Contrôle de la production et de la maintenance des systèmes industriels non fiables pour les produits périssables

par

Raouia KADDACHI

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CE MÉMOIRE A ÉTÉ ÉVALUÉ

PAR UN JURY COMPOSÉ DE :

M. Ali Gharbi, directeur de mémoire
Département de génie de la production automatisée à l'École de technologie supérieure

M. Jean-Pierre Kenné, codirecteur de mémoire
Département de génie mécanique à l'École de technologie supérieure

M. Armin Jabbarzadeh, président du jury
Département de génie de la production automatisée à l'École de technologie supérieure

M. Mustapha Ouhimmou, membre du jury
Département de génie de la production automatisée à l'École de technologie supérieure

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RÉSUMÉ

Le travail présenté dans ce mémoire vise à traiter le problème relatif à la commande optimale. Il fait rapport à un système manufacturier non fiable et complexe. D'une part, le système de production étudié est sujet à des temps de pannes et réparations aléatoires. D'autre part, la famille de produits fabriqués est de nature périssable possédant une durée de vie limitée et aléatoire.

Ce projet porte alors sur la détermination des politiques de commande de production et de la maintenance pour les produits périssables. Il s'agit de développer des politiques de commande qui intègrent les différents aspects du système tout en optimisant ses paramètres. En premier lieu, compte tenu de l'équilibre important qui doit avoir lieu entre les coûts de rupture de stock d'une part et les coûts de possession et de rejet du stock d'autre part, l'objectif est de proposer une politique de commande de production appropriée qui minimise le coût total en respectant la contrainte de la satisfaction de la demande. En plus, les durées de vie des produits périssables prises dans les modèles étudiés sont considérées à la fois fixes et aléatoires. Ce type d'hypothèses est considéré consistant, car il permettra d'examiner plusieurs cas de systèmes industriels et de voir l'effet de la variabilité de la durée de vie sur le comportement du système. En outre, les systèmes manufacturiers font face à plusieurs facteurs qui peuvent engendrer la détérioration des machines et l'augmentation des taux de pannes. Dans ce contexte, ils visent à maximiser leurs disponibilités et minimiser l'occurrence des pannes en exécutant des interventions de maintenance préventive. Cette tâche devient plus critique si la détérioration de la machine a un impact sur la durée de vie des produits fabriqués. L'objectif est alors de développer une politique de contrôle de la maintenance qui tient compte de toutes les interactions qui peuvent exister dans le système.

D'une part, la première partie de ce mémoire porte sur la détermination d'une politique de commande de production optimale spécifique aux systèmes manufacturiers non fiables produisant des produits périssables ayant des durées de vies aléatoires. D'autre part, les stratégies de la maintenance préventive sont introduites dans la deuxième partie pour étudier comment mieux synchroniser les activités de production et les interventions de maintenance afin d'améliorer la disponibilité de la machine tout en intégrant la nature des produits périssables. Dans cette deuxième partie, nous nous intéressons à étudier l'effet de la dégradation de la machine sur la durée de vie des produits et comment cette relation peut influencer la politique combinée de maintenance et de production.

Afin de résoudre les problèmes considérés, nous présentons tout d'abord une solution analytique qui sert à déterminer une politique de commande de la production pour un système manufacturier non fiable sujet aux pannes. Les conditions d'optimalité sous la forme d'équations de Hamilton – Jacobi – Bellman (HJB) sont développées. Ensuite, en résolvant numériquement les équations HJB, la politique de production est établie. Par la suite, en raison de la complexité du système traité et des limites des modèles analytiques, nous adoptons une approche expérimentale basée sur la simulation comme outil d'optimisation des paramètres de décision. Cette dernière intègre la méthodologie de surface de réponse, les plans d'expérience et les analyses de sensibilité. Des exemples numériques des modèles développés ont été établis pour évaluer la performance du système et confirmer la robustesse et la pertinence de l'approche utilisée. Cette approche expérimentale est aussi adaptée dans la deuxième partie du mémoire pour optimiser les paramètres de la politique combinée de maintenance et de production.

Mots-clés : Systèmes manufacturiers non fiables, produits périssables, planification de la production, maintenance préventive, simulation, politique de commande, dégradation de la machine, méthodologie de surface de réponse.

Production and maintenance control of failure-prone manufacturing systems for perishable products

Raouia KADDACHI

ABSTRACT

The work presented in this thesis deals with problems related to optimal control. It studies an unreliable and complex manufacturing system. On one hand, the studied production system is subject to random failure and repair times. On the other hand, the family of products manufactured is of a perishable nature with a limited and random shelf life.

This project focuses on the design and the optimization of production and maintenance control policies for perishable products. It aims to develop control policies that integrate the different aspects of the system while optimizing its parameters. First taking into account the important balance that must take place between the costs of backlog on the one hand and the costs of disposal on the other hand, the objective is to conduct an appropriate production control policy that minimizes the total cost while respecting the constraint of meeting demand. In addition, the shelf life of perishable products considered in the developed models is both fixed and random. This is considered consistent because it will allow to examine several cases of industrial systems and to see the effect of shelf life variability on the behavior of the system. Moreover, manufacturing systems face several factors that can lead to machine deterioration and increased failure rates. As a result, they aim to maximize their availability and minimize the occurrence of breakdowns by performing preventive maintenance interventions. This task becomes more critical if the deterioration of the machine has an impact on the shelf life of the manufactured products. The objective is then to develop a maintenance control policy that takes into account all the interactions that may exist in the system.

On the one hand, the first part of this thesis deals with determining an optimal production control policy specific to unreliable manufacturing systems producing perishable products with random shelf lives. On the other hand, preventive maintenance control policies are introduced in the second part to study how to integrate production activities and maintenance interventions in order to improve machine availability while considering the nature of perishable products. In this second part, we are interested in studying the effect of machine degradation on the product's shelf life and how this relationship can influence the joint maintenance and production control policy.

In order to solve the considered problems, we first adopt an analytical solution in order to develop a parameterized production control policy for an unreliable manufacturing system prone to random failure and repair times. The optimality conditions in the form of Hamilton - Jacobi - Bellman equations (HJB) are developed. Then, by numerically solving the HJB equations, the production policy is established. Subsequently, due to the complexity of the system under consideration and the limitations of the analytical models, we adopt an experimental approach based on simulation as a tool for optimizing decision parameters. The latter integrates the response surface methodology, experimental design and sensitivity

analysis. Numerical examples of the models developed were established to assess the performance of the system and confirm the robustness of the used approach. This experimental approach is also adapted in the second part of the thesis to optimize the combined maintenance and production policy.

Keywords: Unreliable manufacturing systems, perishable products, production planning, preventive maintenance, simulation, control policy, machine degradation, response surface methodology.

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$x_i(t)$	Niveau de stock au temps t pour la partie du stock se trouvant à l'état $i, i \in \{1, 2, 3\}$
$U(t)$	Taux de production (produit/ unité de temps)
U_m	Taux maximum de production (produit/ unité de temps)
D	Taux de la demande (produit/ unité de temps)
D_i	Taux de la demande pour la partie du stock se trouvant à l'état i (produit/ unité de temps)
$\lambda_{\alpha\beta}$	Taux de transition du mode α au mode β
q_{ij}	Taux de transition de la partie du stock se trouvant à l'état i vers la partie du stock se trouvant à l'état j
$MTTF$	Temps moyen de panne
$MTTR$	Temps moyen de réparation
$MTPM$	Temps moyen de la maintenance préventive
PM	Maintenance Préventive
CM	Maintenance Corrective
$a(.)$	Âge de la machine depuis la dernière opération de maintenance
A	Âge PM critique de la machine
Z_i	Seuil critique des produits se trouvant à l'état 1 $i \in \{1, 2\}$
Y	Seuil critique des produits se trouvant à l'état 2
Z_{PM}	Seuil critique des produits pour exécuter les interventions de PM
ω_p	Variable de contrôle de la maintenance préventive
C_i^+	Coût unitaire de possession en stock pour la partie du stock se trouvant à l'état i (\$/produit/ unité de temps)
C_i^-	Coût unitaire de la pénurie pour la partie du stock se trouvant à l'état i (\$/produit/ unité de temps)
C_p	Coût unitaire de rejet des produits périmés (\$/ produit)
C_{pm}	Coût d'une maintenance préventive (\$/ opération de PM)
C_{cm}	Coût d'une maintenance corrective (\$/ opération de CM)

SL	Durée de vie du produit
Av	Disponibilité de la machine
$g(.)$	Coût total instantané encouru
$J(.)$	Coût total moyen
$V(.)$	Fonction Valeur
ρ	Taux d’actualisation (produit/ unité de temps)

INTRODUCTION

Nul ne peut nier que les systèmes industriels sont en développement continu et que la mondialisation a fait évoluer leurs natures et les a rendus de plus en plus complexes. D'une part, la chaîne logistique est devenue immense, les produits sont fabriqués et/ ou assemblés à partir de composants pouvant provenir de n'importe où dans le monde entier. D'autre part, les clients sont devenus plus exigeants en termes de qualité, coût et délais. Pour faire face à ces difficultés et rester compétitives dans le marché, les entreprises doivent être capables de s'adapter dans un environnement non fiable. En fait, les systèmes industriels ont besoin d'un contrôle continu pour pallier ces changements et atteindre la performance voulue. En d'autres termes, les entreprises ne cessent pas d'explorer des nouvelles politiques pour augmenter la productivité et satisfaire le client tout en minimisant le coût.

Un système industriel est souvent sujet à plusieurs et à divers facteurs aléatoires qui perturbent son fonctionnement quotidien. Nous citons à titre d'exemples : les demandes aléatoires, les pannes des machines, les interventions préventives, les délais de livraisons, les durées de vie des produits … Sur cette dernière, beaucoup de produits et, par conséquent, leurs chaînes logistiques sont sensibles au facteur temps, tels que les produits laitiers, les agroalimentaires, les banques de sang ainsi que certains produits électroniques qui sont soumis aux changements fréquents de goût des consommateurs, étant remplacés par de nouveaux produits.

L'existence d'un environnement dynamique et aléatoire nécessite la mise en place d'une bonne politique de contrôle de la production. Cependant, pour les systèmes manufacturiers produisant des produits à durée de vie limitée, la gestion de la production pose des défis particuliers. Ces défis deviennent de plus en plus complexes si la durée de vie des produits est aléatoire (Vrat et al., 2018). Des exemples de produits périssables dont la durée de vie est aléatoire sont les produits qui n'ont pas de date d'expiration étiquetée comme les légumes et les fruits. Très souvent aussi, la durée de vie d'un produit varie en raison de plusieurs facteurs, tels que l'humidité, la température ou les conditions de stockages …. En fait, les produits existants en stock et qui dépassent leurs durées de vie deviennent inutilisables et doivent être jetés. Ils peuvent alors aboutir à des coûts élevés en raison de la perte de stock ou d'autres conséquences telles que la perte de marché. D'ailleurs, selon Chen et al., (2014), les produits périssables, tels que les laiteries, les viandes, les légumes, les fruits et la volaille, représentent la majorité des revenus des ventes des supermarchés et des épiceries. En 2005, le Food Market Institute a rapporté que les produits périssables représentent 50,12% du chiffre d'affaires total, ce qui équivaut à 383 milliards de dollars, et il atteint 444 milliards de dollars en 2010. Et, selon Jbira et al. (2018), les produits périssables sont responsables de plus de 36 milliards de dollars de pertes dans l'industrie de l'agroalimentaire aux États-Unis. Du coup, l'effet crucial de la périssabilité ne doit pas être ignoré. Cela pousse les industriels à planifier leurs politiques de contrôle avec vigilance. D'un point de vue opérationnel, les systèmes manufacturiers sont confrontés avec un manque de stratégies prenant en compte la nature des produits périssables tout en conservant leur efficacité économique. Dans ce contexte s'inscrit notre projet de recherche. Nous étudions des problèmes de contrôle des systèmes manufacturiers non fiables sujets à des temps de pannes aléatoires produisant des produits périssables ayant une durée de vie limitée et aléatoire. Dans ce contexte de la théorie de commande optimale stochastique, nous abordons des problèmes de la production et de la maintenance dans le but de minimiser un coût total obtenu.

Pour les systèmes manufacturiers faisant face à des événements aléatoires, ainsi que les limitations mathématiques, il est difficile de résoudre ces types de problèmes analytiquement (Boukas et Haurie, 1990). D'où, nous allons opter pour des approches empiriques en combinant la simulation avec des méthodes statistiques d'optimisation. Cette approche expérimentale est fréquemment utilisée dans la résolution des problèmes complexes (Assid et al., 2020). En premier lieu, nous déterminons la structure de la politique de contrôle optimale basée sur la théorie de la commande optimale stochastique. Les conditions d'optimalité sous forme d'équations de Hamilton - Jacobi - Bellman (HJB) sont formulées afin de vérifier l'optimalité de la politique de contrôle proposée. Par la suite, nous adoptons une approche expérimentale basée sur une combinaison de la simulation, l'analyse de la variance et la méthodologie de surface de réponse. Cette approche nous permet d'optimiser les paramètres de décisions. Fu, 2002 indique que le fait de coupler la simulation et les méthodes statistiques d'optimisation a été utilisé avec succès dans la résolution de multiples problèmes complexes de prise de décision. Le modèle de simulation est établi avec Arena Software, un outil de modélisation efficace pour décrire le système de production des produits périssables. Selon Kelton et al., (2007), cet outil est considéré puissant et souvent utilisé grâce à sa capacité d'imiter les systèmes complexes. L'optimisation est faite à travers le logiciel STATGRAPHICS.

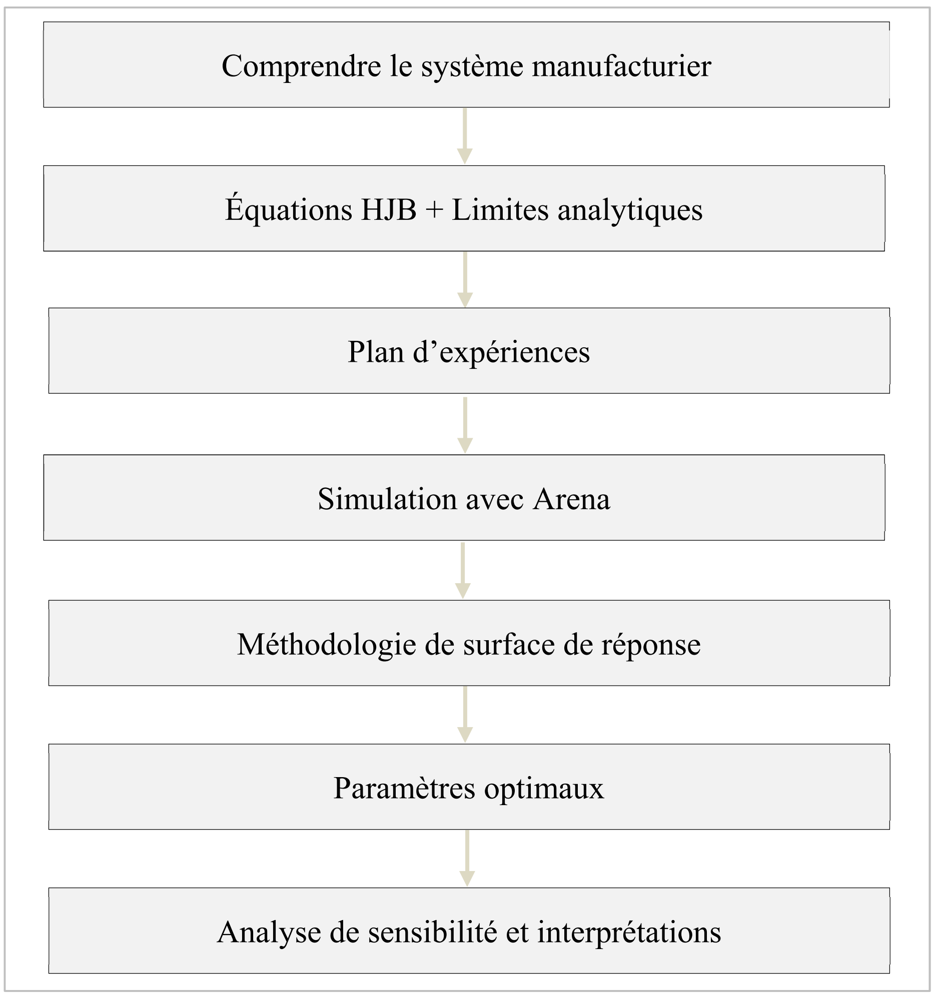

Figure 0.1 Diagramme des étapes de l'approche de résolution adoptée

Nous présentons dans la Figure 0.1 les différentes étapes de la méthode de résolution adoptée dans ce travail. En premier lieu, nous commençons par comprendre tous les aspects du système et du problème traité ainsi que spécifier toutes les hypothèses prises. Par la suite, nous présentons une modélisation du problème de la commande optimale analytiquement ainsi que les conditions d'optimalité à travers les équations HJB. La politique développée est par la suite modélisée à travers l'outil Arena. Les variables d'entrées de modèles sont les paramètres de décisions que nous cherchons à optimiser et sont conçues à partir d'in plan d'expérience adéquat. Ensuite, les résultats sortis avec Arena vont servir à déterminer les paramètres optimaux en utilisant l'analyse de la variance (ANOVA) ainsi que la méthodologie de surface de réponse. À travers cette dernière, nous pouvons sortir les paramètres qui influencent le plus la performance du système (les facteurs significatifs) et leurs interactions. Par la suite, nous menons une analyse de sensibilité pour tester la robustesse de l'approche adoptée et observer divers phénomènes.

Ce mémoire est divisé en trois chapitres et une conclusion générale. Le premier chapitre représente une revue de la littérature générale qui inclut des définitions, des notations et des approches de résolution qui nous permettent de positionner ce travail par rapport aux anciens travaux et de montrer sa contribution. Dans le même chapitre, nous définissons la problématique, le cadre général de ce projet ainsi que ses objectifs. Le deuxième chapitre est un article scientifique soumis à « International Journal of Production Economics », intitulé « Production planning for unreliable manufacturing systems under perishable product and shelf life variability » dans lequel nous traitons le problème des politiques de commande optimale de la production pour un système qui se compose d'une seule machine et produisant des produits périssables. Le troisième chapitre présente également un article scientifique soumis à « International Journal of Advanced Manufacturing Technology », intitulé « Integrating production and maintenance control policies for failure-prone manufacturing systems producing perishable products ». Ce dernier est considéré comme une extension du deuxième chapitre où le système sera étudié avec l'existence d'une politique de maintenance préventive afin d'augmenter la disponibilité du système et minimiser le coût total. Dans ce chapitre, nous étudions la relation entre la dégradation de la machine et la réduction des durées de vie de produits et comment cette relation impacte la politique de production et de maintenance. Enfin, une discussion générale de l'étude avec une conclusion de mémoire et quelques perspectives de travaux futures sont fournies.

CHAPITRE 1

REVUE DE LA LITTÉRATURE

1.1 Introduction

La gestion des produits périssables devient de plus en plus importante et les industries sont de plus en plus conscientes qu'il est essentiel de mettre en place une politique de contrôle dédiée aux produits périssables qui diffère des politiques ordinaires en prenant en compte leurs durées de vie limitée. Dans ce contexte, ce chapitre vise à passer en revue les recherches et études antérieures liées aux principaux concepts entourant la gestion des produits périssables dans un environnement dynamique.

Ce chapitre est structuré alors comme suit : la première partie traite des concepts généraux liés aux systèmes de production non fiables et à la gestion des stocks. Par la suite, nous présentons les différentes méthodes de modélisation. Nous concentrons après sur les politiques de la commande optimale en particulier la politique à seuil critique. La considération des produits périssables dans les anciens travaux de recherche est abordée ainsi que les limites de la littérature. Ensuite, nous nous intéressons à passer en revue les études qui ont intégré les stratégies de maintenance. En fait, une classification des activités de maintenance est présentée ainsi que les politiques de contrôle de la maintenance préventive. Nous terminons par définir le cadre général du projet : problématique, motivations, objectifs en nous basant sur la critique de la littérature pour bien nous positionner par rapport aux anciens travaux. Finalement, l'approche de résolution est présentée avant de conclure.

1.2 Les systèmes manufacturiers

Dans cette section, nous allons fournir des définitions et des généralités sur les systèmes manufacturiers et par la suite détailler ceux qui sont non fiables qui font l'objet de notre travail.

1.2.1 Généralités sur les systèmes manufacturiers

Dans un environnement manufacturier, Gershwin (1994) définit un système de production par l'interaction entre les ressources humaines et matérielles. Cette interaction est munie au travers des flux qui peuvent être physiques (mouvements des produits) et informationnels (ordre d'achat, ordre de production, quantité ...). Le rôle d'un tel système est de transformer la matière première en produits finis afin de satisfaire les exigences des clients.

Plusieurs critères sont utilisés pour classifier les systèmes manufacturiers selon leur mode de fonctionnement. Nous citons trois types principaux de classification souvent utilisés et nous donnons un aperçu général sur ces trois catégories :

- volume de production ou bien quantité produite : Selon ce critère de catégorisation, Hounshell (1985) distingue trois catégories : unitaire, par lots (Bouslah et al., 2013) et de masse (Sethi et al., 1997);

- politique de gestion de la production : Selon ce critère de catégorisation, trois façons de gestion sont définies : la gestion de la production en flux poussés, c'est-à-dire produire pour stocker (Gharbi et al., 2011), la gestion de la demande c'est-à-dire en flux tirés, ou la gestion d'une façon hybride;

- nature de la production : Selon ce critère de catégorisation, nous distinguons trois types de systèmes de production : à flux continu c'est-à-dire le mouvement de matière se fait d'une façon continue (par exemple le cas des raffineries ...), flux discrets ou bien par lots où les produits finis représentent l'assemblage des pièces fabriquées séparément (par exemple le cas des industries d'automobiles) et les flux hybrides qui représentent la plupart des cas pratiques en combinant les deux flux continus et discrets (Bhattacharya and Coleman, 1994). Cette dernière catégorie permet la gestion de flux de matière d'une façon continue, mais dans un système caractérisé par des états discrets.

Dans un environnement dynamique, les systèmes manufacturiers sont en tout temps sujets à des évènements imprévus et à des aléas. Cet environnement imparfait rend les actions de contrôle et de gestion difficiles. Parmi ces aléas est la non-fiabilité des machines vu que ces derniers ne sont jamais disponibles à 100 pour cent. Ils sont sujets à tomber en panne, être en maintenance corrective ou préventive, se dégradent avec le temps ... Et, les industriels sont en mesure de prendre ces facteurs en considération afin d'atteindre leurs objectifs. D'ailleurs, les systèmes de production non fiables étaient toujours au centre des recherches, ce qui fait l'objet de la prochaine section.

