maintenance

Figure-A II.1 Simulation model with no preventive maintenance

ANNEXE II

SIMULATION MODEL OF A PRODUCTION SYSTEM, CASE OF CHAPTER 2 WITH QUALITY RESPONSIVE DEMAND AND PREVANTIVE MAINTENANCE MEASUREMENTS BASED ON CUMULATIVE PRODUCED PARTS, CASE 1

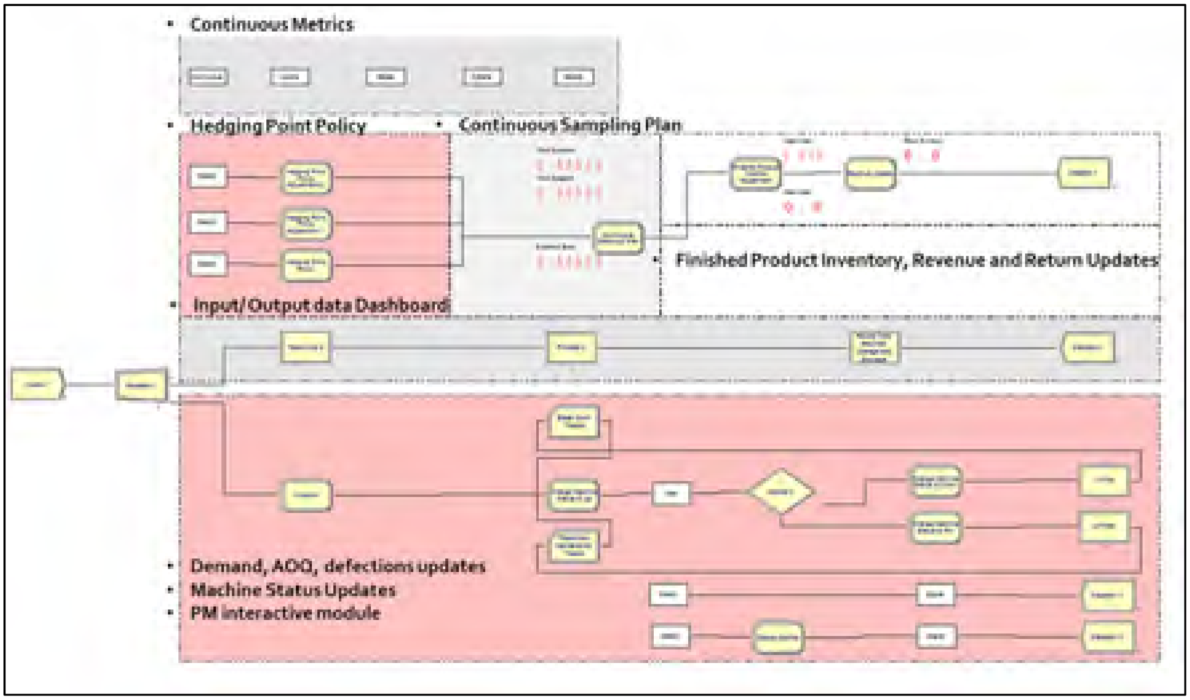

Figure-A III.1 Simulation model with age-based preventive maintenance

ANNEXE III

SIMULATION MODEL OF A PRODUCTION SYSTEM, CASE OF CHAPTER 2 WITH QUALITY RESPONSIVE DEMAND AND DEMAND RESPONSIVE PRICE, CASE 2

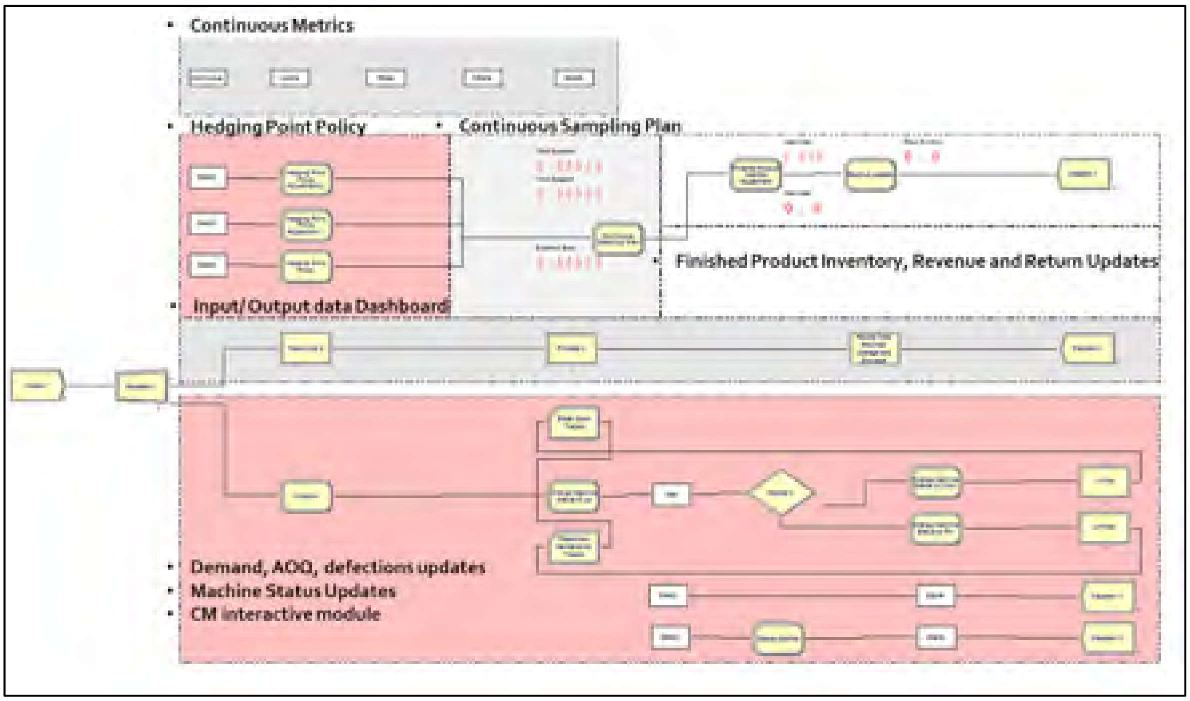

Figure-A IV.1 Simulation model with price-based preventive maintenance

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