1.2.2 Structure des systèmes de production non fiables

Les systèmes de production sujets aux pannes ont été principalement introduits par Rishel (1975) et s'appelaient Systèmes manufacturiers sujets aux pannes ou en anglais « Failure-Prone Manufacturing Systems (FPMS) ». Depuis, les FPMS ont intégré de nombreux domaines de recherche, tels que les politiques de contrôle, les politiques de distribution, de réapprovisionnement ... Nous nous intéressons dans cette partie à réviser les travaux en relation avec les politiques de contrôle et les stratégies de production pour les systèmes manufacturiers non fiables. Nous citons les travaux de (Battini et al., 2013; Kenne et Gharbi, 2001; Mourani et al., 2008). Aussi, Chelbi et al. (2008) considéraient une entreprise alimentaire comme un système de fabrication peu fiable soumis à des temps de panne aléatoires et ont proposé un modèle de production optimal indiquant que pendant les périodes de panne et de maintenance aléatoires, la demande doit être satisfaite à partir d'un inventaire tampon dont la capacité S doit être identifiée. Ils ont considéré qu'aucune panne de la machine ne devait se produire pendant le temps d'accumulation du stock S. Cette hypothèse peut être jugée acceptable si la période de « build-up » du stock est relativement courte. Cependant, pour des autres paramètres d'entrées, S peut augmenter, ainsi la période d'accumulation T augmente, ce qui affaiblit l'hypothèse énoncée et ne reflète pas le cas réel dans les industries.

Les FPMS ont été formulés comme un problème de commande optimale stochastique par Older et Souri (1980) et plus tard par les travaux de Kimemia (1982) et Kimemia et Greshwen (1983).

Le contrôle de la production d'un système manufacturier sujet aux pannes a été étudié à grande échelle et une riche littérature est trouvée (Kenné et al., 2007). La nature dynamique et imprévisible de ces systèmes rend difficile et complexe la détermination des taux de production optimaux. Les FPMS sont souvent classifiés comme des problèmes de commande optimale stochastique ce qui fait l'objet de la prochaine section.

1.3 Commande optimale stochastique pour les systèmes manufacturiers

Dans cette section, nous allons présenter des généralités sur les problèmes de la commande optimale et par la suite présenter les politiques de commande rétroactives.

1.3.1 Généralités

La commande optimale est définie comme une approche théorique de modélisation d'un système bien déterminé. Elle est basée sur des méthodes mathématiques en tenant compte de la nature dynamique des phénomènes. Au début, cette théorie était utilisée dans les domaines des mathématiques appliquées et l'ingénierie, et aie intégrée par la suite l'étude des systèmes manufacturiers dans un environnement stochastique en prenant en considération divers volets (production, qualité, maintenance, rejet, refabrication ...). Pour un problème de planification de la production d'un système manufacturier, l'objectif est de trouver le taux de production optimal suite à un certain critère bien défini de la performance. Pour ce faire, plusieurs outils de commande optimale stochastique ont étaient établis dont deux sont les plus utilisées : Le principe de maximum de Pontryagin (Pontryagin et al., 1962; Seierstad et Sydsaeter, 1987) et les équations de Hamilton-Jacobi-Bellman (HJB) obtenus avec de la programmation dynamique stochastique. Ce dernier outil a permis Rishel (1975) de développer les conditions d'optimum suffisantes et nécessaires qui sert à trouver la solution optimale pour les problèmes de commande optimale stochastique pour un système dynamique markovien avec des états finis. En fait, plusieurs travaux étudient les problèmes de la commande optimale avec des évènements aléatoires qui suivent des processus Markoviens et qui perturbent la production. Nous citons l'exemple des pannes et des réparations des machines qui affectent leurs disponibilités, ce que nous allons étudier dans ce travail. En se basant sur les résultats de Rishel

(1975), Older et Suri (1980) ont réussi à développer la structure de la politique de contrôle optimale d'un tel système manufacturier ayant des pannes et des réparations qui suivent un processus Markovien. Cette structure est de nature à seuil critique. Dans une telle politique, un niveau d'inventaire optimal est maintenu afin de se prémunir contre une future pénurie de capacité causée par des pannes de machine. Nous allons détailler cette politique dans la section suivante.

1.3.2 Politique de commande à seuil critique

La politique de contrôle à seuil critique est classée parmi les politiques de commande rétroactives ou en anglais « feedback control policy » qui ont intégré plusieurs travaux de recherche. En fait, dans un contexte dynamique, ce type de politique agit d'une façon très efficace et efficiente. Akella et Kumar (1986) ont réussi à résoudre le problème analytiquement en utilisant les équations HJB pour un système qui se compose d'une seule machine sujette à des temps de pannes et réparations aléatoires produisant un seul produit avec une demande connue et constante. La politique optimale trouvée est appelée le « Hedging Point Policy » (HPP) et a pour but la minimisation du coût total qui est la somme des coûts d'inventaire et des coûts de pénurie. Elle consiste à maintenir un stock de sécurité des produits finis à un niveau optimal appelé un seuil critique Z^*. Ce stock est maintenu pour éviter les risques de pénurie pendant les périodes de la non disponibilité de la machine. Le concept de la politique indique que si le niveau de stock actuel dépasse le seuil optimal Z^*, la machine ne doit pas produire, si c'est strictement moins, la machine doit produire à sa capacité maximale. S'ils sont exactement égaux, il faut produire exactement assez pour répondre à la demande, ce qui signifie que la machine fonctionne avec le taux de la demande. Ceci est détaillé par l'équation suivante (1.1). Bielecki et Kumar (1988) ont confirmé plus tard cette structure en utilisant la théorie des files d'attente avec un modèle M/M/1.

$$U\big(x(t),\alpha(t)\big) = \begin{cases} Um & si\ x(t) < Z^* et\ \alpha(t) = 1 \\ D & si\ x(t) = Z^* et\ \alpha(t) = 1 \\ 0 & si\ x(t) > Z^* ou\ \alpha(t) = 0 \end{cases} \tag{1.1}$$

Avec :

$x(t)$	Niveau instantané de l'inventaire au temps t
$U(t)$	Taux de la production au temps t
D	Taux de la demande
U_m	Taux maximal de production
Z^*	Seuil critique optimal
$\alpha(t)$	Processus stochastique décrivant l'état du système au temps t ($\alpha(t)$ = 1 si la machine est opérationnelle et $\alpha(t)$ = 0 sinon)

L'utilisation de la HPP a incité nombreux chercheurs à développer plusieurs extensions basées sur cette politique afin d'étudier les problèmes de la commande optimale dans différents contextes industriels. Hajji et al., (2009) étudient une politique de production et de réapprovisionnement en deux étapes et ont proposé une politique de rétroaction basée sur la HPP en mettant l'accent sur la non-fiabilité des fournisseurs. Autres travaux ont traité des problématiques de maintenance tel que (Assid et al., 2014). Pour les systèmes manufacturiers de plusieurs types de produits, Bai et Elhafsi (1997) ont développé la politique du corridor de couverture (HCP) pour traiter un système manufacturier fabriquant deux types de produits. Leur travail a été continué par Hajji et al. (2011) avec une politique de corridor de couverture multiple (MHPP) pour les systèmes ayant plusieurs états. Bouslah et al. (2013) traitent une politique conjointe de production optimale et de dimensionnement des lots où les actions de contrôle qualité sont effectuées. Ben Salem et al. (2014) étudient la commande optimale en intégrant les aspects environnementaux pour les systèmes peu fiables. L'étude de la commande optimale pour les produits de nature périssable a également suscité de nombreux travaux de recherche. Nous citons (Boukas et Al-Sunni, 1999) traitant la recherche de la politique de production optimale dans un système de fabrication peu fiable produisant des produits à durée de vie fixe. Nous pouvons également citer les travaux de (Chung et al., 2011; Hesham et al., 2005). Aussi, Sajadi et al., (2011) traitent le cas d'un réseau de machines non fiables où le produit final est périssable avec une durée de vie fixe en se basant sur la HPP.

Tous les travaux mentionnés et plusieurs autres sont basés sur la HPP. Cependant, résoudre ces problématiques et trouver la solution optimale des équations HJB analytiquement est complexe et seulement possible que pour le cas d'un système manufacturier se composant d'une seule machine produisant un seul produit. Ce qui a poussé Boukas et Haurie (1990) a utilisé une approche numérique pour résoudre ces équations en se basant sur l'approche du Kushner (Kushner et Dupuis, 1992) pour un système fabriquant plus qu'un produit dans un processus markovien non homogène. Plusieurs travaux se sont basés sur cette approche et plusieurs chercheurs choisissent de combiner cette approche numérique avec une approche expérimentale pour l'optimisation. Parmi les approches expérimentales, nous citons la simulation combinée avec les plans d'expériences et la méthodologie de surface de réponse ou en anglais « Response Surface Methodology » (RSM). Cette approche est adoptée dans ce travail pour résoudre le problème de commande optimale.

Dans la section suivante, nous nous intéressons à décrire le système étudié.

1.4 Système étudié

Dans ce travail, nous étudions un système manufacturier non fiable sujet à des temps de panne et réparation aléatoires et produisant des produits périssables ayant une durée de vie limitée et aléatoire.

La Figure 1.1 représente une illustration du système étudié. Il se compose des éléments qui sont liés entre eux par deux types de flux (flux de matière et flux d'information). Le système manufacturier étudié se compose d'une entité de production sujette à des pannes et des réparations stochastiques (corrective et/ou préventive) et produisant un seul type de produit de nature périssable. Ces derniers possèdent une durée de vie qui est limitée et aléatoire. Si un produit est encore en stock et dépasse sa durée de vie avant être tiré par la demande, il est rejeté. Le système de production opère suivant une politique de production rétroactive basée sur le niveau de stock et l'état de la machine.

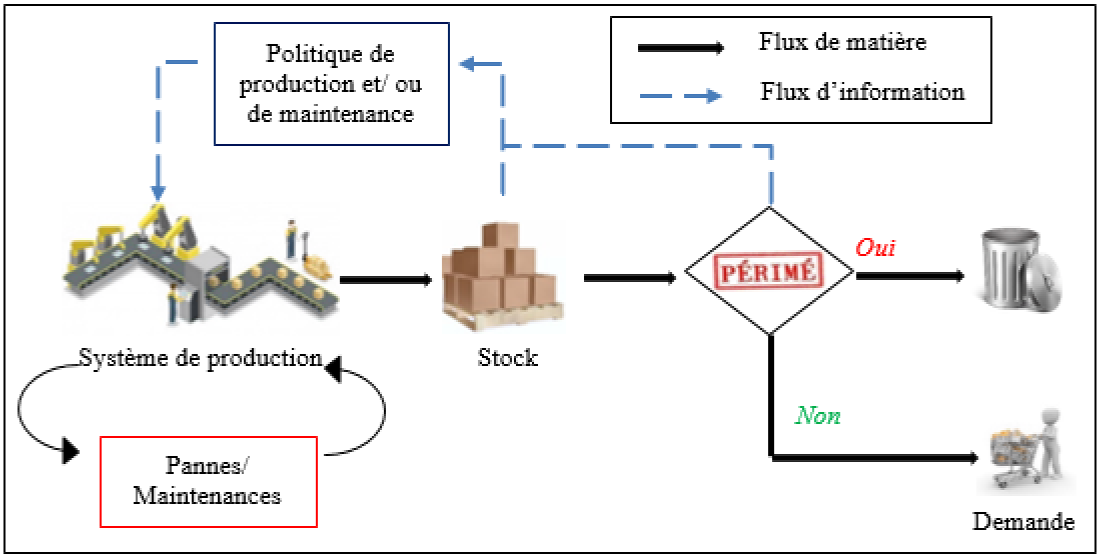

Figure 1.1 Structure du système étudié

Dans la section suivante, nous intéressons à définir des notions générales en relation avec les produits périssables et passer en revue des travaux qui traite ce type de produit.

1.5 Produits périssables dans le milieu industriel

Cette section est divisée comme suit : nous allons commencer par des définitions et des aspects liés aux produits périssables. Par la suite, nous allons traiter les travaux de gestion de stock des produits périssables. Finalement, nous allons examiner les stratégies de contrôle de la production des systèmes peu fiables pour les produits périssables.

1.5.1 Généralités et définitions

Commençons par définir ce que signifie un produit périssable ou la périssabilité. Leandro et Gilbert (2014) définissent les produits périssables comme les produits qui ont simplement une date d'expiration, après laquelle un produit ne peut plus être utilisé. Ils ajoutent que ce n'est pas seulement le cas pour les produits réglementés tel que les médicaments et les aliments, mais aussi d'autres produits dont la valeur marchande, l'attrait ou la qualité diminue avec le temps, tel que les produits cosmétiques, les journaux, les fleurs, les peintures, les articles de mode ou les articles électroniques. Dans ce cas, nous parlons de produits à courte durée de vie vendable. Dans ce contexte, Lee et Kim (2014) définissent la détérioration comme toute action qui bloquent l'utilisation initiale désirée d'un produit. Ils continuent en décrivant ces actions et en les classant en trois formes : l'épuisement physique comme le cas des aliments frais, la détérioration ou la perte d'efficacité originelle comme l'exemple des médicaments, et la dégradation ou la perte de valeur perçue comme les articles de mode ou les articles électroniques. Nahmias (1982) est le premier travail à présenter une revue globale des problèmes et des méthodes de résolution liés aux produits périssables. Il a donné une classification des différents modèles d'inventaire des produits périssables en trois types en fonction des caractéristiques de la durée de vie :

- le premier type décrit des produits dont la valeur reste constante pendant un certain temps fixe, puis devient immédiatement inutilisable, comme les articles avec une date d'expiration spécifique : yogourt, agroalimentaire, médicaments…;

- le deuxième type décrit des éléments dont l'efficacité, la nature ou les fonctionnalités diminuent progressivement avec le temps. La durée de vie ici est aléatoire, où chaque produit est rejeté après une durée aléatoire s'il n'est pas consommé par la demande. Des exemples typiques sont les fruits, les légumes et les fleurs;

- le troisième type décrit des produits dont l'efficacité ne diminue pas, cependant, c'est la demande qui se dégrade au fil du temps, en raison du changement de comportement des clients envers l'utilité : produits électroniques ou produits de mode qui sont jetés après une date précise ou quand une nouvelle génération d'articles est promue sur le marché, ou des articles dont le contenu informationnel se détériore : journaux, calendriers ...

1.5.2 Gestion des stocks des produits périssables

L'étude des problèmes de gestion des stocks des produits périssables a toujours été au centre de la recherche traitant des aspects liés aux réapprovisionnement, la réduction des prix, le dimensionnement des lots, les politiques de commande ... Nahmias (2011) fournit un état de l'art détaillé dans ce domaine. Aussi, les références (Pahl et VoB, 2014; Li et al., 2010; Goyal et Giri, 2001; Raafat, 1991) donnent une vue d'ensemble des travaux réalisés dans ce domaine. Nandakumar et Morton (1993) et Liu et Lian (1999) ont été les premiers à modéliser des systèmes d'inventaire pour les produits périssables ayant une durée de vie fixe. Nahmias (1975) aborde le problème de politiques de réapprovisionnement optimales pour un seul produit avec une durée de vie fixe qui s’étalent sur plusieurs périodes. Kouki et al., 2015 étudient un modèle de gestion des stocks (r, Q) pour les produits périssables à durée de vie fixe. Balugani et al. (2019) étudient un modèle de gestion de stock (T, S) pour les produits périssables à durée de vie fixe. Quant aux produits à une durée de vie aléatoire, Nahmias, 1982 étudie des produits périssables avec des durées de vie aléatoires et examine l’impact de la variabilité de la durée de vie sur la politique de réapprovisionnement. Ce n’était pas le seul à étudier les produits périssables à durées de vie aléatoires. En fait, Kouki, et al. (2014) considèrent une politique de réapprovisionnement caractérisée par les deux variables (T, S) pour les produits périssables avec une durée de vie aléatoire modélisée par une distribution exponentielle. Une suite de cette étude a été réalisée par Kouki et Jouini (2015) qui cherchaient également la politique de réapprovisionnement optimale pour les produits périssables avec une durée de vie modélisée une distribution m-Erlang. Ils confirment dans leur travail l'importance de considérer la variabilité de la durée de vie à l'aide des exemples numériques et que le fait de l'ignorer affecte significativement les coûts encourus. Kouki et al. (2016) étudient également l'effet de la variabilité de la durée de vie sur la performance du système et confirment que lorsqu'il s'agit de produits périssables, les informations sur l'âge de produit sont essentielles. Barron (2019) étudie un modèle de gestion de stock (s, S) avec des durées de vie aléatoires et des demandes aléatoires.

Le nombre de travaux sur les produits périssables a augmenté au fil des années (Janssen et al., 2016). Cependant, en ce qui concerne la planification de la production de produits périssables pour les systèmes manufacturiers non fiables, nous avons trouvé peu de travaux dans ce domaine. Dans la section suivante, nous allons citer quelques travaux qui ont traité les problèmes de contrôle de la production des produits périssables pour un système manufacturier non fiable.

1.5.3 Contrôle de la production des produits périssables

Dans cette partie, nous allons concentrer sur la revue des travaux qui ont considéré des problématiques de contrôle de la production des produits périssables qui sont principalement basés sur des politiques de seuils critiques pour des systèmes manufacturiers non fiables. Le travail de Bounkhel et Tadj (2005) a étudié l'application de la HPP comme politique de contrôle de la production afin de déterminer le taux de production pour les produits périssables ayant une durée de vie fixe. Le système est considéré non fiable avec des temps de pannes et réparations aléatoires. Hedjar et al., (2007) ont aussi basé leur travail sur la politique de contrôle classique HPP pour un système de production des produits périssables à durée de vie fixe ayant pour objectif la minimisation de la fonction coût total. Quant au travail de Sajadi et al. (2011), il traite un système composé d'un réseau de machines sujettes à des temps de pannes aléatoires. Le produit final est périssable avec une durée de vie fixe avec une demande constante. La HPP est utilisée afin de trouver le taux de production optimal qui minimise le coût total du système. La technique de simulation d'événements discrets couplée avec la méthode de Taguchi a permis de déterminer les valeurs optimales des variables de décision qui représentent les seuils critiques des machines du système. Nous ajoutons aussi le travail de Tavan et Sajadi (2015) qui est considéré comme extension du travail précédent. Il considère également un réseau de machines sujettes aux pannes, produisant des produits périssables avec des durées de vie fixes et applique la technique de simulation avec le test de Taguchi afin de trouver le taux de production optimal pour la politique HPP. Le travail de Malekpour et al. (2016) étendu dans le travail de Hatami-Marbini et al. (2020) traite des problèmes de contrôle de la production pour un système composé d'un réseau de machines où le produit final est périssable. Dans les deux travaux, la durée de vie est considérée comme fixe et la politique de contrôle utilisée est la HPP.

La section suivante est dédiée à passer en revue les travaux qui ont étudié les politiques de contrôle de la maintenance préventive.

1.6 Activités de maintenance

Les travaux de recherche portant sur les problèmes de maintenance sont multiples et de nombreux modèles ont été proposés pour déterminer des politiques de contrôle de la maintenance. Dans cette section, nous citons quelques politiques de maintenance qui sont généralement adaptées dans les systèmes manufacturiers et nous passons en revue des travaux qui ont considéré des politiques de contrôle de maintenance.

1.6.1 Classification des activités de maintenance

La maintenance fait référence aux actions planifiées ou non planifiées qui sont exécutées pour maintenir ou remettre un système donné dans un état de fonctionnement acceptable. Ces méthodes de maintenance visent à améliorer les performances des systèmes, augmenter la disponibilité, et réduire les occurrences des pannes, le tout au moindre coût possible. Une première et là plus répondue classification des activités de maintenance désigne deux catégories : la maintenance corrective et la maintenance préventive. Certains auteurs définissent la maintenance corrective comme toute action menée à la suite d'une défaillance, cherchant à restaurer le système dans un état spécifié. Et, la maintenance préventive peut être définie comme toute action menée lorsque le système est opérationnel, comme une tentative de maintenir le système dans un état spécifique afin de diminuer les risques de pannes.

Une deuxième classification des activités de maintenance est basée sur le degré auquel le système est remis en état de fonctionnement, cela conduit à définir plusieurs types de maintenance comme indiqué par Pham et Wang (1996) et Wang (2002), comme suit :

- réparation parfaite : désigne l'action d'entretien qui a la particularité de restaurer le système à des conditions comme neuves. Par conséquent, avec une réparation parfaite, le système a la même durée de vie et la même intensité de défaillance qu'un tout nouveau système;

- réparation minimale : implique une activité de maintenance qui n'est pas aussi complète que la précédente catégorie, puisqu'elle ne porte que sur une partie du système, elle a donc la particularité de restaurer le système dans des conditions aussi mauvaises que l'ancien. En d'autres termes, l'intensité de la défaillance reste inchangée dans les mêmes conditions qu'il avait avant la panne;

- réparation imparfaite : cette activité de maintenance sert à modéliser des situations plus réalistes dérivées des deux cas extrêmes de réparation parfaite et minimale. Ce type de maintenance peut ne pas rendre le système aussi bon qu'un tout nouveau, mais certainement les performances peuvent être grandement améliorées avec cette réparation;

- pire réparation : ce type de réparation a la particularité d'augmenter l'intensité de la défaillance ou influencer tout autre paramètre du système, cependant le système reste opérationnel, mais dans un état dégradé avant sa défaillance.

Plusieurs facteurs peuvent engendrer une détérioration de la machine tels que l'usure accumulée de divers éléments du système et l'influence de l'environnement, comme observé sur l'analyse de données réelles dans Lam (2007).

1.6.2 Politique de contrôle considérant la détérioration

La détérioration des machines était au centre de plusieurs travaux. Love et al. (2000) ont considéré le cas d'une machine sujette à des pannes, et ont proposé une politique de réparation/ remplacement. Leur modèle indique si, en cas de panne, il faut réparer la machine pour démunir un peu la fréquence des pannes, ou s'il est préférable de remplacer la machine et restaurer le système à un état « comme neuf ». Ils ont supposé que la fréquence des pannes dépende de l'âge de la machine. Cependant, ils n'ont pas intégré les décisions de production dans leur étude.

Dans une autre étude, Lai et Chen (2006) ont étudié la politique de remplacement optimale d'un système à deux unités de production où il existe une interaction de taux de panne entre les unités. Cette interaction implique que lorsque la première machine tombe en panne, elle aboutit à une augmentation de taux de panne de la deuxième machine. Et lorsque la deuxième machine tombe en panne, la première machine tombe immédiatement en panne. De plus, les taux de panne des machines augmentent également en raison de vieillissement.

Lam (2007) a développé une politique de maintenance qui indique que le système sera réparé chaque fois que l'une des deux conditions suivantes se produit en premier ; il tombe en panne ou son temps de fonctionnement atteint un certain niveau. Le système est remplacé alors par un nouveau. L'effet de la détérioration entraîne que le temps de fonctionnement après réparation diminue tandis que les temps de réparation augmentent après les pannes. De plus, ils ont introduit une distribution de l'âge de la machine prenant en compte l'effet des activités de maintenance.

1.6.3 Politique de maintenance préventive

La mise en œuvre d'une maintenance préventive pour les systèmes manufacturiers non fiables représente une stratégie extrêmement efficace pour augmenter leurs durées de vie et réduire les coûts de production. L'effet de la maintenance préventive sur les systèmes de production a été étudié par plusieurs chercheurs comme Chelbi et Ait-Kadi (2004), qui ont proposé un modèle de système de production réparable où la maintenance préventive est régulièrement effectuée à des périodes définies, et un stock tampon est constitué pour pallier les perturbations causées par les pannes. Leur modèle mathématique considère le temps de réparation et la durée de maintenance préventive pour déterminer une politique optimale.

D'autres considérations sur la planification de la production et la maintenance préventive se trouvent dans Berthaut et al. (2010), ils ont étudié le cas d'un système manufacturier à une machine et à un produit où les actions de maintenance sont aléatoires et ont des durées non négligeables. La politique obtenue est une combinaison d'une politique de contrôle de production et d'une stratégie de maintenance préventive périodique modifiée, où cette action est menée lorsque le niveau de stock dépasse un niveau déterminé.

Nodem et al. (2011) ont développé un modèle qui détermine le taux de production et ils ont inclus une variable de décision pour déterminer quand effectuer la maintenance préventive. Dans leur modèle, la probabilité d'occurrence de pannes causées par le vieillissement de la machine augmente avec l'âge de la machine et les temps de réparation augmentent également dus à des réparations imparfaites. L'avantage de la maintenance préventive consiste à restaurer complètement l'état de la machine comme neuve.

Ayed et al. (2012) étudient un système sujet aux pannes face à une demande aléatoire où la sous-traitance est disponible pour satisfaire le niveau de service requis. Le système fonctionne avec un taux de production variable et le processus de vieillissement de la machine dépend de son taux de production. Dans ce cas, une politique de contrôle de la production pour le système de production principal et pour le sous-traitant est déterminée. En plus, cette politique a été combinée avec une politique de contrôle de la maintenance préventive pour minimiser le coût total.

Nous terminons cette sous-section par une brève remarque, l'ensemble des travaux présentés ci-dessus se concentre sur l'effet de la maintenance préventive sur l'amélioration de la disponibilité du système, et il y a peu d'études qui relient les stratégies de maintenance préventive avec la durée de vie de produits. À notre avis, il peut être exploité beaucoup plus. Par conséquent, il semble logique de s'attendre à une potentielle extension des modèles actuels de maintenance préventive sous l'angle de la périssabilité.

1.7 Critique de la revue de littérature

Nul ne peut nier que les anciens travaux que nous avons présentés ont fourni beaucoup de résultats importants relatifs à la gestion de stock des produits périssables d'un côté et aux politiques de contrôle de la production et de la maintenance de l'autre côté. Mais, des limites existent encore au niveau de ces travaux. En fait, l'étude des produits périssables est souvent étudiée dans les problèmes de gestion des stocks tels que les politiques de réapprovisionnement. Bien que les problèmes de gestion des stocks des produits périssables sont largement étudiés dans la littérature, la coordination des activités de planification de la production tout en tenant compte de la spécificité de la durée de vie limitée et aléatoire reste une question ouverte. Cet écart est accentué en raison de la complexité du caractère aléatoire et du comportement dynamique des systèmes manufacturiers. En fait, comme nous avons cité dans les sections ci-dessus, seulement quelques travaux ont étudié les problèmes de contrôle pour les systèmes manufacturiers des produits périssables, mais ils ne traitent que le cas des durées de vie fixes. De plus, ils utilisent la HPP classique pour le contrôle de la production et aucune nouvelle politique n'a été développée qui prenne en compte la nature périssable des produits. La variabilité des durées de vie de produits n'a jamais été traitée au niveau opérationnel. Compte tenu de cette caractéristique, trouver la politique de production optimale devient un véritable défi. De plus, outre la contrainte de périssabilité, les systèmes de fabrication de tous les secteurs sont soumis à de multiples sources d'incertitudes qui rendent les décisions de planification de la production beaucoup plus difficiles, en particulier lorsqu'il s'agit d'un système sujet aux pannes dans des contextes dynamiques et stochastiques.

Quant aux travaux qui traitent les problèmes liés aux systèmes manufacturiers non fiables, la politique de contrôle à seuil critique (HPP) a été étudiée dans plusieurs contextes industriels, par exemple, en prenant en compte la maintenance de la machine (Rivera- Gomez, 2013), la qualité des produits (Bouslah et al., 2013), les aspects environnementaux (Ben Salem et al., 2015). À notre connaissance, il n'existe pas un travail qui a proposé une politique qui intègre la périssabilité des produits.

Au vu des travaux mentionnés ci-dessus, nous pouvons en déduire que dans le contexte de la détérioration des systèmes, il est clairement évident qu'aucun des articles considérés ne fait appel au fait que la détérioration peut également avoir un effet sur la durée de vie des pièces produites. De plus, même si beaucoup des études confirment que la dégradation des machines peut entraîner une diminution de la durée de vie d'un produit, aucune relation quantitative n'a été proposée à ce sujet. En fait, l'impact de cette relation entre la réduction de durée de vie de produit et la dégradation de machine sur le comportement du système manufacturier n'a jamais étaient étudiés. En plus, construire une politique combinée de contrôle de la production et de la maintenance préventive qui tient en considération des différentes interactions du système n'a jamais été abordée.

En outre, au meilleur de nos connaissances, la majorité des études faites ont utilisé des approches mathématiques pour modéliser les problèmes et des approches analytiques pour la résolution (Kouki et Jouini, 2015; Kouki et al., 2014; Chen et al.; 2014; Widyadana et Wee, 2012). Cependant, même si les approches mathématiques contribuent à des résultats importants, ils ont leurs limites et certaines relaxations et hypothèses sont prises et ils ne peuvent pas tenir compte de l'aspect stochastique et dynamique du système.

1.8 Cadre général de la recherche

Cette section est conçue pour bien présenter le cadre général de ce projet. En nous basant sur la revue faite dans les sections précédentes, nous allons présenter la problématique, la motivation, les objectifs de ce projet de recherche et la méthodologie de résolution adoptée.

1.8.1 Problématique

De nombreux produits ont des durées de vie limitées, notamment les produits agroalimentaires, les liquides volatils, les médicaments, les composants électroniques, les produits de haute technologie et les articles de mode. Les produits périmés doivent être rejetés de l'inventaire après leur date d'expiration. Outre les pertes encourues qu'ils imposent lors de leurs rejets, dans de nombreux cas, les produits périssables peuvent affecter d'autres produits s'ils sont stockés ensemble. Un bon exemple serait la détérioration des fruits, légumes, fruits de mer, viandes, fromages et volailles.

Dans les sections précédentes, nous avons établi une critique de la littérature traitant les problématiques des produits périssables. Nous avons remarqué que la problématique de commande optimale des systèmes manufacturiers des produits ayant une durée de vie limitée dans un contexte dynamique n'a pas était étudiée suffisamment d'un point de vue opérationnel. Du coup, nous posons les questions suivantes :

- Est-ce qu'il y a des politiques de contrôle rétroactives dédiées au contrôle de la production des produits périssables dans un contexte dynamique et stochastique ? Quels sont les effets de l'intégration de la durée de vie limitée d'un produit sur les actions de la production et de la maintenance ? Quels sont les effets de la variabilité de la durée de vie d'un produit sur la politique de contrôle et sur les coûts encourus ?

- Quels sont les phénomènes qui doivent être pris en considération et qui peuvent affecter les nombres de produits périmés et les coûts encourus ? À titre d'exemple, la dégradation de la machine peut-elle avoir un impact sur les durées de vie des produits? Quelles sont les décisions au niveau de la production et surtout au niveau de la maintenance à prendre en prenant en considération la dégradation de la machine ?

- Est-ce que nous pouvons adapter des méthodes de résolutions autres que les approches mathématiques pour mieux illustrer la réalité industrielle ?

1.8.2 Objectifs de la recherche

Dans la pratique, de nombreuses entreprises fabriquant des produits périssables ont commencé à reconnaître qu'elles avaient besoin d'une politique de contrôle différente pour leurs produits qui tient compte de la caractéristique de durée de vie limitée et de la variabilité. Donc l'objectif principal de ce travail est l'étude des systèmes manufacturiers non fiables fabriquant des produits périssables. En se basant sur la commande optimale stochastique, des politiques de commande rétroactives seront proposées qui tiennent en considération l'âge d'un produit et sa nature périssable dans les décisions de production et/ ou de maintenance dans le but de minimiser le coût total et satisfaire la demande. Cela signifie fournir des stratégies de contrôle de la production et/ ou de maintenance en conjonction avec l'aspect de périssabilité du produit au niveau de la prise de décision opérationnelle.

Le problème à résoudre est considéré complexe, en particulier avec les aspects stochastiques entourant le système, soit avec des temps de pannes et réparations aléatoires, soit avec des durées de vie aléatoires, ce qui nous a poussé à formuler les deux objectifs spécifiques suivants :

- Déterminer une politique de contrôle de la production pour un système manufacturier non fiable fabriquant des produits périssables qui tient en considération l'âge du produit.

- Intégrer les activités de la maintenance préventive au premier modèle pour déterminer une politique de contrôle de la production et de la maintenance d'un système manufacturier mon fiable des produits périssables. Dans ce contexte, nous étudions également le lien existant entre la dégradation de la machine et la durée de vie des produits.

Pour contribuer à la solution de ces problèmes et pouvoir modéliser le contexte dynamique du système, nous proposons une méthodologie bien déterminée qui sera l'objet du paragraphe suivant.

1.8.3 Approche de résolution

En théorie de la commande optimale stochastique, les solutions optimales sont parfois difficiles à obtenir à partir des méthodes d'optimisation traditionnelles et sont souvent approchées par des méthodes numériques dans des conditions spécifiques (Gharbi et al. 2006). Dans la littérature, plusieurs méthodes ont été établies et utilisées dans la résolution de plusieurs problèmes. Nous avons mentionné dans les sections ci-dessus que la HPP est considérée comme la politique de commande rétroactive optimale (Akella et Kumar, 1986). Cette dernière a été adaptée dans plusieurs travaux de recherche des systèmes plus complexes intégrant plusieurs aspects (réseaux de machines, sous-traitance, multiples produits ...) ce qui a rendu difficile l'approche de résolution analytique. Alors, plusieurs méthodes de résolution ont été appliquées afin de pallier les limites analytiques. Parmi ces approches, nous citons l'approche numérique basée sur la méthode de Kushner (Kushner et Dupuis, 1992). Cette méthode sert à résoudre le problème de la commande optimale lorsque le système est régi par des processus Markoviens non homogènes. Aussi, Kenne et Gharbi (2001) ont développé une autre approche de résolution qui combine la théorie de commande optimale stochastique avec les techniques d'optimisation basées sur la simulation et les plans d'expériences. Depuis, cette approche a été appliquée par plusieurs travaux vu qu'elle a montré son efficacité pour résoudre les problèmes complexes de contrôle des systèmes non fiables. Donc, compte tenu des limites et des difficultés numériques, une approche comprenant la simulation, les plans d'expériences (Design Of Experiment DOE) et la méthodologie de surface de réponse (Response Surface Methodology RSM) sont utilisés pour résoudre les problèmes soulevés, proposés en deux articles, lors de ce projet et estimer la valeur optimale des variables de décision. Les principales étapes de l'approche sont présentées à la Figure 1.2 et sont comme suit :

- Étape 1 : Définition de la politique de commande

  Cette étape consiste à définir la structure paramétrée de la politique de contrôle de production et/ ou de maintenance. Les paramètres définis représentent les inputs du modèle de simulation.

- Étape 2 : Simulation

Le modèle de simulation est conçu pour refléter la dynamique du système régie par la politique de contrôle proposée. Il évalue le comportement du système sur l'horizon de planification et génère des outputs qui servent à calculer le coût total. Dans ce travail, le modèle de simulation est construit avec Arena en utilisant le langage SIMAN. Il s’agit d’un modèle combinant le discret et le continu qui permet d’évaluer la politique proposée et génère le coût total.

- Étape 3 : Plan d’expériences et méthodologie de surface de réponse

Dans cette étape, le nombre d'expériences et les facteurs considérés sont définis. Pour préciser les effets principaux et quadratiques des facteurs sur le coût total et l'interaction entre les variables indépendantes, l'analyse de variance (ANOVA) est réalisée. Enfin, une méthodologie de surface de réponse est utilisée pour déterminer la relation entre la ou les variables indépendantes et la variable dépendante (le coût total), et par conséquent, pour l'optimiser en trouvant la meilleure combinaison de paramètre(s) de contrôle résultant au moindre coût.

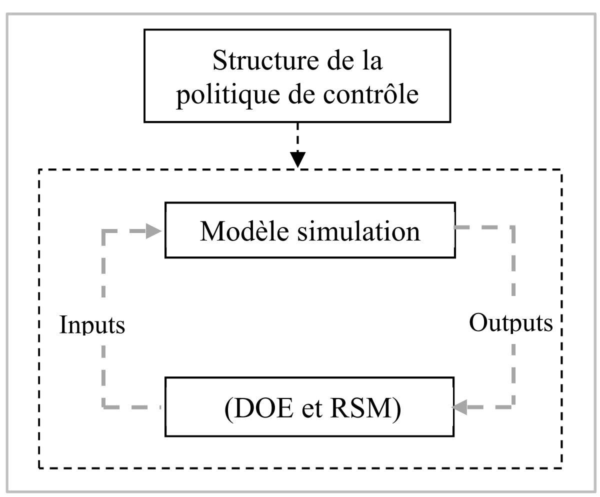

Figure 1.2 Méthodologie de résolution

1.9 Conclusion

Dans ce chapitre, nous avons présenté une revue de littérature qui inclut les différents aspects qui sont en relation avec le travail fait lors de ce projet de recherche. Nous avons présenté la théorie de commande optimale stochastique ainsi que la politique de contrôle à seuil critique. Nous avons également passé en revue les travaux antérieurs pertinents qui ont examiné les systèmes manufacturiers non fiables. Aussi, nous avons abordé les problèmes liés aux produits périssables ainsi que les politiques de taux de production optimales. Et, en se basant sur les limites des anciens travaux, nous avons pu fixer la problématique ainsi que les objectifs de notre recherche. Enfin, nous avons présenté la méthodologie de résolution utilisée dans cette étude.

CHAPITRE 2

PRODUCTION PLANNING FOR UNRELIABLE MANUFACTURING SYSTEMS UNDER PERISHABLE PRODUCT AND SHELF LIFE VARIABILITY

Raouia Kaddachi [a], Ali Gharbi [b], Jean Pierre Kenné [c]

[a,b] Département de génie de la production automatisée, École de Technologie Supérieure, 1100 Notre-Dame Ouest, Montréal, Québec, Canada, H3C 1K3
[c] Département de génie mécanique, École de Technologie Supérieure, 1100 Notre-Dame Ouest, Montréal, Québec, Canada, H3C 1K3

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Abstract: This paper studies a production planning and control problem for a manufacturing system evolving in a stochastic and dynamic environment and producing perishable products. The production system under study is unreliable since it is prone to random failure and repair times in the context of perishable manufactured products with limited and random shelf lives. This article focuses on developing a control policy that aims to minimize the total cost, composed of backlog, inventory holding and disposal costs. To solve the considered optimal control problem, we develop a stochastic dynamic programming model. The obtained optimality conditions of Hamilton–Jacobi–Bellman (HJB) type are solved using a numerical approach to determine the parametrized structure of the resulting optimal control policy. A simulation-based optimization approach is then used to optimize the parameters of the proposed control policy. The policy developed is subsequently analyzed using multiple sensitivity analyses and compared to other policies from the literature. We also study the shelf life variability and its influence on the system performance. Numerical examples show that in the case of a random shelf life, the proposed control policy presents a lower total cost in comparison with other policies adapted from the literature.

Keywords: Stochastic process, Manufacturing systems, Production control, Perishable products, Random shelf lives, Numerical approach, Simulation.

2.1 Introduction

Perishable products are considered a major source of revenue for many industries, including the grocery and pharmaceutical industries. Yet, they represent a major source of waste due to their limited shelf life. According to Jbira et al. (2018), perishable products account for over 36 billion dollars in losses for the grocery industry in the US. Therefore, the effect of perishability cannot be ignored, and has prompted many manufacturing systems to reevaluate their supply chain operations to reduce total costs. The effect is studied either with discounting pricing policies combined with inventory management, replenishment policies, or Production Planning and Control (PPC) problems.

From an operational perspective, manufacturing systems are confronting a lack of strategies that consider the nature of perishable products, while maintaining economic efficiency. Indeed, perishable products are characterized by a limited shelf life, which can be either deterministic or random. Karaesmen et al. (2011) reported that inventory control issues appear whenever there is a need to track the age categories of on-hand inventory. They added that shelf life randomness of the shelf lives makes the standard rules for inventory control unsuccessful. Examples of perishable products with a random shelf life are products with no labeled expiry dates, such as vegetables, seafood, and fruits. Also, any change related to storage conditions has a major effect on the shelf life of a product. Very often, this shelf life will vary as a function of several factors, such as humidity, temperature and lighting (Vrat et al., 2018). When a product exceeds its shelf life, it must be removed from inventory, and this leads to incurred costs, either associated with inventory loss or other unintended consequences, such as lost sales. Consequently, it is important for manufacturing system managers to reevaluate their operational decisions regarding how to regulate the production rate based on developing the optimal control policy, which considers product perishability in order minimize the total cost. It should be mentioned that a significant proportion of the studies that have examined manufacturing system problems for perishable products often address the issue in a deterministic context with the assumption that the manufactured system is reliable. In other words, repair and failure times are not taken into consideration (Pandey, 2017; Chen and Teng, 2014). However, manufacturing systems in all sectors, including those with perishable products, are subject to multiple sources of uncertainties. Among these are failure and repair times. The availability of the manufacturing system has a major effect on its performance and ignoring it may indeed result in high cost and difficulty meeting demand. During repairs and failures, there is no production, and so the system risks facing backlogs or lost sales if there is no stock on hand to satisfy demand. This unpredictable nature of failure-prone manufacturing systems makes finding the optimal control policy more challenging and results in difficulty determining the production rate needed to maintain an inventory level that satisfies demand. The response here may be to increase the inventory level to hedge against backlogs, which means keeping products in inventory longer. However, when dealing with products having a limited shelf life, this increase in inventory level leads to high disposal costs. This risk is bigger when product shelf lives are random. Consequently, the questions for this research can be expressed as the following: (i) What is the optimal inventory level to maintain to reduce backlogs and perishability? (ii) What is the best control policy that should be applied to minimize the total cost? (iii) Knowing that the variability of any aspect generally affects the inventory level, how does shelf life variability in particular effect the inventory level set to hedge against backlogs and perishability? Accordingly, in this paper, we aim to develop a new optimal control policy for unreliable manufacturing systems while considering the perishable nature of finished products and the variability of the shelf life. The new policy developed aims to minimize the total cost, composed of backlog, inventory holding and disposal costs.

The organization of this paper is as follows: The literature review is discussed in Section 2.2. The notations used and the description of the system studied are presented in Section 2.3. The adopted resolution approach is detailed in Section 2.4. The formulation of the stochastic optimal control problem is presented in Section 2.5. Section 2.6 presents the combined simulation-optimization method used to determine the optimal control parameters. Sensitivity analyses based on the proposed control policy are conducted in Section 2.7. Section 2.8 is dedicated to a comparative study between the proposed control policy and other policies adopted from the literature. Managerial insights and implementation issues are discussed in Section 2.9. Finally, in Section 2.10, we conclude the.

2.2 Literature review

In this section, a review of the literature, including inventory control models, production and inventory polices and Production Planning and Control (PPC) policies for perishable products, is presented. A classification and a summary of the research related to our study is presented in Table 2.1 and is divided into three categories. The first category includes inventory control models for perishable products. The second represents work dealing with production and inventory strategies for perishable product manufacturing systems. The third category reviews PPC policies for manufacturing systems for non-perishable and perishable products. To better understand the contribution of this work as compared to previous studies, Table 1 summarizes relevant articles based on key criteria in terms of control policy type; whether or not product perishability is considered, and if so, the type of shelf life (random or deterministic); whether or not the shelf life is represented by a single period or a multi-period model; reliability of the manufacturing system and the possibility of production rate control.

Table 2.1 Bibliographic review relevant to this study

Articles	Type of shelf life		Perishability of products	Manufacturing system		Multi-periodic Shelf life	Production rate control	Determination of new policy
	Random	deterministic		Reliable	Unreliable			
Category 1: Inventory control models								
Nandakumar and Morton (1993)		✓	✓			✓		
Chen et al. (2014)		✓	✓			✓		
Balugani et al. (2019)		✓	✓			✓		
Kalpakam and Sapna (1994)	✓		✓			✓		
Lian et al. (2009)	✓		✓			✓		
Barron (2019)	✓		✓			✓		
Kouki and Jouini (2015)	✓		✓			✓		
Kouki et al. (2016)	✓		✓			✓		
Category 2: EPQ models								
Liao (2007)		✓	✓	✓				
Chen and Teng (2014)		✓	✓	✓				
Pandey (2017)		✓	✓	✓				
Thangam and Uthayakumar (2009)	✓		✓	✓				
Palanivel and Uthayakumar (2015)	✓		✓	✓				
Chung et al. (2011)		✓	✓		✓			
Widyadana and Wee (2012)		✓	✓		✓			
Wee and Widyadana (2013)		✓	✓		✓			
Rahim and Ben-Daya (2001)	✓		✓		✓			
Lin and Gong (2006)	✓		✓		✓			
Category 3: Feedback control models								
Emami-Mehrgani et al. (2016)					✓		✓	✓
Polotski et al. (2019)					✓		✓	✓
Afshar-Bakeshloo et al., 2018					✓		✓	✓
Rivera-Gómez et al. (2020)					✓		✓	✓
Bounkhel and Tadj (2005)		✓	✓	✓			✓	
Hedjar et al. (2007)		✓	✓	✓		✓	✓	
Sajadi et al. (2011)		✓	✓		✓	✓	✓	
Tavan and Sajadi (2015)		✓	✓		✓	✓	✓	
Malekpour et al. (2016)		✓	✓		✓	✓	✓	
Hatami-Marbini et al. (2020)		✓	✓		✓	✓	✓	
Our study	✓	✓	✓	✓	✓	✓	✓	✓

The first category of this literature review is related to inventory control models for perishable products. Janssen et al. (2016) and Chaudhar et al. (2018) provide an overall review of the work done in this area. When dealing with an inventory of perishable products, the type of the shelf life (random or deterministic) represents a key factor for problem resolution (Karaesmen et al., 2011). Nandakumar and Morton (1993) were the first to model inventory systems for perishable products with deterministic shelf lives. Chen et al. (2014) study an inventory control model for perishable products with a deterministic shelf life. Also, Balugani et al. (2019) study an order-up-to-level (T, S) inventory control model for perishable products having deterministic shelf lives. However, many products have a random shelf life. These include fresh fruits and vegetables, poultry and meat, with the shelf life following an arbitrary probability distribution such as exponential, lognormal or Weibull distributions. Kalpakam and Sapna (1994) were the first to model inventory systems for perishable products with random shelf lives by studying an (s, S) model, in which the shelf life of products follows an exponential distribution. Then, Jain and Silver (1994) developed a stochastic dynamic programming model to determine the optimal ordering policy for perishable products with random shelf lives. In addition, Lian et al. (2009) studied a periodic review inventory control system based on perishable products with random shelf lives, following an exponential distribution. As for a continuous review policy, Barron (2019) developed an inventory control model (s, S) with both random shelf lives and random demands. Moreover, Kouki and Jouini (2015) developed the optimal replenishment policy for perishable products with a shelf life following an m-Erlang distribution. They highlight the importance of considering shelf life variability in inventory control using numerical examples, and that ignoring it can affect incurred losses. The same conclusion was confirmed in Kouki et al. (2016), who studied the effect of shelf life variability on the performance of a multi-item inventory system for perishable products. The literature laid out thus far deals with inventory control models for perishable products for both types of shelf lives, and shows that information about the age of the product is critical. However, it does not include production planning and control. This brings us to the next two categories of this literature review, which deal with production planning and control policies.

The second category of the research studies Economic Production Quantity (EPQ) models for perishable products. There is a wide area of research on the production planning of manufacturing systems for perishable products based on EPQ to find the optimal lot size. Research regarding EPQ models has been carried out in many contexts of reliability of manufacturing systems and/or shelf life variability, mostly addressing manufacturing system models, but without consideration of machine failure. In this regard, we cite the work of Liao (2007), which is based on an EPQ model under the assumption of a deterministic constant production rate for perishable products. In the same context, the works of Chen and Teng (2014) and Pandey (2017) are based on EPQ models for perishable products having a deterministic shelf life in a reliable manufacturing system. Thangam and Uthayakumar (2009) and Palanivel and Uthayakumar (2015) study an EPQ model for perishable products having a random shelf life in a reliable manufacturing system. As for the work of Chung et al. (2011), it studies an EPQ model for perishable products for two manufacturing systems having two different stochastic distributions for machine failure, under the assumption of constant production and deterioration rates. Widyadana and Wee (2012) study an EPQ model for perishable products with deterministic shelf lives while adding preventive maintenance for an unreliable manufacturing system. Their work was extended in Wee and Widyadana (2013) while adding rework using the First-In First-Out rule. In the aforementioned EPQ models, the manufacturing system reliability and the shelf life variability are considered separately. However, these two issues are often seen simultaneously in practice. When dealing with a random shelf life, manufacturing systems are considered reliable. And even when considering an unreliable manufacturing system, there are often limitations regarding either the number or the distribution of failure occurrences in each production run. Only a few consider the two issues simultaneously. For example, Rahim and Ben-Daya (2001) study an EPQ model for perishable products including inspection schedules for product quality, under the assumption that the failures of the machine and the deterioration of products follow arbitrary probability distributions. Also, Lin and Gong (2006) study an EPQ model for an unreliable manufacturing system having random failure times and deterministic repair times, where the shelf lives of perishable products follow an exponential distribution.

EPQ models are very commonly used in production planning. However, despite their popularity, these models have certain limitations, and cannot be seen as universal production planning models, especially for perishable products. A main limitation is that EPQ models are not addressed in a dynamic context, which leads to no production rate control during a production cycle. When dealing with perishable products, this leads to many assumptions, such as the fact that all the products manufactured in the same lot have the same shelf life. However, undoubtedly, one lot of products can contain products with different ages, especially when a machine failure occurs during one production cycle and continues to the next one while the build-up of a lot is not yet complete. Moreover, EPQ models for perishable products are often single-period inventory models, which often clashes with the reality that many perishable products have a multi-periodic shelf lives. In this context, analytical models are often used to solve the optimization problems. However, they often do not consider the uncertainties that could be caused by the unreliability of the machine in a stochastic context.

In practice, manufacturing systems are often unreliable and evolve in a stochastic and dynamic context. This brings us to the third category, which focuses on PPC models in a stochastic environment. In fact, studying PPC problems for unreliable manufacturing systems has been at the center of research for decades, with the focus constantly on feedback control policies. For stochastic dynamic environments, the class of the hedging point policies (HPP) is an efficient and widely used strategy in PPC for unreliable manufacturing systems faced with random events such as random failure and repair times. This policy, introduced first by Kimemia and Gershwin (1983), considers a ‘’safety stock’’ which is an optimal production surplus that should be maintained in order to hedge against future shortage brought by machine breakdowns. This policy aims to minimze the total long-term cost. The work of Akella and Kumar (1986) illustrates that HPP is optimal for failure-prone manufacturing systems whose dynamics are described by a homogeneous Markov Chain. Many researchers have been prompted to develop several extensions based on the HPP to study different system configurations and create Multiple Hedging Point Policies (MHPP) for many industrial contexts. In this respect, we cite, for instance, works including maintenance (Emami-Mehrgani et al., 2016), remanufacturing (Polotski et al., 2019), environmental regulations (Afshar-

Bakeshloo et al., 2018) and quality control (Rivera-Gómez et al., 2020). All these works, as well as many others, have focused on studying the implementation of feedback control policies for unreliable manufacturing systems in different contexts. However, there has been relatively little work that considers perishability issues in a dynamic stochastic context. Only a few articles deal with problems of PPC of perishable products. Bounkhel and Tadj, 2005 study optimal control problem for a manufacturing system of perishable products with a deterministic shelf life, without considering machine failure. That is also the case with the work of Hedjar et al. (2007), which studies production control problems for a reliable manufacturing system producing perishable products having a deterministic shelf life. However, in the latter, they consider a variable demand rate. Other works such as Sajadi et al. (2011) and Tavan and Sajadi (2015) consider failure-prone manufacturing systems and use the classical HPP for production control of perishable products with a deterministic shelf life. The works of Malekpour et al. (2016) and Hatami-Marbini et al. (2020) deal with production control problems for unreliable manufacturing systems composed of a network of machines, where the final product is perishable in nature. In both works, shelf life is considered deterministic, and the classical HPP is used for production control. It is worth mentioning that on the one hand, most studies on failure-prone manufacturing systems in a stochastic context do not consider product perishability., and on the other hand, research that has dealt with perishable products in a stochastic and dynamic settings has focused only on deterministic shelf lives. Thus, when studying PPC policies, problems related to shelf life variability and machine unreliability in a stochastic context have never been studied together. Moreover, the aforementioned work which deals with feedback control policies for perishable products opted for the use of the classical HPP without proving its optimality. No new policy has thus been developed that considers the specificity of perishable products and limited shelf lives.

To sum up, we clearly see that inventory control models for perishable products do not consider production planning. However, on the one hand, we see that EPQ models are very commonly used for the production planning of perishable products. Nevertheless, there are always limitations surrounding the production rate for a single-period model. Moreover, these models generally assume that the production facility is always available and can provide a deterministic production rate. On the other hand, for the feedback control policy, which is commonly used for unreliable manufacturing systems, only a few works consider perishable shelf lives, while most only address the case of deterministic shelf lives. Moreover, the works use the classical HPP for production control, and no new policy has been developed that takes into consideration the perishable nature of products. To the best of our knowledge, no previous work has considered all these aspects simultaneously. More precisely, the gap is defined by a lack of control policies for a failure-prone manufacturing system for perishable products with the consideration of shelf life variability.

In this work, our objective is to propose a control policy for failure-prone manufacturing systems under dynamic and stochastic settings, that considers the nature of perishable products having a limited and random shelf life. The proposed control policy allows decision makers to decide when the time is right to increase or decrease the production rate based on the age and the quantity of products on hand. It enables the manufacturer to minimize the total cost, composed of backlog, inventory holding, and disposal costs of perished products. To formulate the model, we adopt a stochastic dynamic programming approach based on control theory. Numerical methods are used to solve the associated Hamilton-Jacobi-Bellman (HJB) equations and to determine the structure of the optimal control policy. Finally, a discrete-continuous simulation model, combined with Response Surface Methodology (RSM), is developed to optimize the control parameters.

2.3 Notation and system description

In this section, the notations used and the description of the studied system are presented.

The following are the definitions of the notations used in this paper.

$x_i(t)$	Inventory level at time t for the portion of stock being at state i
ρ	Discount rate (product /unit of time)
D_i	Demand rate for the portion of stock at state i (product /unit of time)

D	Total demand rate (product /unit of time)
$U(t)$	Production rate at time t (product /unit of time)
U_m	Maximum production rate (product /unit of time)
C_i^+	Holding cost for the portion of stock at state i (\$/ product /unit of time)
C_i^-	Backlog cost for the portion of stock at state i (\$/ product /unit of time)
C_p	Disposal cost due to perishability (\$/ product)
$\lambda_{\alpha\beta}$	Transition rate from mode α to mode β
q_{ij}	Transition rate between the portion of stock at state i to the portion of stock at state j
SL	Shelf life of a product
Av	System availability
$J(.)$	Cost function
$V(.)$	Value function

The studied manufacturing system is represented in Figure 2.1. It is composed of one unreliable machine prone to random failure and repair times, producing one perishable product family type, with a limited and random shelf life in order to meet demand over an infinite horizon. Due to machine downtimes, unsatisfied demands are delayed, and incur a penalty cost. Also, we consider a holding cost for each product in inventory. Since products are of a perishable nature, we take into account the cost of disposing of the products after their expiration date. The control policy is feedback in nature, and takes into consideration the mode of the manufacturing system (operational, failure), as well as the inventory level, to determine the production rate accordingly. The machine is set to produce with different rates and cannot produce at all during repair times.

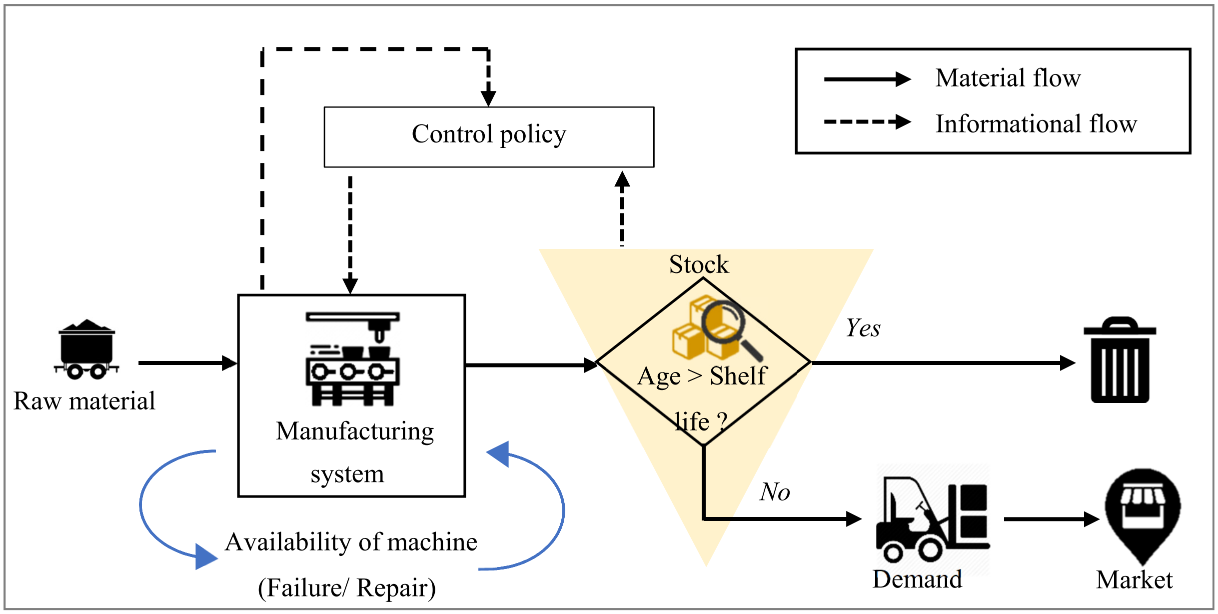


Figure 2.1 Studied manufacturing system

The next section details the resolution approach adapted in this paper.

2.4 Resolution approach

The resolution approach adopted combines control theory, numerical methods, simulation modeling, design of experiment (DOE) and Response Surface Methodology (RSM). In fact, stochastic optimal control has successfully been coupled with simulation and optimization methods to resolve multiple complex decision-making problems, and it has been used in multiple control problems, such as in Assid et al. (2020). The process starts with the determination of the structure of the optimal control policy based on optimal control theory. Next, a coupled simulation-optimization approach is used to model the system and optimize the control policy parameters. Then, a sensitivity analysis is conducted, as well as a comparative study with other policies from the literature. Figure 2.2 illustrates a block diagram of the adopted resolution approach. The main steps are as follows:

<u>Step 1:</u> Control policy determination

In this step, the control problem is formulated. The objective is to determine the parametrized structure of the optimal control policy using stochastic optimal control theory (See section 2.5). The proposed policy is established by equations (2.14) to (2.16) and is characterized by certain control parameters that represents the different hedging points of the finished product stock. This policy in turn represent input of the simulation model.

<u>Step 2:</u> Simulation model

A simulation model is built to reflect the system dynamics governed by the proposed control policy. The objective is to assess the system behavior over the planning horizon and generate outputs that will serve to compute the total cost (See section 2.6.1).

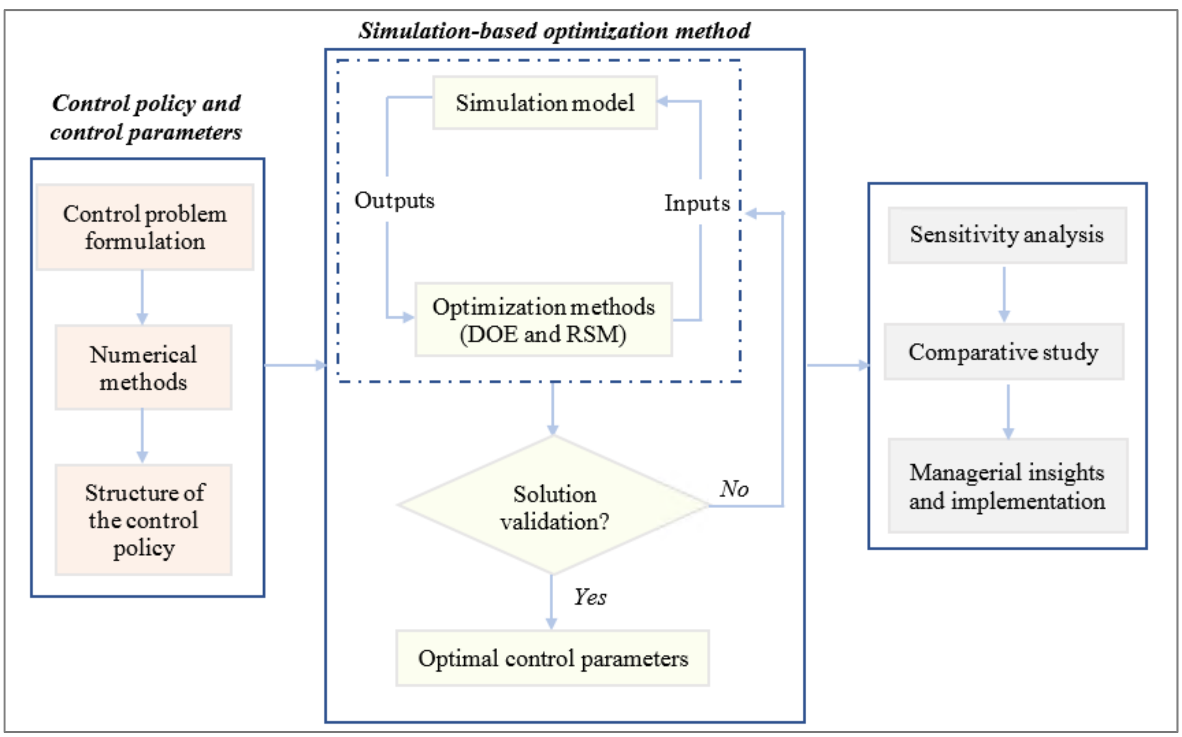


Figure 2.2 Block diagram for the resolution approach

Step 3: Optimization using Design of Experiment (DOE) and Response Surface Methodology (RSM)

The objective of this step is to optimize the control parameters using the outputs generated from the simulation model to minimize the incurred total cost. The Design of Experiment (DOE) is used to create a combination of control parameters defining the experimental space for simulation runs. For each combination, the total cost is computed using simulation. Then, using collected data, the response surface methodology (RSM) is applied in order to find the effect of significant control parameters, their interactions and their quadratic effect with the incurred total cost. The objective is to find an estimation of the total cost that can be written as a function of control parameters as follows:

$$\widehat{Cost_{PHPP}} \cong \beta_0 + \beta_1.A + \beta_2.B + \beta_3.C + \beta_{12}.AB + \beta_{13}.AC + \beta_{23}.BC + \beta_{11}.A^2 + \beta_{22}.B^2 + \beta_{33}.C^2 + \varepsilon \tag{2.1}$$

with A, B and C representing the control parameters, $\beta_0, \beta_i, \beta_{ij}$ $(i, j \in \{1,2,3\})$ being unknown coefficients that are estimated from data, and ε being a random error.

The total cost is then minimized to determine the optimal control parameters. This step detailed in Section 2.6.2.

Step 4: Sensitivity analysis

This step aims to evaluate the control policy proposed and see its performance for a wide range of system and cost parameters, and thus confirm the robustness of the approach adapted (see Section 2.7).

<u>Step 5:</u> Comparative study

A comparative study between the developed control policy and other policies from the literature is conducted based on the optimal total cost computed for a wide range of system and cost parameters. The control policy that generates the lowest optimal total cost is considered as the most effective one (see section 2.8).

<u>Step 6:</u> Implementation of the control policy

In Section 2.9, the implementation of the proposed control policy is established. The purpose here is to provide the decision maker with insights to help him effectively implement the proposed control policy. It highlights the information that should be taken into consideration during the production process, such as the state of the machine and inventory level in comparison with control parameters. An example is provided to guide the manager step by step through the implementation of the proposed policy.

2.5 Stochastic optimal control

The first step of the adapted resolution approach is detailed in this section, in which the stochastic optimal control problem is detailed, as well as the numerical methods used to obtain the structure of the control policy.

2.5.1 Problem formulation

Here, we assume that the state of the machine is modeled as a Markov process in continuous time, with a discrete state $\xi(t)$, where the machine operates under two modes. The manufacturing facility under study can be described at time t by the random stochastic process $\xi(t)$, with $B = \{1, 2\}$ such that:

$$\xi(t) = \begin{cases} 1 \; machine\ is\ operational \\ 2 \; machine\ under\ repair \end{cases}$$

The transition rates matrix of the stochastic process $\xi(t)$ is denoted $Q = \{\lambda_{\alpha\beta}\}$ with $\lambda_{\alpha\beta} \geq 0$ if $\alpha \neq \beta$ and $\lambda_{\alpha\alpha} = -\sum_{\alpha \neq \beta} \lambda_{\alpha\beta}$, otherwise for $\alpha, \beta \in B$. The transition rates matrix Q is as follows:

$$Q = \begin{pmatrix} -\lambda_{12} & \lambda_{12} \\ \lambda_{21} & -\lambda_{21} \end{pmatrix}.$$

The following relation establishes the link between the transition probabilities from mode α to mode β and the transition rates:

$$prob\ (\xi(t+\delta t) = \alpha \mid \xi(t) = \beta) = \begin{cases} \lambda_{\alpha\beta}\delta t + o(\delta t) & \alpha \neq \beta \\ 1 + \lambda_{\alpha\beta}\delta t + (\delta t) & \alpha = \beta \end{cases}$$

From a practical point of view, and in order to model the nature of perishable products having a limited shelf life, we opted to characterize the dynamics of stocks by transitions from sub-stock x_i to sub-stock x_{i+1}, each representing a state of the product age, as described in Figure 2.3. In such a model, the machine operates with a production rate U, and manufactures a product with a limited shelf life SL equal to n units of time. The first sub-stock created is x_1, representing the newest sub-stock at state 1. Afterwards, stock that is not pulled by demand gets older and passes on to sub-stock x_2 (state 2), with a rate equal to q_{12}, and so on to the next sub-stock until the maximum shelf life is reached (state n). Beyond this state, products that have not been pulled by demand are no longer fit for consumption and are disposed of (state n+1). The transition rates from x_i to x_{i+1} are denoted $q_{i,i+1}$. The sub-stock x_{n+1} represents the perished products. As for the total demand D, it is discretized into sub-demands D_i set such that each D_i is satisfied from the corresponding sub-stock x_i with $0 \leq D_i \leq D$. The value of each D_i is set to assure a certain queuing policy for products, meaning that the demand is set such that it pulls from the oldest stock x_i until it becomes empty and then moves on to newer stock x_{i-1} and so on. For this considered system, the state space is given by $(x_1, x_2, \ldots, x_n, x_{n+1})$.

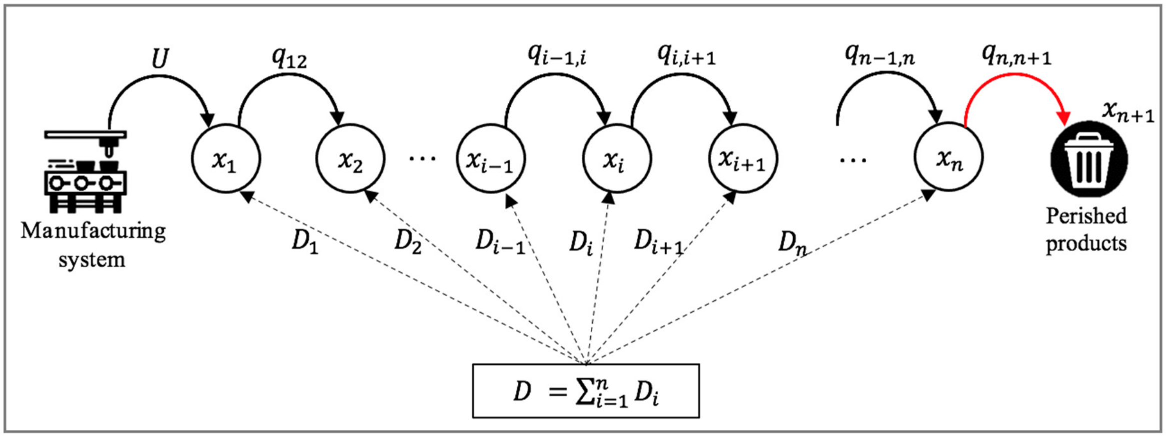


Figure 2.3 Modeling perishable products with shelf life SL = n

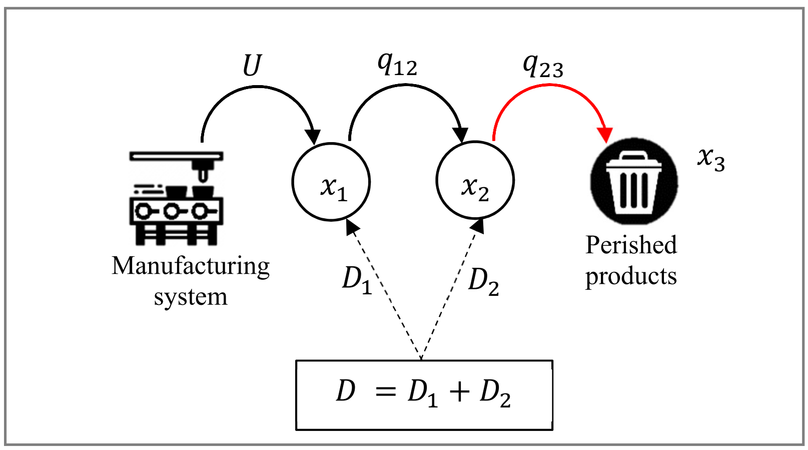


Figure 2.4 Modeling perishable products – Shelf life = 2

Due to the complexity of the system and the high number of parameters surrounding a numerical resolution, without loss of generality, we study the case of a manufacturing system producing a perishable product with a random exponential shelf life SL having a mean equal to 2 units of time, as shown in Figure 2.4. In this case, the dynamic of the stock is characterized by transitions from sub-stock x_1 to sub-stock x_2 each representing a specific age of the total stock. This model is considered a generalized approach to modeling a limited shelf life of perishable products as it can always be divided into 2 sub-stocks with the appropriate transition rates: new produced stock (x_1) and older stock (x_2). The perished products are represented as the sub-stock (x_3). We express the dynamic of the stock levels given by the following differential equations, where x_1^0, x_2^0 denote the levels of each sub-stock at the initial time.

$$\begin{aligned} \dot{x}_1 &= \mathrm{U} - q_{12}\, x_1^+ - D_1 \qquad &, x_1(0) = x_1^0 \\ \dot{x}_2 &= q_{12}\, x_1^+ - q_{23}x_2 - D_2 \qquad &, x_2(0) = x_2^0 \end{aligned} \tag{2.2}$$

with : $x_1^+ = \ max\ (x_1, 0)$

x_1^+ is used to express the fact that backlogs are only allowed in the first sub-stock. Only x_1 can have negative values. In fact, as stated above, the demand is set such as to allow a First-In First-Out ($FIFO$) policy to pull products from the oldest sub-stock x_2 until it becomes empty and to then move on to the sub-stock x_1. When the latter becomes empty, demand is backlogged and x_1 takes negative values. This statement is expressed through the following equations:

$$D_2 = \begin{cases} D & if\ (x_2 > 0) \quad \text{or} \quad (x_2 = 0 \text{ and } x_1 > {}^{D}/_{q_{12}}) \\ q_{12}\, x_1 & if\ x_2 = 0 \text{ and } x_1 \le {}^{D}/_{q_{12}} \qquad\qquad (*) \\ 0 & otherwise\ (x_1 \le 0) \end{cases} \tag{2.3}$$

$$D_1 = \begin{cases} 0 & if\ (x_2 > 0) \quad \text{or} \quad (x_2 = 0 \text{ and } x_1 > {}^{D}/_{q_{12}}) \\ D - q_{12}\, x_1 & if\ x_2 = 0 \text{ and } x_1 \le {}^{D}/_{q_{12}} \qquad\qquad (**) \\ D & otherwise\ (x_1 \le 0) \qquad\qquad (***) \end{cases} \tag{2.4}$$

where $D = D_1 + D_2$

The condition ($*$) is applied when $x_2 = 0$ and $x_1 \le {}^{D}/_{q_{12}}$. This corresponds to the case where x_2 is positive and decreasing to 0. It means that only a part of the demand is satisfied by the sub-stock x_2, and results in $\dot{x}_2 = 0$ and $x_2 = 0$ for some time while $q_{12}x_1 \le D$. Condition ($**$) means that the remaining portion of the demand is satisfied by the sub-stock x_1. If possible (that is until $x_1 = 0$), the remaining portion will result in a backlog. The latter corresponds to $(***)$, and in this case, x_1^+ is used in the first equation.

We note that the feasibility constraint presented in equation (2.5) must be satisfied at any given time:

$$U_m \text{ x } Av \geq D + \theta \quad (2.5)$$

With $Av = MTTF/\,(MTTF + MTTR)$

$MTTF = {}^{1}/_{\lambda_{12}}$; $MTTR = {}^{1}/_{\lambda_{21}}$; $\theta = q_{23}x_2$

We denote the domain of admissible decisions by the following:

$$\Gamma\,(\alpha) = \{\mathrm{U} \mid 0 \leq \mathrm{U} \leq \mathrm{U}_m\ Ind\ \{\alpha = 1\}\} \quad (2.6)$$

With $\xi(t) = \alpha$

To be able to penalize costs relating to inventory holding, disposal and backlogs, we define the instantaneous cost function $g(.)$:

$$g(x_1, x_2, x_3, U) = C_1^+.\ x_1^+ + C_1^+.x_2 + C_1^-.\ x_1^- + C_p\,.x_3 \quad (2.7)$$

Where $x_1^+ = \max(0, x_1)$ and $x_1^- = \max(-x_1, 0)$.

Knowing the value of q_{23}, we consider the following statement: $x_3 \cong q_{23}x_2$. The cost function is now therefore expressed as follows:

$$g(x_1, x_2, U) = C_1^+.\ x_1^+ + C_1^+.x_2 + C_1^-.\ x_1^- + C_p\,.q_{23}x_2 \quad (2.8)$$

The overall cost function $J(.)$ is giving by:

$$J(\alpha, x_1, x_2, U) = E\left\{\int_0^{\infty} e^{-\rho t} g(x_1, x_2, U)\,\mathrm{dt}|\; x_1(0) \;=\; x_1^0\,, x_2(0) = \; x_2^0, \xi(0) = \alpha, \right\}, \forall\, \alpha \in \mathrm{B},$$

$$\mathrm{U} \in \Gamma(\alpha) \tag{2.9}$$

The value function of this stochastic optimal control problem is given by:

$$V(\alpha, x_1, x_2) = \min_{\mathrm{U}\in\Gamma(\alpha)} J\,(\alpha, x_1, x_2, U) \tag{2.10}$$

The value function stated in equation (2.10) satisfies specific optimality conditions called Hamilton–Jacobi–Bellman (HJB) equations. These optimality conditions are a set of coupled partial derivatives equations derived from the application of the dynamic programming principle. Based on Akella and Kumar (1986), it can be stated that the value function $V(\alpha, x_1, x_2)$ is the solution of the following HJB equations:

$$\rho V(\alpha, x_1, x_2) = \min_{\mathrm{U}\in\Gamma(\alpha)} \left\{g(\alpha, x_1, x_2) + \sum_{i=1}^{2} \frac{\partial V\,(\alpha, x_1, x_2)}{\partial x_i}\, \dot{x}_i + \sum_{\beta\in\mathrm{B}} \lambda_{\alpha\beta} V(\beta, x_1, x_2)\right\}; \forall\, \alpha\, \in B \tag{2.11}$$

Finding the optimal production rate requires the resolution of equation (2.11). However, the HJB equations are known to be difficult to solve analytically (Kouedeu Annie et al., 2015). Therefore, in many research studies, numerical algorithms are selected in order to determine the value function and the corresponding control policy. In fact, when dealing with a system having a finite number of modes, a numerical method based on the work of Kushner and Dupuis (1992) is often used to solve HJB equations. This approach is widely used for stochastic optimal control problems (Ouaret et al., 2013; Polotski et al., 2019). The resolution approach based on Kushner and Dupuis (1992) is detailed in Appendix 2.A.

2.5.2 Optimal control policy

The numerical methods adopted in order to define the structure of the optimal control policy are presented in this section using a numerical example. Table 2.2 presents the chosen parameters for the numerical example. The computational domain is set as: $D \;=\; \{(x_1, x_2):\, -$

$10 \le x_1 \le 20, 0 \le x_2 \le 20\}$. The transition rates of the machine are defined by λ_{12} = 0.01, λ_{21}= 0.1, giving the system an availability of 90.9%.

Table 2.2 Parameters for the numerical example

Parameters	U_m	D	C_1^-	(C_1^+, C_2^+)	C_p
Values	*0.8*	*0.5*	*20*	*(1, 1)*	*15*
Parameters	q_{12}	q_{23}	h_1	h_2	ρ
Values	*0.2*	*0.2*	*0.25*	*0.25*	*0.1*

The results found represents the structure of the control policy. The decision variable is presented as a function of (α, x_1, x_2). We only show the control policy in mode 1 (operational mode).

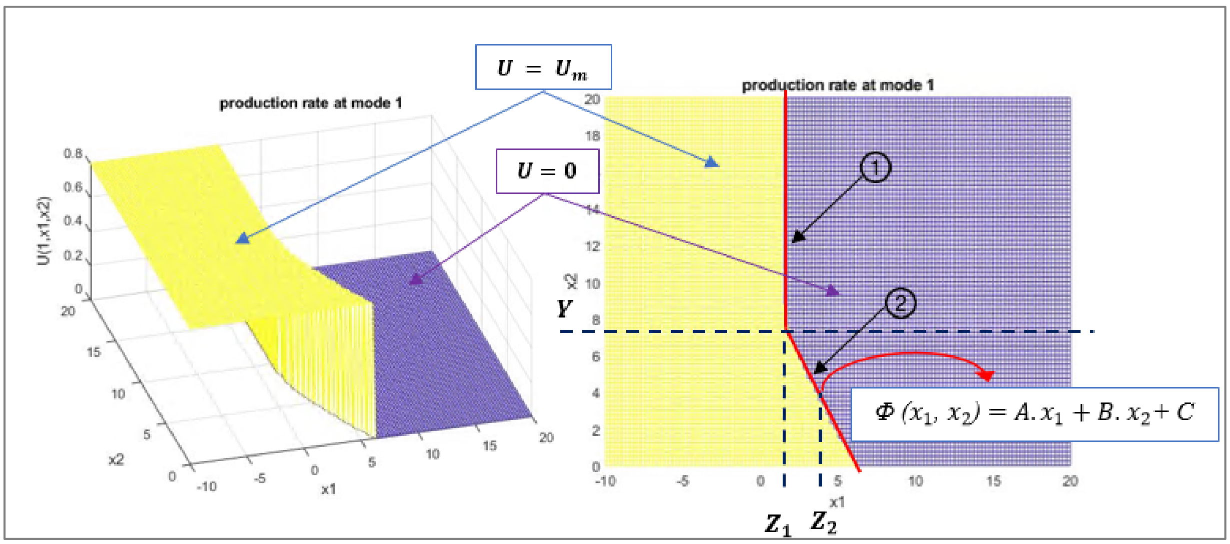


Figure 2.5 System production rate in mode 1

Figure 2.5 shows the obtained control policy corresponding to the studied numerical example (Table 2.2) when the system is operational (mode 1). The resulting control policy is of hedging point nature and it divides the inventory space into different regions delimited by three threshold levels. Arrow 1 and arrow 2 in Figure 2.5 point to the line that splits the computational domain into two sides: on the left, the machine produces at maximum capacity and on the right, it stops producing. We notice that the optimal production rate depends on the values of the two sub-stock levels x_1 and x_2. Arrow 1 represents the hedging point Z_1

corresponding to the sub-stock x_1. As for arrow 2, it points to the hedging level equation $\Phi(x_1, x_2) = A.x_1 + B.x_2 + C$, which depends on both values of x_1 and x_2. A, B and C are constant coefficients that depend on system parameters. The intersection between arrow 1 and 2 corresponds to the hedging level Y for sub-stock x_2.

From Figure 2.5, we can set the structure of the control policy as follows:

***If* $\boldsymbol{x_2 \geq Y}$**

$$\mathrm{U}\,(1,.) = \begin{cases} U_{\mathrm{m}} & if \;\; x_1\,(t) \; < \; Z_1 \\ q_{12}\,.Z_1 & if \;\; x_1\,(t) \; = \; Z_1 \\ 0 & if \;\; x_1\,(t) \; > \; Z_1 \end{cases} \tag{2.12}$$

***If* $\boldsymbol{x_2 < Y}$**

$$\mathrm{U}\,(1,.) = \begin{cases} U_{\mathrm{m}} & if \;\; \Phi\,(x_1,\, x_2) \; < \; 0 \\ F(x_1,\, x_2) & if \;\; \Phi\,(x_1,\, x_2) = \; 0 \\ 0 & if \;\; \Phi\,(x_1,\, x_2) \; > \; 0 \end{cases} \tag{2.13}$$

With $U(2,.) = 0$.

The function $F(x_1,\, x_2)$ in equation (2.13) represents the value of the production rate when the sub-stock x_2 is less than the hedging level Y, that is, when the sub-stock levels x_1 and x_2 are equal to the hedging level obtained with the function $\Phi(x_1, x_2) = A.x_1 + B.x_2 + C$. These functions are exceedingly difficult to implement since they depend on the values of both x_1 and x_2, which change over time. For that reason, we are going to approximate the hedging level $\Phi(x_1,\, x_2)$ by a fixed hedging level Z_2. The modified developed policy, called hereinafter the Perishable Hedging Point Policy ($PHPP$), is described by equations (2.14), (2.15) and (2.16).

If $\boldsymbol{x_2 \geq Y}$

$$U\,(1,.) = \begin{cases} U_{\mathrm{m}} & if \;\; x_1\,(t) \;<\; Z_1 \\ q_{12}\,.Z_1 & if \;\; x_1\,(t) \;=\; Z_1 \\ 0 & if \;\; x_1\,(t) \;>\; Z_1 \end{cases} \tag{2.14}$$

If 0 $\boldsymbol{< x_2 < Y}$

$$U\,(1,.) = \begin{cases} U_{\mathrm{m}} & if \;\; x_1\,(t) \;<\; Z_2 \\ q_{12}\,.Z_2 & if \;\; x_1\,(t) \;=\; Z_2 \\ 0 & if \;\; x_1\,(t) \;>\; Z_2 \end{cases} \tag{2.15}$$

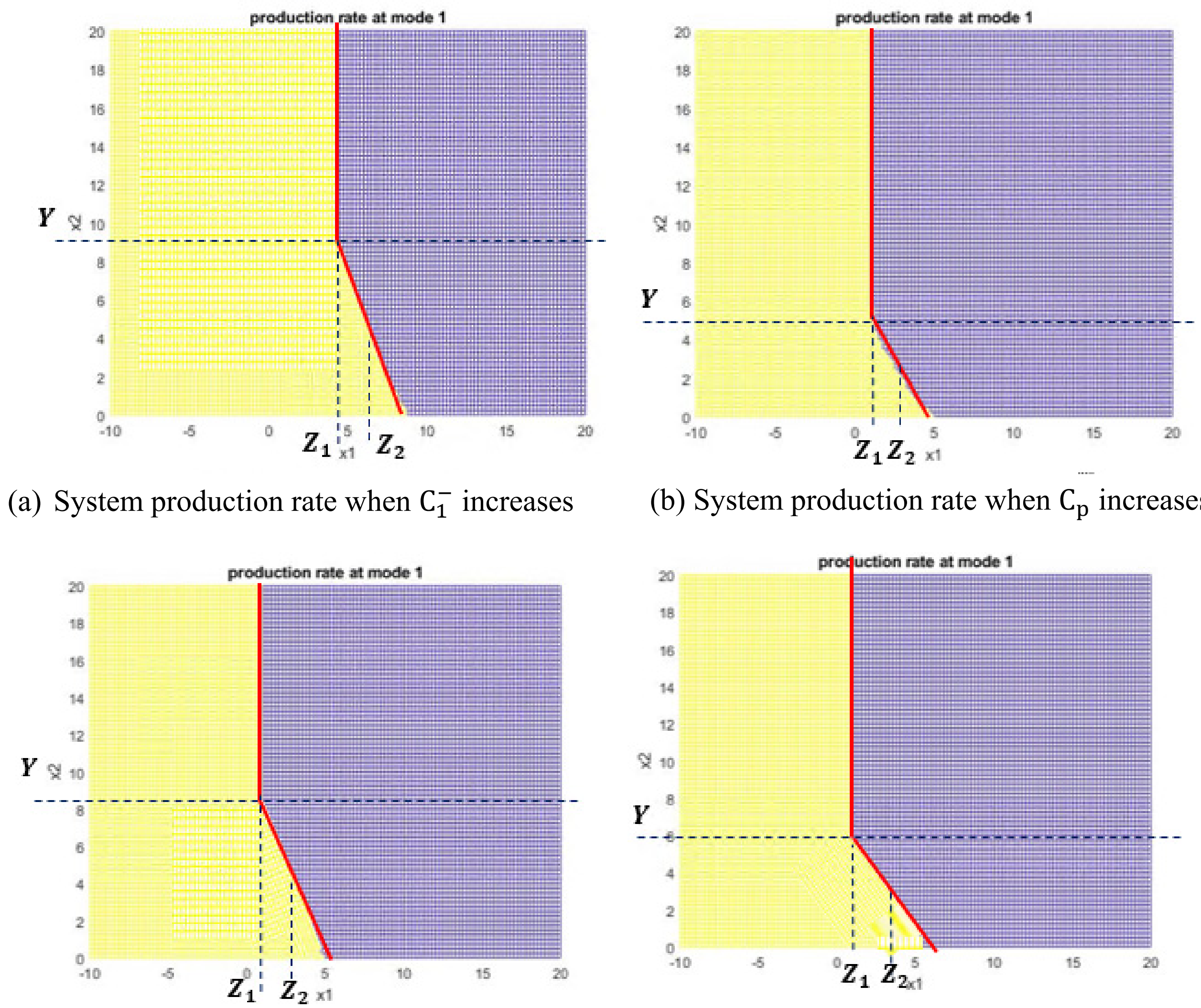
If $\boldsymbol{x_2 = 0}$

$$U\,(1,.) = \begin{cases} U_{\mathrm{m}} & if \;\; x_1\,(t) \;<\; Z_2 \\ D & if \;\; x_1\,(t) = \; Z_2 \\ 0 & if \;\; x_1\,(t) > \; Z_2 \end{cases} \tag{2.16}$$

With $Z_1 \leq Z_2$ and $U(2,.) = 0$.

The production rate in equations (2.14) to (2.16) is determined based on the dynamics of the stock expressed in equation (22.) and the value of the demand expressed in equations (2.3) and (2.4). The thresholds represent the security inventory levels to maintain in order to hedge against future machine unavailability caused by failure. The proposed control policy is characterized by three control parameters: Z_1, Z_2 and Y.

We notice that equation (2.16) represents the classic HPP for a single machine producing one product type, governed by one threshold equal to Z_2. It represents the case where only one sub-stock exists in inventory ($x_2 = 0$).



(a) System production rate when C_1^- increases

(b) System production rate when C_p increases

(c) System production rate when C_1^+ increases

(d) System production rate when C_2^+ increases

Figure 2.6 System production rate in mode 1 while varying cost parameters

The obtained control policy is described by three control parameters Z_1, Z_2 for x_1 (state 1 of product) and Y for x_2 (state 2 of product). Multiple sensitivity analyses were carried out in order to confirm the robustness of the proposed control policy given by equations (2.14) to (2.16). We show a few of the results obtained when varying system parameters in Figure 2.6. The structure of the control policy is the same in every case governed by the three control parameters (Z_1, Z_2, Y). However, they increase when the backlog cost C_1^- increases (Figure 2.6(a)). This is due to the fact that the system needs to protect itself against high backlog costs due to an increase in C_1^-. On the other hand, the value of the control parameters decreases when the disposal cost C_{p} increases (Figure 2.6(b)) or when the holding costs C_1^+ (Figure 2.6(c)) and C_2^+ (Figure 2.6(d)) increase. Due to high disposal cost, the manufacturing system lowers the value of the control parameters in order to limit the number of perished products and the incurred loss. The same behavior is noted when the value of the holding cost increase, with the value of the decision parameters decreasing to minimize the cost of holding inventory. A more thorough sensitivity analysis for a wide range of system and cost parameters is conducted in Section 2.7.

The next section is dedicated to the next step of the resolution approach using a simulation-based optimization method.

2.6 Simulation-based optimization method

We should note that when dealing with complex systems with dynamic and stochastic settings, obtaining analytical solutions is difficult. As discussed in Berthaut et al. (2010), the irregularities regarding the boundary of the numerical methods make approximating the control parameters challenging. Also, the optimization process at an operational level is considered time-consuming to apply. This is mainly due to the fact that such an approach is dependent on the size of the discrete grid used. Therefore, a simulation-based optimization method is used to evaluate the economic performance of the proposed control policy. It combines DOE, simulation and RSM to determine the optimal control parameters.

2.6.1 Simulation model and validation

The simulation model is built using Arena Software. It combines discrete and continuous events using the SIMAN language. Figure 2.7 describes the block diagram of the model built for the manufacturing system governed by the proposed control policy. In Figure 2.7, the first step (block 1) is the initialization of the simulation model with the needed input parameters stated in Table 2.3 (D, U_m, simulation time, Y, Z_1, $Z_2, etc.$). Then, the manufacturing system (block 2), which is prone to random failures and repair times (block 3), is governed by the production and control policy (block 5) in order to meet demand (block 6). Block 5 details the proposed production policy ($PHPP$) described by equations (2.14) to (2.16). It shows the variation of the production rate depending on the stock levels (Y, Z_1, Z_2). Block 4 represents the evolution of stocks due to their perishable nature. In this step, the inventory age is checked, and if the product exceeds its shelf life, then it must be disposed of; if not, then it satisfies demand (block 6). The state of the system is represented in block 7. Afterwards, as the simulation time advances (block 8), the inventory is updated accordingly (block 9). In this block, the total inventory is divided into the twos sub-stocks allowing the tracking of age. Before the simulation run ends, we compute the total cost (block 10), taking into consideration the disposal cost of perishable products, backlog and inventory holding.

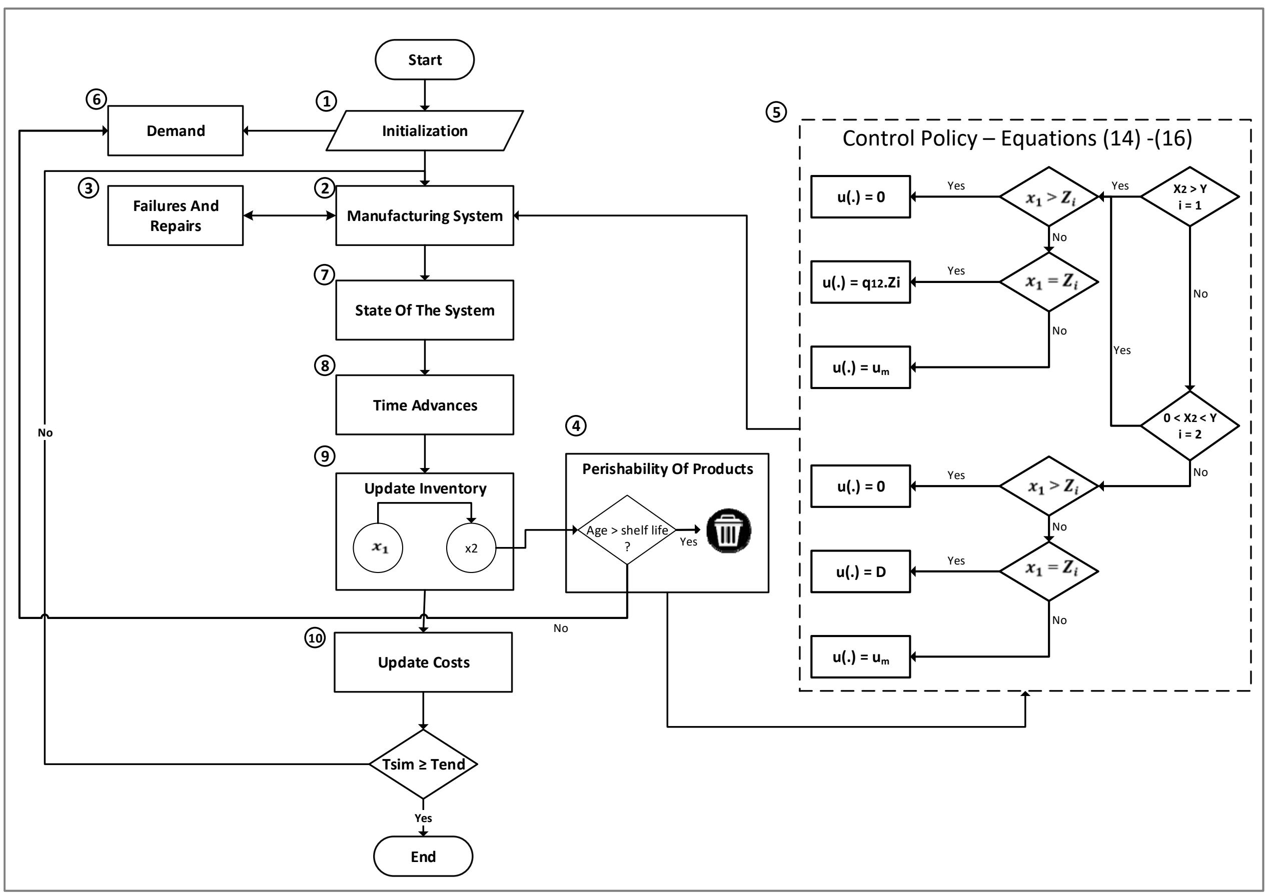


Figure 2.7 Simulation model bloc diagram

The simulation model developed aims to faithfully represent the manufacturing system governed by the proposed control policy described by equations (2.14) to (2.16). Once the simulation model is developed, several steps are conducted to validate it. These include, for example, the testing of different data, and observing, monitoring, and displaying animations. Figure 8 represents a sample of the behavior of the manufacturing system governed by $PHPP$. It is displayed as a set of sub-figures showing variations of the production rate $U(.)$, inventories x_1 and x_2, and the perished products x_3. The data used by the simulation model are summarized in Table 2.3.

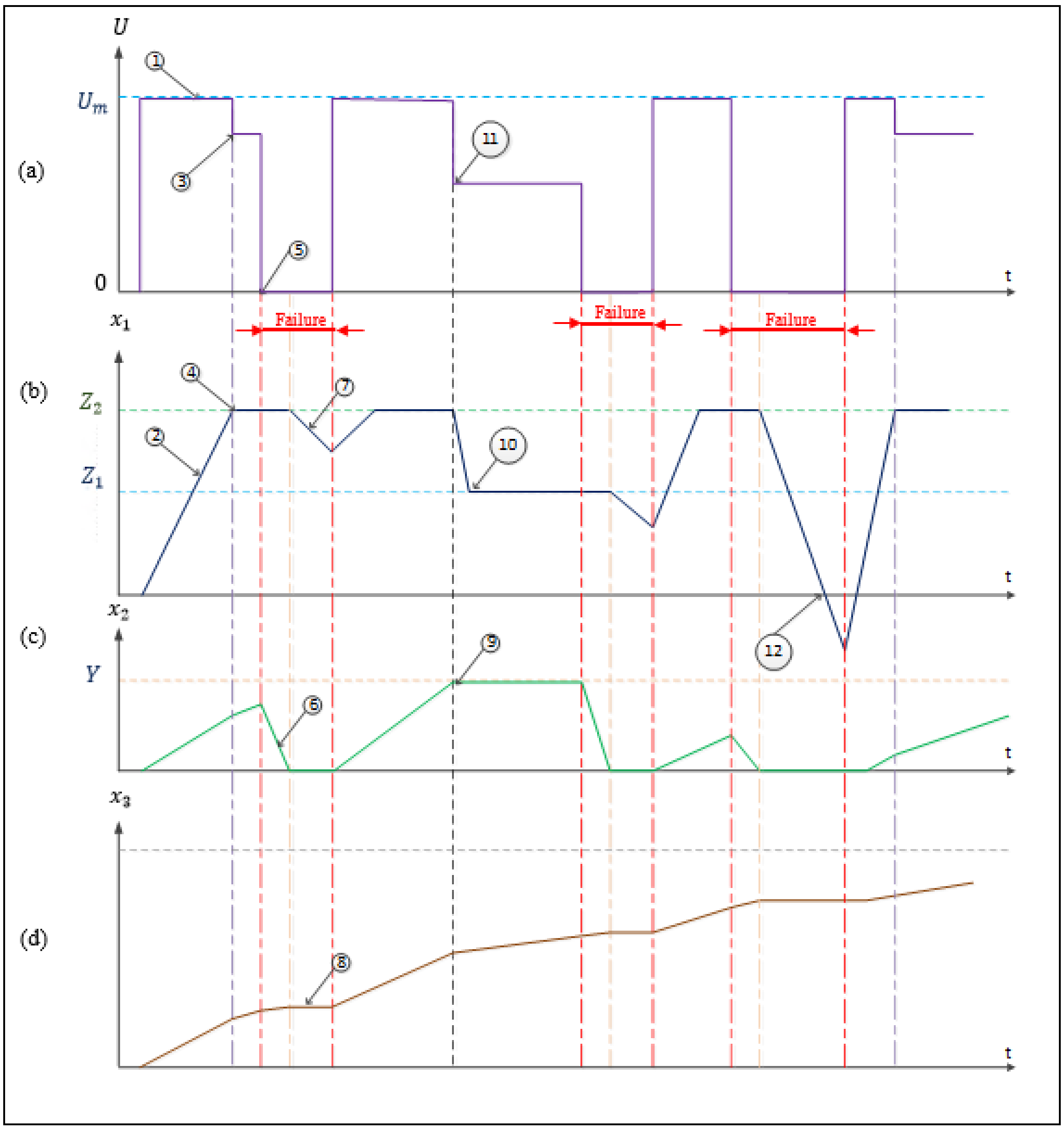


Figure 2.8 Dynamics of the simulation model when the proposed PHPP is used

Table 2.3 System parameter values

Parameters	U_m	D	C_1^-	(C_1^+, C_2^+)	C_p
Values	*120*	*100*	*20*	*(1, 1)*	*15*
Parameters	q_{12}	q_{23}	TTF	TTR	SL
Values	*0.04*	*0.04*	exp (90)	exp (10)	$LOGN(48, 9.6)$

From Figure 2.8, we see in (arrow ①, Figure 2.8.a) that the production rate is set at its maximum capacity U_m as the inventory level x_1 increases (arrow ②, Figure 2.8.b) according to a rate equal to $(U_\mathrm{m} - q_{12}\, x_1^+ - D_1)$. The inventory level serves to satisfy demand, and the products remaining are used to build the safety stock at level Z_2 (arrow ④, Figure 2.8.b). When the inventory level reaches Z_2, the production rate is set to a value equal to $q_{12}\, Z_2$ (arrow ③, Figure 2.8.a). Given that the age of products is continuously growing, the level of x_2 rises according to $(q_{12}\, x_1^+ - q_{23}\, x_2 - D_2)$ as shown in Sub-figure 2.8(c) as well as the age of perishable products according to a rate equal to $q_{23}\, x_2$ as in Sub-Figure 2.8(d). When a failure event occurs (arrow ⑤, Figure 2.8.a), its impact is first seen in inventory x_2 as it decreases until reaching zero (arrow ⑥, Figure 2.8.c). In fact, since the demand is set such as to follow equations (2.3) and (2.4), products are pulled from the oldest inventory x_2 until it is empty, and then they start being pulled from x_1. At that time x_1 starts decreasing (arrow ⑦, Figure 2.8.b) with a rate equal to $(- q_{12}\, x_1^+ - D_1)$. Also, when x_2 reaches zero, the increase in the number of perished products stops (arrow ⑧, Figure 2.8.d). We notice that the evolution of x_3 is always increasing but with different slopes, depending on the stock level of x_2. In (arrow ⑨, Figure 2.8.c), the inventory level x_2 reaches the threshold Y, which means that the manufacturing system has enough products in stock to reduce production. In such a situation, the hedging level decreases to Z_1 (arrow ⑩, Figure 2.8.b) and the production rate is reduced to $q_{12}\, Z_1$ (arrow ⑪, Figure 2.8.a). In (arrow ⑫, Figure 2.8.b), backlog occurs and the stock level of x_1 decreases bellows zero, x_2 is equal to zero and x_3 is constant.

2.6.2 RSM model and optimization

This section corresponds to step 4 of the resolution approach. The optimization of the parameters of the control policy is performed with outputs from the simulation model for the considered case (table 2.3). The software STATGRAPHICS is used to statistically process data and for the analysis of variance. First, the established DOE is considered as input for the simulation model. Second, the output of the simulation model is returned to STATGRAPHICS for the analysis of variance and the determination of the regression model's best fitting equation (2.1). A full factorial design with three control parameters (Z_1, Z_2, Y) at three levels is applied for the proposed control policy. We use such a factorial design since it provides more accurate results because in this case each interaction is being estimated separately. It provides an evaluation of all possible sets of combinations, and hence more precise results (Montgomery, 2017). We use five replications for each combination of design variables, giving a total of 135 (3^3 x 5) simulation runs. The simulation run period is set to a value of 500,000 units of time. This value is considered high enough to allow the system to reach the steady state.

The effect of each independent factor (Y, Z_1, Z_2), their interactions, and their quadratic effect on the total cost (response variable) are obtained using a multifactorial ANOVA. From Figure 2.9, we can see the Pareto plot of the proposed policy, showing the significance level of the control parameters, their quadratic effect and their interactions. It shows that, except for the quadratic effect of Z_1, all factors, interactions and quadratic effects are significant.

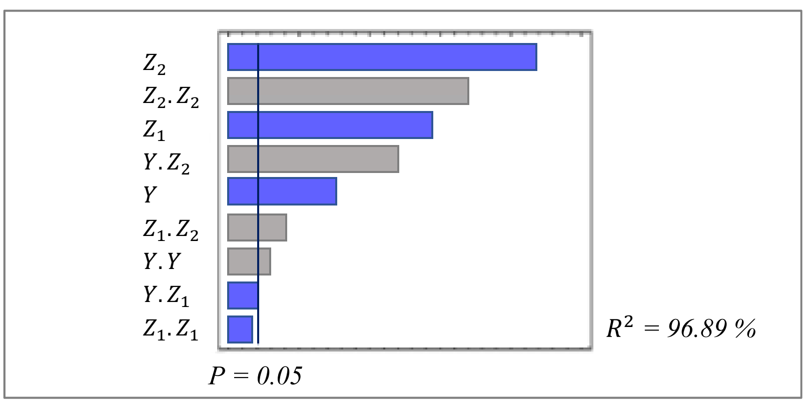


Figure 2.9 Standardized Pareto plot for the proposed policy

The correlation coefficient $R^2_{adjusted}$ is equal to 96.89%. We can say that almost 97% of the variability is explained by the regression model (2.17) (Montgomery, 2012). Also, an analysis of the residual normality and the homogeneity of variance is conducted in order to check the conformity of the model.

The RSM allows finding the relation between the significant factors and the total cost function. Such a function is given by equation (2.17):

$$\begin{aligned}\widehat{Cost_{PHPP}} = {} & 3801.83 - 627.6\ 10^{-3}\ .Z_1 - 688.23\ 10^{-3}\ .Z_2 - 489.28\ 10^{-3}\ .Y \\ & + 76.25\ 10^{-6} .Z_1\ Z_2 - 103.7\ 10^{-6}\ .Z_1 .\ Y + 396.6\ 10^{-6}\ .Y .Z_2 \\ & - 62.9\ 10^{-6}\ Z_1^2 + 287.38\ 10^{-6}\ Z_2^2 + 201.3\ 10^{-6}\ Y^2 + \varepsilon\end{aligned} \tag{2.17}$$

The resulting model is optimized in order to find the best combination of control parameters that minimizes the total cost. The solution obtained is as follows: $Cost^{*}_{PHPP}$ =3030.60, Z_1^* =1438, Z_2^* =1951 and Y^* =957. Figure 2.10 presents the estimated total cost contour plot:

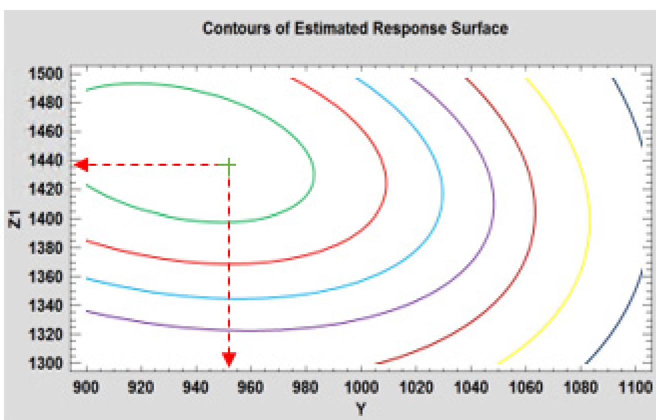


Figure 2.10 The estimated total cost contour surface plot

In addition, to cross-check the validity of the developed model, we confirm that the optimal total cost falls within the 95% confidence interval. The confidence interval is obtained based on an additional 50 simulation runs. Results confirm that the optimal total cost $Cost^{*}_{PHPP}$ = 3030.60 falls within the 95% confidence interval [3024.39, 3039.27].

2.7 Sensitivity analysis

In order to confirm the robustness of the resolution approach used and the proposed policy, an extensive sensitivity analysis is conducted. We observe and analyze the variations of the control parameters of $PHPP$ (Z_1, Z_2 and Y) as a function of system and cost parameters (C_1^-, C_p, shelf life variability and Av).

2.7.1 Variation of backlog cost C_1^-

The variation of control parameters (Z_1, Z_2 and Y) when varying the backlog cost C_1^- is shown in Figure 2.11. As can be seen, when C_1^- increases, the values of the optimal control parameters Z_1 and Z_2 increase as well. This is logical since the system will try to protect itself from backlogs and acts by increasing the two hedging levels. As for the variation of the threshold Y, mainly related to the sub-stock x_2, it varies in the same direction as Z_1 and Z_2. Here, an increase of the inventory level of the second sub-stock to satisfy demand and minimize the backlog can be seen. Also, by increasing Y, the model guarantees that the inventory level of the first sub-stock is maintained at the highest threshold Z_2 for a longer time, and as such, the system has more inventory, which decreases the risk of backlog.

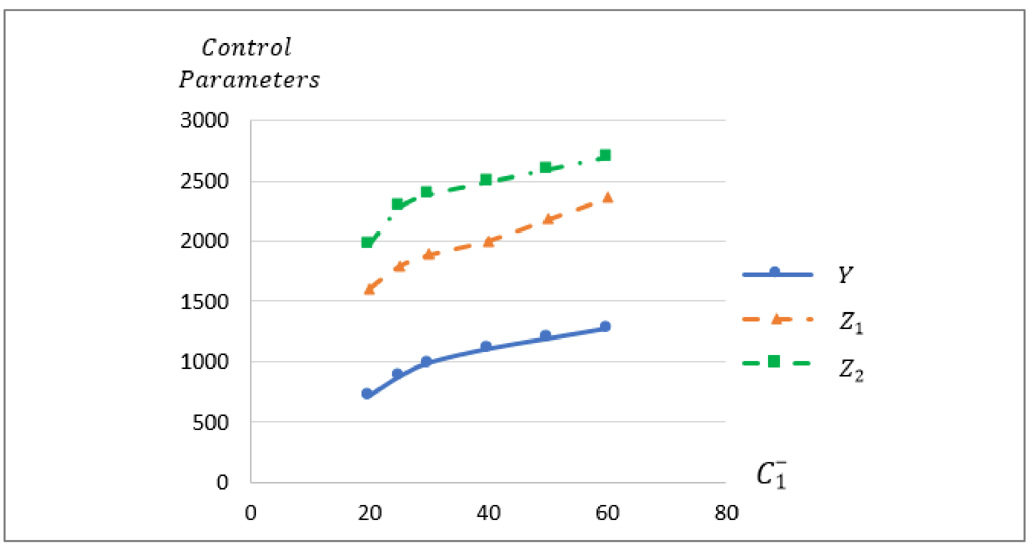


Figure 2.11 Variation of control parameters when varying the backlog cost C_1^-

2.7.2 Variation of and disposal cost of perishable products C_p

The variation of control parameters (Z_1, Z_2 and Y) when varying the disposal cost C_p is shown in Figure 2.12. The first thing that can be noted is that when varying C_p, no major effect is seen on Z_2. However, the variation of C_p affects mainly the hedging level Z_1, which decreases as C_p increases. Here, the system tries to minimize the risk of having perishable products by reducing the value of Z_1 related to the first sub-stock. As for the variation of Y, when C_p increases, the system reacts by increasing the level of Y. In fact, when C_p increases, Z_1 decreases, and so the inventory decreases, also decreasing the risk of perishability. However, the risk of backlog becomes higher since there are not enough products to satisfy demand. That is why there is no major variation in the value Z_2 related to the first sub-stock. It is why also an increase can be seen in the value of Y related to the second sub-stock used to reduce backlog. It can also be noted that the gap between the two hedging levels Z_1 and Z_2 is reduced when the disposal cost C_p decreases, which leads to the structure of the classical HPP in the case of negligible disposal cost C_p .

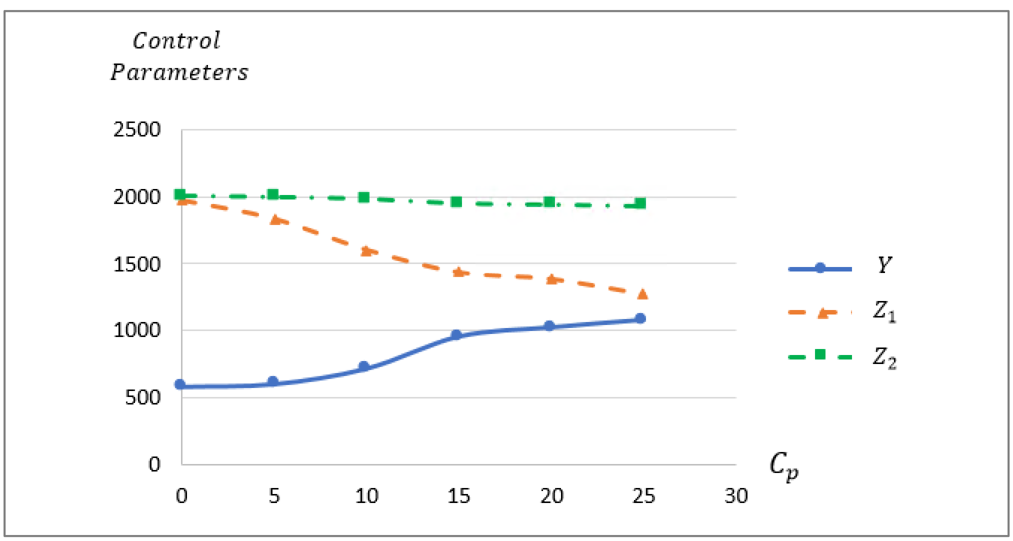


Figure 2.12 Variation of control parameters when varying the disposal cost C_p

2.7.3 Variation of system availability (Av)

In this sub-section, we observe the effect of system availability $Av = (\text{MTTF})/(\text{MTTF+MTTR})$ on its performance. Figure 2.13 shows the variation of the control parameters (Z_1, Z_2 and Y) when varying the system availability (Av) from 90% to 95%. When this availability increases, the probability of machine failure decreases. This means that the production capacity is higher, which leads to lower values of safety stocks needed to meet demand. As can be seen in Figure 2.13, when the availability of the system increases, the values of the control parameters Z_1, Z_2 and Y decrease. When the values of the thresholds decrease, they reduce the risk of having perished products. Moreover, improving the availability of the system leads to a smaller risk of backlogs since the operational times of the machine are longer.

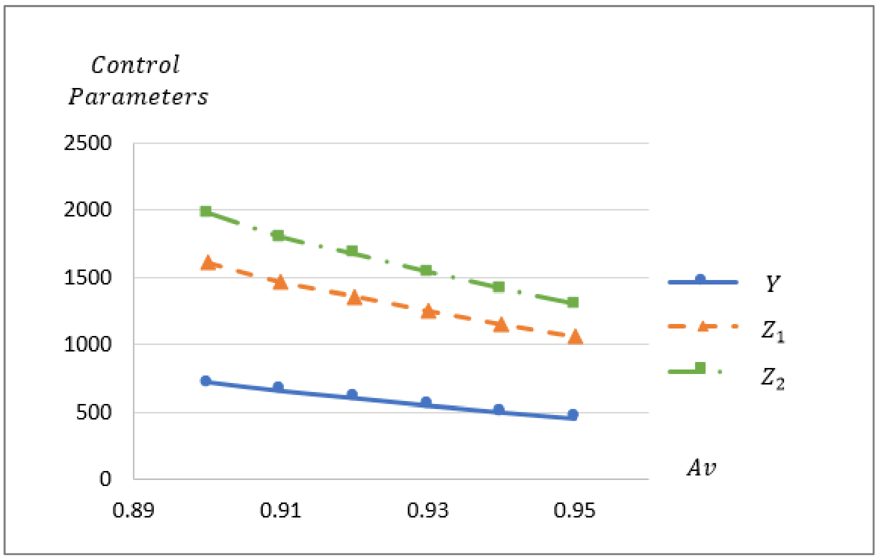


Figure 2.13 Variation of control parameters when varying Av

2.7.4 Variation of shelf life variability

As discussed in the literature review, the lognormal distribution is widely used to approximate the shelf life of many perishable products. Thus far, the shelf life has been considered following a lognormal distribution $SL \sim \text{Lognormal}(\mu, \sigma)$ with a coefficient of variation $C_v = \frac{\sigma}{\mu} = 0.2$. For this sub-section, the aim is to vary the level of variability accorded to a shelf life by varying the coefficient of variation C_v. Figure 2.14 shows the effect of shelf life variability on the control parameters of the system (Z_1, Z_2 and Y). It can be seen that the variability of the shelf lives significantly affects the values of the control parameters, which increase as C_v increases. In fact, when the variability increases, the number of perished products increases as well, as does the corresponding cost component. Moreover, if the number of perished products increases, the smaller the inventory available to satisfy demand, which means more backlogs. In this case, the system will increase the value of the control parameters to protect itself from high costs, especially those due to backlogs.

In addition, in cases of high variability, the effect of the unit costs on backlog C_1^- and disposal C_p is higher. That is why the increase of control parameters is more visible in cases of high variability. As can be seen in Figure 2.14, as the variability increases, the gap between the safety stock levels increases. This is explained by the fact that when the variability is high, the number of perished products is high, as are the backlogs.

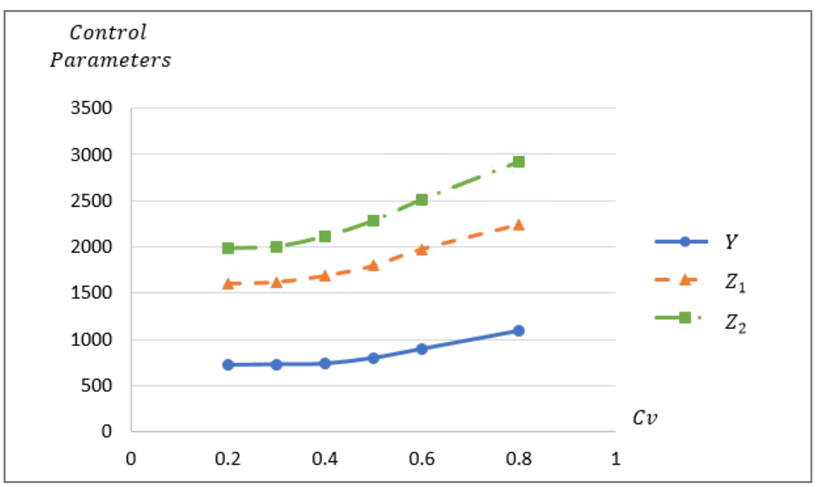
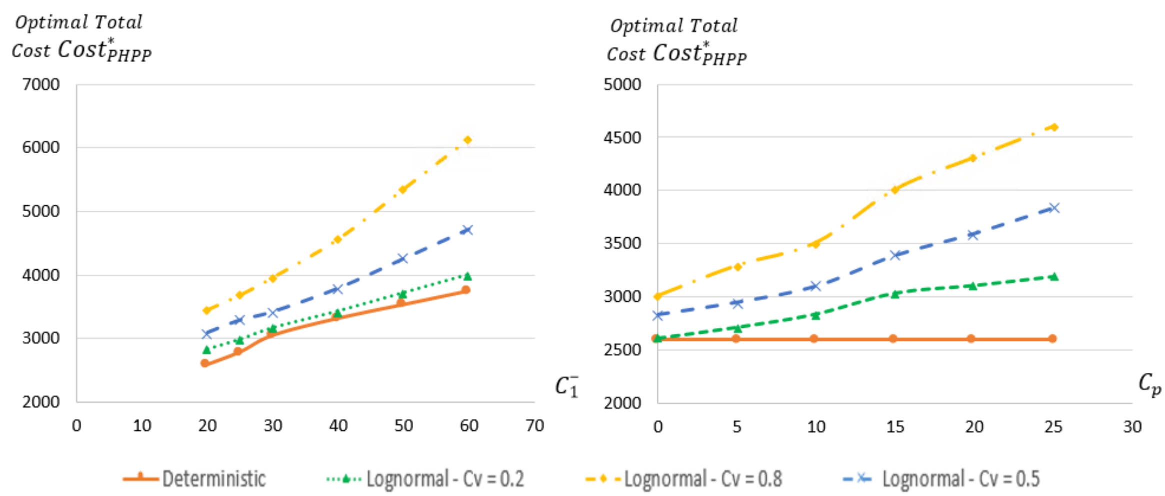


Figure 2.14 Variation of control parameters in function of C_v

Afterwards, we conducted a comparison of the optimal total cost when applying $PHPP$ for different cases of shelf life variability: deterministic and random, with different levels of variability. We varied C_v from 0 to 0.8 simultaneously as we varied the backlog cost C_1^- and the disposal cost C_p . Results are presented in Figure 2.15.



a) Varying simultaneously C_1^- and C_v (b) Varying simultaneously C_p and C_v

Figure 2.15 Variation of the optimal total cost of PHPP when varying shelf life variability $\mathrm{C_v}$ simultaneously with C_1^- and $\mathrm{C_p}$

First, it is important to note that the optimal total costs in the case of deterministic shelf lives are always lower than those for random shelf lives. The deterministic lifetime case represents a lower bound of the optimal total cost computed.

Second, the optimal total cost increases as the variability of the system increases. Also, the gap between the different optimal total costs gets higher as the variability increases. In fact, when the variability increases, the number of perished products increases as well. This leads to fewer products being available to satisfy demand, which leads to higher backlogs. When the backlog cost increases simultaneously with the shelf life variability (Figure 2.15(a)), the gap between the optimal total costs gets higher due to the greater effect of the backlog cost. Also, when the disposal cost increases simultaneously with the shelf life variability (Figure 2.15(b)), the gap between the optimal total costs increases because of the greater effect of the disposal cost.

Third, it can be seen from Figure 2.15(b) that for the deterministic shelf life case, the optimal total cost is constant when varying the disposal cost. This indicates that in the case of deterministic shelf life, the cost component of a disposal is zero, which indicates that there are no perished products. This is due to the fact that when the shelf life and the demand rate are deterministic, the system produces in a way that guarantees zero disposal.

2.8 Comparative study

In this section, we use the simulation-based optimization approach described in Section 2.4 to compare between the optimal total cost of the proposed PHPP and that of the two most relevant policies from the literature. We consider the same parameters used in previous sections.

2.8.1 Policies considered for comparison

The existing policies from the literature that are most relevant to this work are the classical Hedging Point Policy (HPP) and Economic Production Quantity (EPQ).

2.8.1.1 The Hedging Point Policy HPP

As the studied system is failure-prone, we consider the classical hedging point policy (HPP) since it represents an effective common policy used for dynamic and stochastic contexts of such systems. This policy is governed by one threshold Z, representing the safety stock to be built to hedge against machine breakdowns. We refer readers to Akella and Kumar (1986) for more details on HPP. Knowing Z allows the system to determine the optimal production rate, as shown in equation (2.18):

$$U(1,.) = \begin{cases} U_m & \text{if } x(t) < Z \\ D & \text{if } x(t) = Z \\ 0 & \text{if } x(t) > Z \end{cases} \tag{2.18}$$

With U $(2,.)$ =0 and $x\ (t)$ represents the total stock on hand.

2.8.1.2 EPQ model

The second production policy considered is based on lot sizing from EPQ models and is governed by the following equations (2.19) and (2.20).

Production order policy

$$\Omega\,(.) = \begin{cases} Q & \text{if } x(t) \leq s \\ 0 & \text{otherwise} \end{cases} \tag{2.19}$$

Production-inventory control policy

$$U\,(.) = \begin{cases} U_m & \text{if } y(t) \leq Q \text{ and } \xi(t) = 1 \\ 0 & \text{otherwise} \end{cases} \tag{2.20}$$

with $y(t)$ representing the manufactured lot in progress. The lot cannot be transported until it reaches Q, even if machine failure occurs during stock build-up. Once the lot is complete ($y(t)$ reaches Q), it is immediately transported to the final stock $x(t)$. The EPQ model is based on two control parameters (s, Q) and is governed by two policies: a production order policy and a production-inventory control policy. The production order policy is represented by equation (2.19), in which a new production order for a lot Q is launched each time $x(t)$ is less than or equal to the safety stock level s. As for the production-inventory policy, it is represented by equation (2.20). The production rate has two possible levels: U_m (maximum production rate) and 0 (no production). The manufacturing system must produce at maximum rate U_m until the stock level $y(t)$ reaches Q, and then stops producing, waiting for the next production order.

2.8.2 Comparison between the existing policies and the proposed policy

In this sub-section, we compare three policies (PHPP, HPP and EPQ) based on the optimal total costs for the for a wide range of cost and system parameters.

Results from Figure 2.16 reveal that, for each set of parameters, the optimal total cost of the proposed control policy $PHPP$ is always lower than that of other policies. This means that the developed policy PHPP outperforms other policies in terms of optimal total cost. Figure 2.16 also shows that the least economic policy is the EPQ. This is explained by the fact that it does not allow production rate control, meaning that it does not regulate the production rates based on the stock level variations or take into consideration the impact of machine downtimes.

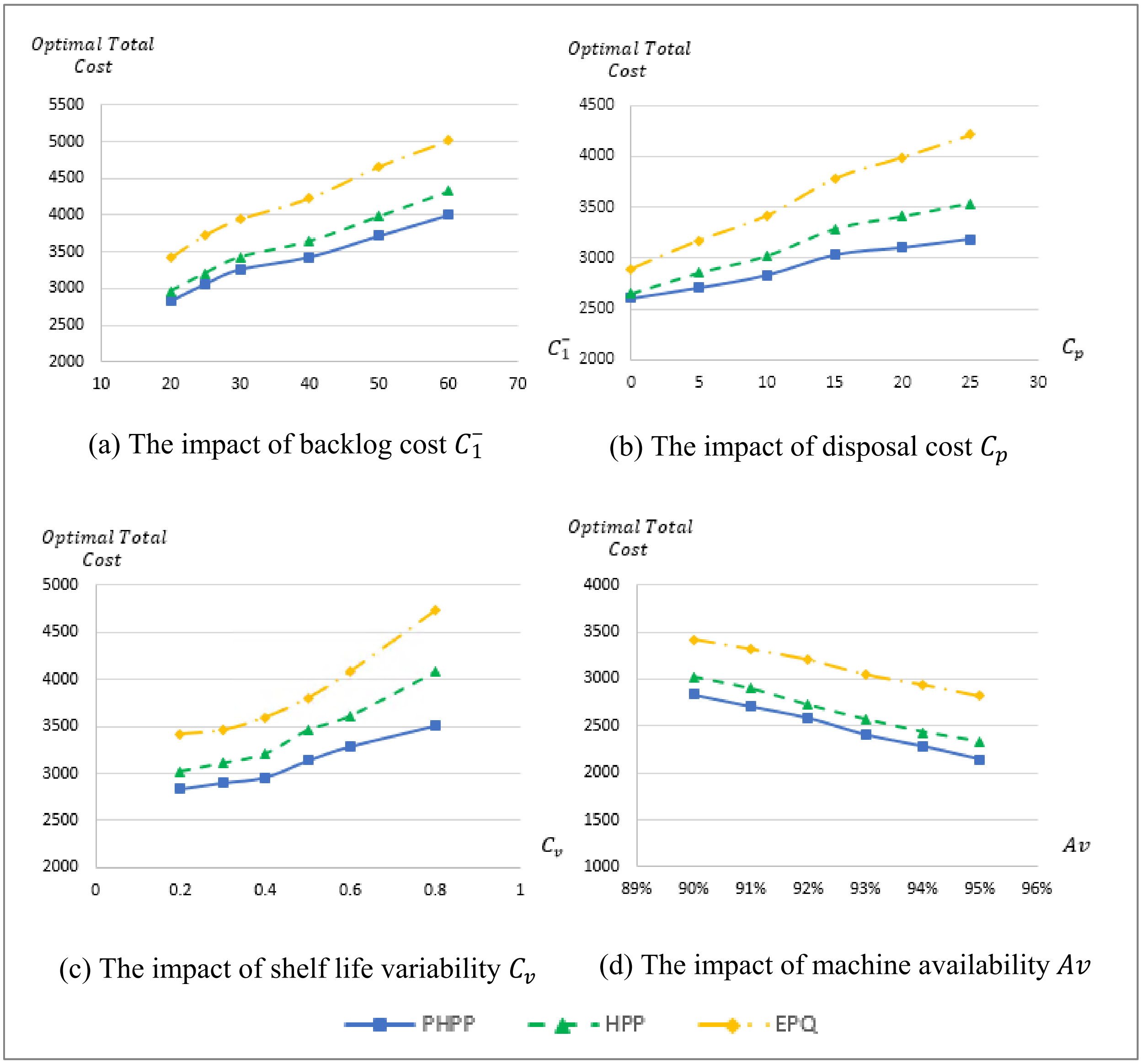


Figure 2.16 Variation of the optimal total cost for PHPP, HPP and EPQ in function of cost and system parameters

It can be seen that the gap between the three optimal total costs for the compared policies increases with an increase in unit cost for backlog C_1^- (Figure 2.16(a)) or for disposal C_p(Figure 2.16(b)). In fact, the cost advantage of PHPP as compared to the other two policies increases as C_1^- increases. This is due to the fact that when applying PHPP, the system is more protected against backlogs since the demand is satisfied in a certain order by pulling from the oldest stock before pulling from the new one. Such a queuing policy allows the system to minimize product disposal, and consequently, the risk of backlogs. The same effect is seen when the disposal cost C_p increases. This is due to the advantage of multiple hedging levels provided by PHPP to monitor different sub-stocks with different ages. PHPP allows the system to minimize the number of perished products since, unlike the other two policies, it integrates the evolution of the age of a product.

From Figure 2.16(c), it can be seen that the optimal total cost for the three policies increases as the variability increases. Moreover, the cost advantage of PHPP rises as the variability increases. In fact, when the variability increases, the number of perished products increases, as do the backlog and disposal costs. Therefore, when applying PHPP, a better control is provided since it allows the system to track the quantity of each sub-stock at each age, and to regulate the production rate accordingly, to minimize the risk of disposal and backlog.

Figure 2.16 (d) shows that the optimal total cost for the three policies decreases as the availability increases. This is because a more reliable system presents a lower risk of backlogs since the machine's non-operational times are short. Also, an increase in the system availability decreases disposal costs since the system maintains low inventory, thereby reducing the perishability risk.

2.9 Managerial Insights and Implementations

Manufacturing systems dealing with products with a limited shelf life face major challenges in terms of finding the best control policy that take into consideration the age of a product to minimize the total cost. Under conditions where the shelf life is random, the biggest challenge is deciding on the production rate that establishes a balance between having too many products that may get perished and not having enough products, and therefore risking backlogs. This challenge becomes even greater when the manufacturing system is prone to random failure times.

By implementing the proposed control policy, the manager is capable of deciding on the production rate as a function of the quantity of inventory on hand. To implement the policy, the manager is required to monitor the different inventory levels and the state of the machine (operational or under repair). In this context, the manager needs to define the different states of the product based on its shelf life.

Figure 2.17 details the implementation process for the proposed control policy PHPP for the basic case studied. Without loss of generality, the manager divides the total stock into two sub-stocks. The first sub-stock is for new manufactured products having the lowest age monitored by the thresholds Z_1^* and Z_2^*. The second sub-stock is for products that can satisfy demand, but have a higher age, and are monitored by the threshold Y^*. Based on the level of each sub-stock in comparison with the corresponding threshold, the manager should be able to regulate the production rate based on equations (2.14) -(2.16). The production rate can be set to its maximum level (120 products/U.T), demand rate (100 products/U.T), $q_{12}Z_1^*$ (60 products/U.T) or $q_{12}Z_2^*$ (80 products/U.T), or zero, based on the inventory level of each sub-stock. Accordingly, if the level of the second sub-stock is less than the threshold Y^* = 957, then the manager has to regulate the production rate using the threshold Z_2^* = 1951. Further, if the level of inventory of the second sub-stock is higher than Y^* = 957, then the manager must regulate the production rate using the threshold Z_1^* = 1438. In this case, for instance, if the inventory level in the first sub-stock is higher than 1438, the machine stops producing. If it is lower than 1438, then the production rate is set to 120 products/U.T. Otherwise, if the inventory level is equal to 1438, then the production rate must be set to $q_{12}Z_1^*$ = 60 products/U.T.

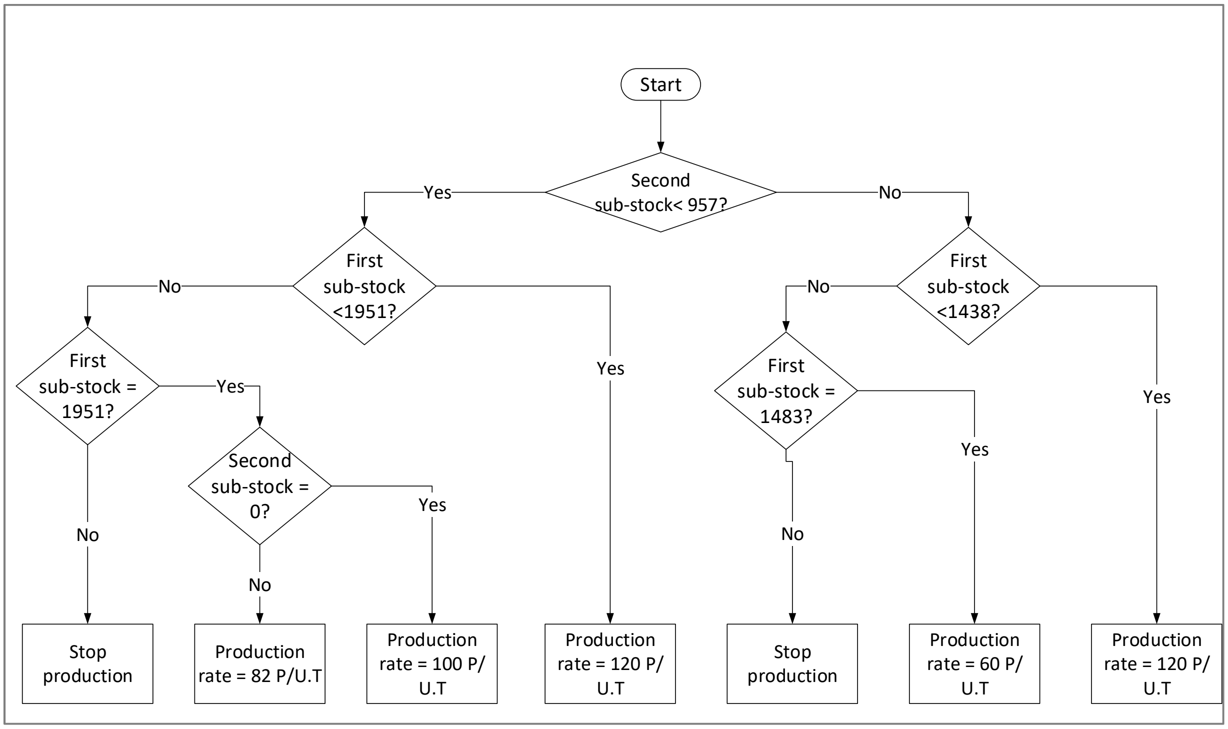


Figure 2.17 Implementation logic chart for PHPP

In addition, a manager should know that the values of the thresholds are affected by the backlog and disposal cost values. When the disposal cost is high, the threshold values decrease in order to avoid the risk of having perished products, and when the backlog cost is high, the values of the threshold increase to avoid the risk of backlogs. It is worth mentioning that the manager should take into consideration the effect of shelf life variability on the total cost. If the variability is high, the manager should make adjustments to reduce it; for example, by improving storage condition.

2.10 Conclusion

In this paper, we address a production planning and control problem when dealing with unreliable manufacturing systems producing perishable products. The studied system consists of one machine subject to random failure and repair times and producing one product type having a limited and random shelf life. A resolution approach that combines control theory, numerical methods, simulation modeling, design of experiment (DOE) and Response Surface Methodology (RSM) is adopted. First, we determine the structure of the control policy using numerical methods that are designed for stochastic optimal control models. The obtained Hamilton–Jacobi–Bellman (HJB) type optimality conditions are solved using a numerical approach to determine the parametrized structure of the resulting optimal control policy. The obtained policy is of hedging point type and consists of a combination of multiple hedging points under which stocks of different ages are built. A simulation model is developed to reflect the dynamic of the manufacturing system, governed by the proposed control policy. An experimental design is applied to see the effects of the control parameters on the total computed cost. RSM is used to estimate the total cost function from which the optimal values of control parameters are determined. Then, the combined simulation-optimization method is applied for a wide range of cost and system parameters to evaluate their effects on the control policy parameters and the total cost. It is seen that the disposal cost and the backlog cost have opposite effects on the control parameters. The combined effect of shelf life variability with the cost parameters on the optimal total cost was also examined. The results reveal the important effect of shelf life variability on the decision-making process and how considering the shelf life variability could lead to better managerial decisions aimed at reducing the optimal total cost. A high shelf life variability is high providing the manager with the opportunity to considerably improve the total cost by making certain adjustments to reduce that variability. Afterwards, we compare the proposed policy with other policies from the literature, and the results confirm that in cases of random shelf lives, the proposed policy gives the lowest optimal total cost. This is due to its ability to integrate the inventory age as it evolves in time and to determine the production rate accordingly.

Future research could be explored based on this work. For example, this could be in the form of studying the case of multiple-type products, since in many domains, it is more likely to find production policies dealing with more than one type of product. In this case, a manager is dealing with multiple random shelf lives. Moreover, regarding the effect of shelf life variability, studies are examining how shelf life variability can be captured using Time Temperature Integrators (TTI) devices. In our study, shelf life variability is not controlled, and therefore, future works could extend the study by combining the proposed control policy with

TTI devices to control the shelf life variability. This would provide cost savings opportunities since the use of such devices could help reduce product shelf life variability.

CHAPITRE 3

INTEGRATING PRODUCTION AND MAINTENANCE CONTROL POLICIES FOR FAILURE-PRONE MANUFACTURING SYSTEMS PRODUCING PERISHABLE PRODUCTS

Raouia Kaddachi [a], Ali Gharbi [b], Jean Pierre Kenné [c]

[a,b] Département de génie de la production automatisée, École de Technologie Supérieure, 1100 Notre-Dame Ouest, Montréal, Québec, Canada, H3C 1K3
[c] Département de génie mécanique, École de Technologie Supérieure, 1100 Notre-Dame Ouest, Montréal, Québec, Canada, H3C 1K3

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Abstract: The problem of integrated production and maintenance control of unreliable manufacturing systems evolving in a stochastic and dynamic environment is studied in this paper. The considered system is subject to degradation and the produced products are perishable with random shelf-lives. The literature of operations management for perishable products reports a correlation between the shelf-life of the product and the machine degradation. In fact, the latter results in shelf-lives reduction. Ignoring this correlation effect may result in inaccurate values of the shelf-lives and inefficient control policies. The objective of this paper is to develop a joint production and maintenance control policy that minimizes the total cost composed of backlog, inventory holding, disposal and maintenance costs. The proposed parametrized joint control policy combines a multi hedging point policy and an age-based preventive maintenance policy. The optimization of the parameters of the proposed joint control policy is obtained using a simulation-based optimization approach and sensitivity analyses are provided to confirm its robustness. The obtained results show that the correlation between machine degradation and shelf-life reduction has a major influence on the control parameters and that preventive maintenance interventions can lead to increasing the shelf-life of products and minimizing the total cost. The proposed joint control policy is then compared to three other polices for a wide range of system and cost data. The obtained results show that the proposed joint control policy outperforms the other polices in terms of total incurred costs.

Keywords: Manufacturing systems, Production control, Preventive maintenance, Perishable products, Random shelf-lives, Machine degradation.

3.1 Introduction

From the inventory control for perishable products side, product's shelf-life is generally estimated regardless of the manufacturing system condition and the degradation of the machine. However, in practice, there is a correlation between the shelf-life of perishable products and machine degradation (Labuza and Breene, 1989; Chelbi et al., 2008). Indeed, the degradation of the machine results in a decrease in shelf-lives. Finding production and maintenance control policies for manufacturing systems of perishable products independently of this correlation, as it is often considered in the literature, may lead to higher costs. In fact, perishable products represent a big part of the market and poorly estimating the shelf-life can lead to major loss in terms of costs (Kouki and Jouini, 2015). This is due to the limited shelf-life characteristics and the fact that they must be disposed from inventory passed their expiration date. Examples of perishables products are fruits, vegetables, medications, seafood, poultry and dairy products.

In manufacturing industries, the maintenance actions are considered a priority and are at the center of industrial concerns given their crucial role in minimizing failure occurrences. Manufacturing systems aim to find a trade-off between maximizing its availability on one hand and minimizing the costs for maintenance activities on the other hand. As the manufacturing systems are prone to breakdowns depending on many factors such as fatigue, cracks and corrosion, the interest in finding efficient strategies for maintenance interventions is increasing every day. Moreover, in the case of failure-prone manufacturing systems producing perishable products, maintenance activities can play a crucial role into minimizing incurred costs as they can lead to increasing the shelf-life of products. Consequently, it is important for manufacturing system managers to revise their strategies by adopting a joint maintenance and production control policy that take into consideration the characteristics of perishable products and the relationship between machine degradation and shelf-life reduction in order to minimize the total incurred cost.

Undeniably, manufacturing systems are subject to multiple sources of uncertainties such as random failure and repair times and the different interactions that may exist between system parameters. In this context, research questions can be presented as follows: (i) How can we quantify the correlation between shelf-life reduction and machine degradation? (ii) How does this correlation affect the maintenance and production control policies? (iii) what is the best joint maintenance and production control policy to adopt to minimize the total incurred cost? Accordingly, in this paper, we aim to develop a joint maintenance and production control policy for failure-prone manufacturing systems while taking into consideration the perishable nature of products and the related variation of the shelf-life. We also take into consideration the impact of machine degradation on the shelf-life of finished products. The objective is to find the optimal maintenance and production control policies that minimizes the total cost composed of backlog, inventory holding, disposal and maintenance costs.

The remainder of this paper is structured as follows: Section 3.2 represents a literature review. Section 3.3 is dedicated to the system description and problem formulation. The proposed joint production and maintenance control policy is detailed in Section 3.4. The adopted resolution approach is presented in Section 3.5. The simulation-optimization method used to obtain the optimal control parameters is presented in Section 3.6. Sensitivity analysis are provided in Section 3.7. A comparative study between the proposed joint policy and other policies adapted from the literature is provided in Section 3.8. Managerial insights and implementation issues are discussed in Section 3.9. Finally, the conclusion is presented in Section 3.10.

3.2 Literature review

In this section, we represent a literature review related to our study. A summary of the reviewed studies is categorized into three groups and is presented in Table 3.1. The first group is dedicated to production and control policies for failure prone manufacturing systems. The second group reviews work dealing with production control policies for perishable products. The third group presents perishable product models that integrate the effect of machine degradation on the shelf-lives of the product. Table 3.1 summarizes relevant articles based on key criteria in terms of whether or not perishability is considered, and if so, the type of shelf-life (random or not), whether the shelf-life is dependent on the machine degradation, unreliable manufacturing systems and the consideration of maintenance control policies and production control policies.

Table 3.1 Summary of relevant literature

Articles	Random shelf life	Perishable products	Unreliable manufacturing system	Operation dependent degradation	Production control	Preventive maintenance control	operation-dependent Shelf-life	Proposal of new policy
Group 1: *Joint production and maintenance control policies*								
Gharbi et al. (2007)			✓		✓	✓		✓
Dhouib et al. (2012)			✓	✓	✓	✓		✓
Kouedeu et al., (2015)			✓	✓	✓	✓		✓
Amelian et al., (2015)			✓	✓	✓	✓		✓
Nourelfath et al., (2016)			✓		✓	✓		✓
Cheng et al., (2016).			✓	✓	✓	✓		✓
Kang and Subramaniam, (2018)			✓	✓	✓	✓		
Rivera-Gómez et al. (2020)			✓	✓	✓	✓		✓
Hajej et al. (2021)			✓	✓	✓	✓		✓
Group 2: *Production control policies for perishable products*								
Bounkhel and Tadj (2005)		✓			✓			
Hedjar et al. (2007)		✓			✓			
Sajadi et al. (2011)		✓	✓		✓			
Tavan and Sajadi (2015)		✓	✓		✓			
Malekpour et al. (2016)		✓	✓		✓			
Hatami-Marbini et al. (2020)		✓	✓		✓			
Polotski et al. (2021)		✓	✓		✓			
Group 3: *Perishable products models and machine degradation*								
Barry-Ryan and O'beirne, 1998	✓	✓					✓	
Martinez-Romero et al. (2002)	✓	✓					✓	
Labuza and Breene (1989)	✓	✓					✓	
Ali et al. (2010)	✓	✓					✓	
Kittur et al. (2001)	✓	✓					✓	
Taormina and Hardin (2021)	✓	✓					✓	
Eskin and Robinson (2000)	✓	✓					✓	
Our work	✓	✓	✓	✓	✓	✓	✓	✓

The first group of the literature review is related to integrated policies for maintenance and production control. According to Berthaut et al., (2011), in a manufacturing context, the shutdowns of production units due to maintenance interventions reduce the availability of the system and can lead to shortages. Hence comes the interest in integrating joint maintenance and production policies. This combination makes it possible to optimize the control parameters related to the production control policies and to the preventive maintenance control policies simultaniously, and at the same time study the variations in inventory levels depending on maintenance interventions (Hajej et al., 2021). In this context, Gharbi et al., (2007) combined in their work the Hedging Point Policy (HPP) with an age-based preventive maintenance policy for unreliable manufacturing systems composed of a single machine producing one family type of finished products. For the same manufacturing system, Dhouib et al., (2012) determined the critical age for preventive maintenance interventions and the optimal inventory level. In the same context, the work of Kouedeu et al., (2015) deals with integrated maintenance and production control policies for unreliable systems and consider that failures are operation dependent. The work of Amelian et al., (2015) studies also a maintenance and production control problem for failure-prone systems and uses simulation techniques for the resolution approach. In the same sense, integrated production and maintenance control policies were studied in Nourelfath et al., (2016) and Cheng et al., (2016). Kang and Subramaniam, (2018) studied as well integrated policies for deteriorating manufacturing systems. Also, Rivera-Gómez et al., (2020) studied an optimization problem of integrated production and maintenance control policies while considering a dynamic sampling strategy. Hajej et al., (2021) studied also a degrading manufacturing system in order to determine a joint maintenance and production control policy with dynamic inspection. The literature laid out thus far deals with integrated production and maintenance control policies for failure-prone manufacturing systems and highlights the importance of considering joint policies. However, it does not include the case where the products are of perishable nature and the fact that they must be removed from inventory passed their shelf-life. This brings us to the next group of this literature review, which deals with production control policies for manufacturing systems producing perishable products.

Studying control problems for unreliable manufacturing systems has been in the center of research for decades with a focus on feedback control policies especially the class of the Hedging Point Policies (HPP). Many researchers were prompted to develop several extensions based on the concept of HPP to study different system configurations for multiple manufacturing contexts, one of whom is the perishability of products. In this area, there has been relatively little work that consider perishability issues in dynamic stochastic systems. We cite the work Bounkhel and Tadj (2005) dealing with perishable products with a deterministic shelf-life while using the classical HPP but for a reliable manufacturing system. Hedjar et al., 2007 studies also control problems for reliable manufacturing systems for perishable products having a deterministic shelf-life and a random demand rate. As for work that include machine failure, we cite Sajadi et al. (2011) and Tavan and Sajadi (2015) that applied the classical HPP for perishable products with a deterministic shelf-life. The work of Malekpour et al. (2016) and Hatami-Marbini et al. (2020) deal with production control problems for unreliable manufacturing systems composed of a network of machines where the final product perishable. In their work, the shelf-life is deterministic and the classical HPP is used for production control. In the same context, the work of Polotski et al., (2021) deals with a production control problem of failure-prone manufacturing systems for perishable products having a deterministic shelf-life. We see that, when dealing with perishable products for a failure-prone manufacturing system, there is always limitation regarding the shelf-life (deterministic shelf-life). Moreover, the aforementioned work that deal with feedback control policies for perishable product used the classical HPP without developing suitable policies that take into consideration the specificities of perishable products and the variability of the shelf-lives. Furthermore, all these studies did not consider any maintenance control policies. Therefore, there is no previous study that combines maintenance control policies with production control policies and take into consideration the perishable nature of products and failure prone manufacturing systems simultaneously in a stochastic and dynamic context. Yet, many researchers highlight that there is a correlation between the shelf-life of perishable products and the degradation of the machine and how the latter can result in a decrease of shelf-lives.

The third group of the literature review focuses on studies related to perishable products and the factors that can affect the value of shelf-lives. One of these main factors is machine degradation. This relationship is confirmed throughout many industrial contexts. For instance, in the work of Barry-Ryan and O'beirne (1998), they confirm that the blades used for slicing carrots degrades over time thus decreasing the products' shelf-lives. Many other studies concentrate on the relationship between machine degradation and shelf-life reduction such as: the work of Martinez-Romero et al., (2002) explaining how shelf-lives of fruits can be extended if the machine providing a certain dosage is well maintained; The work of Labuza and Breene (1989) dealing with a packaging machine for vegetables and highlighting the fact that when the machine ages, the glue nozzle gets less effective which leaves air bubbles in each packed product and leading to a decrease in shelf-life; Ali et al., (2010) studying tomato fruit and Kittur et al., (2001) studying bananas and mangos. This relationship is also discussed in studies related to quality control and how machine degradation can lead to a decrease in products' quality and this result, in practice, in shelf-life reduction (Taormina and Hardin, 2021). This statement is also mentioned in the work of Eskin and Robinson (2000). However, to the best of our knowledge, all these studies spoke about a qualitative relationship between machine degradation and shelf-life reduction and no quantitative relationship has been established. As can be noted, more studied are required to fully integrate maintenance and production activities in a joint control policy that incorporate a quantitative relationship between machine degradation and shelf-life reduction.

To sum up, according to the literature review provided, we see that most manufacturing system models dealing with both maintenance and production control policies do not consider the perishability of products. In addition, the research that deal with manufacturing system models for perishable products does not integrate preventive maintenance policies. Moreover, even thought, numerous studies confirm that machine degradation can result in a decrease in shelf-life, no quantitative relationship has been proposed to this matter.

In the present paper, our objective is to fill the gap in the literature by proposing a joint maintenance and production control policy for a failure-prone manufacturing system producing perishable products having a random shelf-life that decreases as the machine degrades. In the same sense, we propose a quantitative relationship linking the shelf-life of the product with the age of the machine. The proposed joint policy allows the decision maker to jointly decide on both maintenance and production activities to determine how to control the production rate and when it is convenient to execute preventive maintenance activities. The proposed joint policy aims to increase product' shelf-lives and decrease the occurrence of failures in order to minimize the total incurred cost composed of backlog, holding, disposal and maintenance (corrective and preventive) costs.

3.3 System description and problem formulation

The notations used are presented and the studied system is described in this section.

3.3.1 Notations

The notation used in this study are defined as follows:

$x_i(t)$	Inventory level at time t for the portion of stock being at state i at time t
D_i	Demand rate for the portion of stock being at state i (product /unit of time)
D	Total demand rate (product /unit of time)
$u(t)$	Production rate at time t (product /unit of time)
U_m	Maximum production rate (product /unit of time)
$a(.)$	Age of machine since the last maintenance action
A	Critical PM age of the machine
C_i^+	Holding cost for the portion of stock being at state i ($/ product /unit of time).
C_i^-	Backlog cost for the portion of stock being at state i ($/ product /unit of time).
C_p	Disposal cost due to perishability ($/ product)
C_{pm}	Cost of a preventive maintenance (PM) operation ($/ PM operation)
C_{cm}	Cost of a corrective maintenance (CM) operation ($/ CM operation)
TTF	Time To Failure

$MTTF$	Mean Time To Failure
TTR	Time To Repair
$MTTR$	Mean Time To Repair
TPM	Time of Preventive Maintenance
$MTPM$	Mean Time of Preventive Maintenance
$SL(.)$	Shelf life mean of the product
$\sigma(.)$	Variability of the shelf life of the product
ω_p	Binary variable that is equal to 1 if PM is conducted and 0 otherwise.
π_i	Limiting probability at mode i
$J(.)$	Cost function

3.3.2 System description

The considered manufacturing system is composed of a single machine producing one type of finished products having a limited and random shelf-life. Figure 3.1 illustrates the structure of the manufacturing system. The machine is prone to random failure and repair times. Corrective Maintenance (CM) interventions are executed upon each failure. To preventively cope with machine degradation, Preventive Maintenance (PM) interventions are performed to restore the machine to ‘‘as-good-as-new’’ condition. As for CM actions, we assume that they restore the machine to ‘‘as-bas-as-old’’ condition. These assumptions are considered for multiple manufacturing systems in which maintenance interventions can include the replacement of degrading or failed parts.

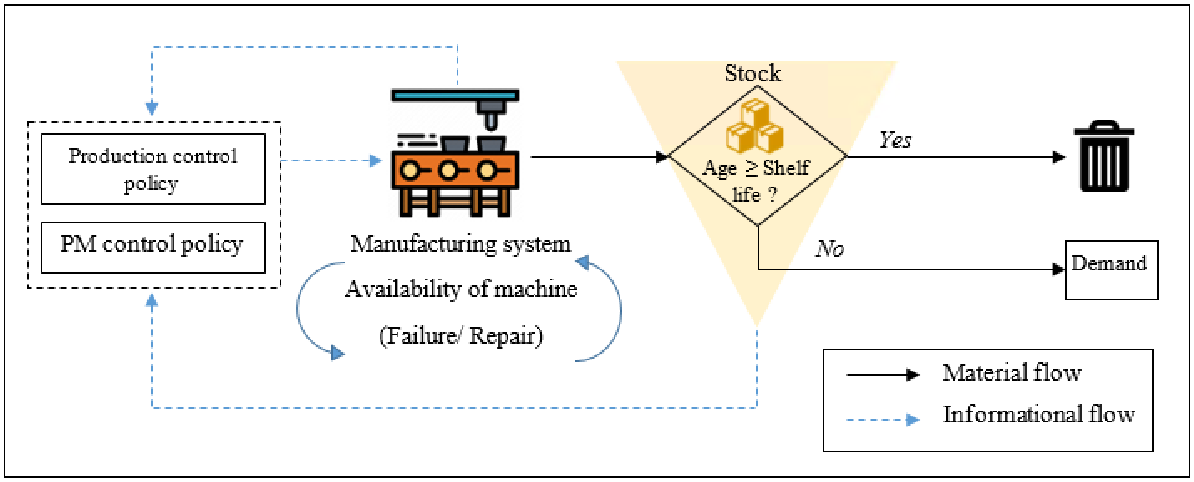


Figure 3.1 Studied manufacturing system

The finished product is of perishable nature having a random and limited shelf-life. Products are stored in inventory before satisfying demand. If the age of a product exceeds its shelf-life while still in inventory, it must be disposed. The shelf-life of the product is related to the degradation of the machine. Basically, when the machine degrades, the shelf-life decreases. This relationship between the shelf-life reduction and machine degradation is detailed in Section 3.3.3 Products passed their shelf-life incur a disposal cost. We consider a holding cost as well for each product in inventory. Also, due to machine failure and repair times, unsatisfied demand is delayed with a backlog cost. In addition, each maintenance activity (preventive or corrective) incurs a maintenance cost.

3.3.3 Problem formulation

The state of the system is described by a discrete and a continuous component. The discrete component is represented by a stochastic process $\xi(t)$ describing the dynamics of the machine. The continuous component consists of the age of the machine $a(t)$ and the stock of produced parts into several sub-stocks x_i.

The dynamics of the machine is described at time t by the stochastic process $\xi(t)$ with value in $B = \{1, 2, 3\}$, such that:

$$\xi(t) = \begin{cases} 1 \; machine \; is \; operational \\ 2 \; machine \; is \; under \; CM \; activities \\ 3 \; machine \; is \; under \; PM \; activities \end{cases}$$

The manufacturing system is subject to PM interventions using the decision variable $\omega_p(.)$ that allows the transition of the machine from an operational mode (mode 1) to PM mode (mode 3). Let's define $\omega_p(.)$ representing a binary variable indicating if PM interventions are executed (equal to 1) or not (equal to 0).

The age of the machine $a(t)$ is measured using the cumulative number of produced parts from the last maintenance. It is described by the following differential equation:

$$\dot{a}(t) = k.u(.) \tag{3.1}$$

where $u(.)$ is the production rate and k is a given positive constant.

The decision variables in this problem are the production rate $u(.)$ of the manufacturing system and the decision of PM interventions $\omega_p(.)$. Regarding the dynamic of inventory, we discretize the total stock into several sub-stocks x_i each representing a part of the total stock with a specific state i representing the sub-stock's age.

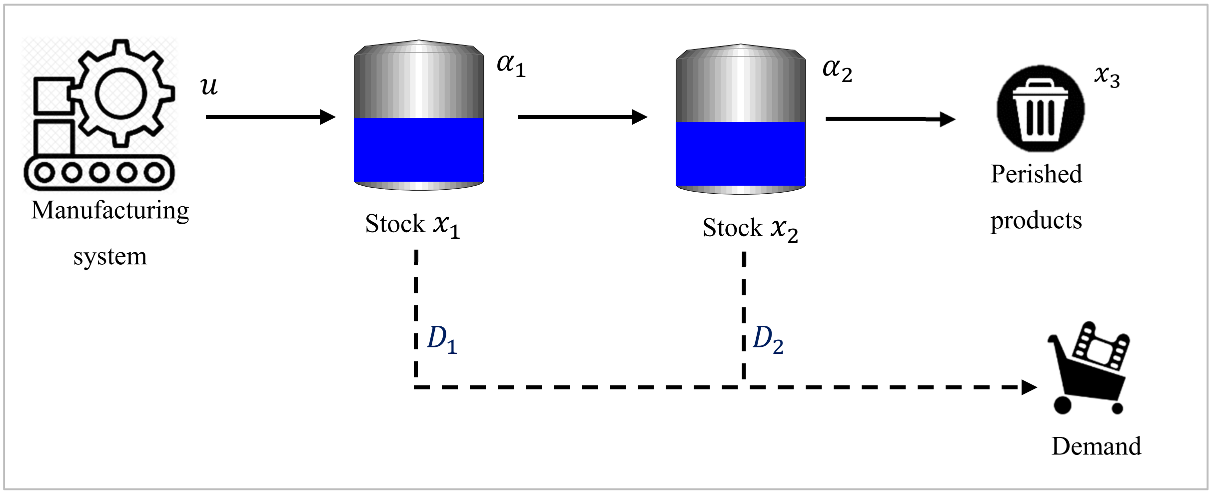


Figure 3.2 Modeling perishable products

As we see in Figure 3.2, the machine operates with a production rate $u(.)$ manufacturing a product with a limited shelf-life with mean SL. The first sub-stock is x_1 which represents the newest stock. As time advances, the stock that is not pulled by demand from that first sub-stock gets older and passes to the next sub-stock x_2 and so on to the next sub-stock x_3 reaching the maximum shelf-life and the product is disposed. In this case the sub-stock x_3 represents perished products. The time that products remains in each sub-stock is denoted α_i. At this point, we introduce the two rates u_1^p and u_2^p that denotes the rate at which products exit each sub stock. They are expressed by the following equations:

$$u_1^p = \frac{x_1^+}{\alpha_1} \tag{3.2}$$

$$u_2^p = \frac{x_2}{\alpha_2} \tag{3.3}$$

The meaning of $x_1^+ = max\,(x_1, 0)$ is to express allowing backlog only in the first sub-stock. In fact, the total demand D is also divided into multiple D_i that each one pulls from the corresponding sub-stock x_i with $0 \leq D_i \leq D$ and $D = \sum_i D_i$ The demand is set in a way that it pulls from the oldest stock x_2 until it becomes empty and then moves on to newest stock x_1. When the latter becomes empty, demand is backlogged.

The dynamic of the stock levels is expressed by the following differential equations:

$$\begin{aligned} \dot{x}_1 &= u - u_1^p - D_1, & x_1(0) &= x_1^0 \\ \dot{x}_2 &= u_1^p - u_2^p - D_2, & x_2(0) &= x_2^0 \end{aligned} \tag{3.4}$$

with x_1^0 and x_2^0 denote the levels of each sub-stock at the initial time.

As stated above, the demand is set in a way to allow a certain queuing policy that allows the products that have the shortest remaining shelf-life to be pulled from inventory. This is expressed with the following equations:

$$D_2 = \begin{cases} D & if\ x_2 > 0 \\ u_1^p & if\ x_2 = 0 \\ 0 & otherwise \end{cases} \tag{3.5}$$

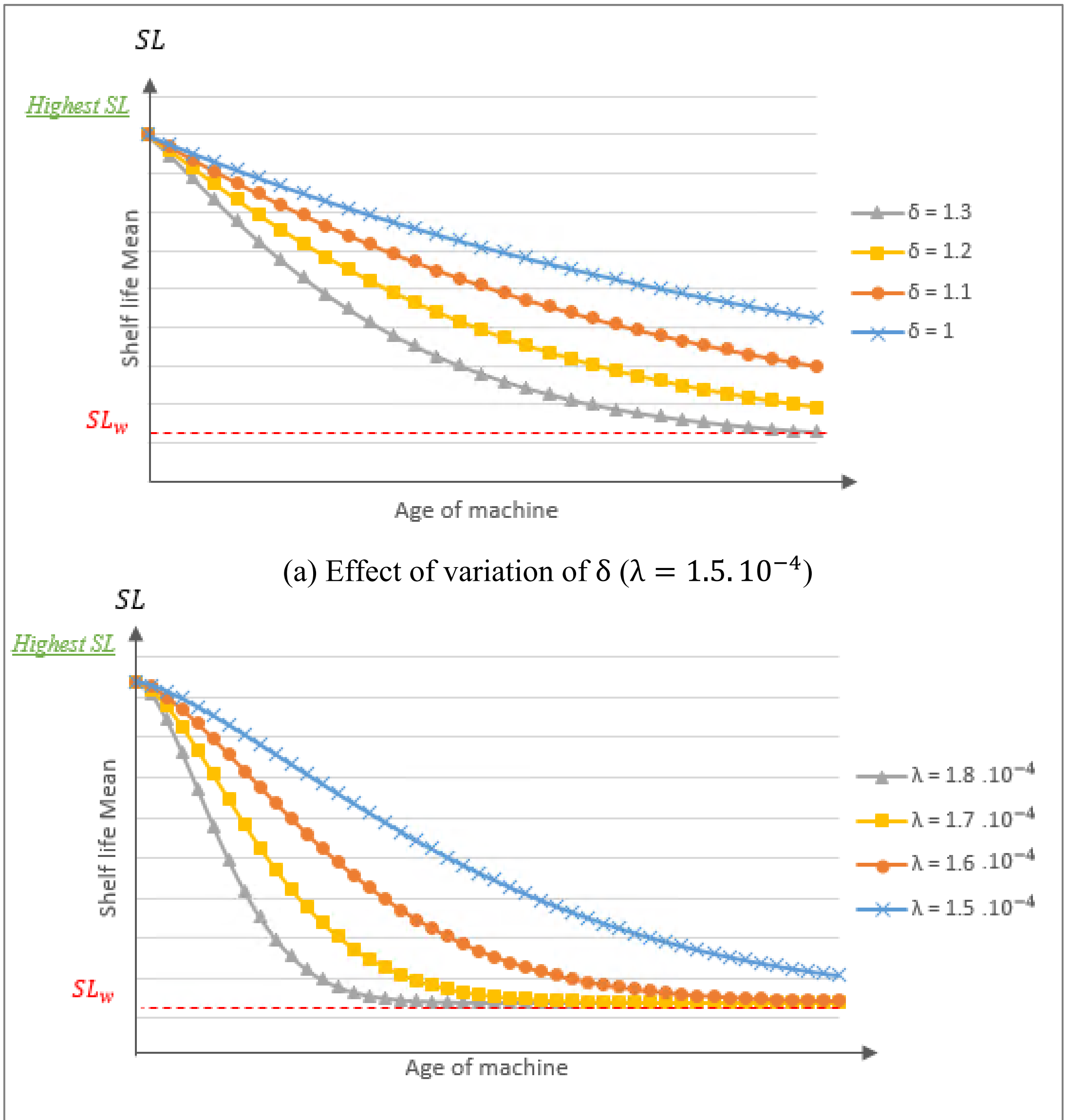
$$D_1 = \begin{cases} 0 & if\ x_2 > 0 \\ D - u_1^p & if\ x_2 = 0 \\ D & otherwise \end{cases} \tag{3.6}$$

Here, we aim to establish a quantitative relationship between products' shelf-life and machine degradation represented by its age. This is based on the work of (Taormina and Hardin 2021) establishing the link between the shelf-life and the quality of the product. It is also based, on the work of (Ait-El-Cadi et al., 2021) establishing the link between the quality of the products and machine degradation in function of the machine's age. The relationship between product's shelf-life and the age of the machine is expressed by equation (3.7).

$$SL(a) = SL_w + \eta\, exp(-\lambda\, a^{\delta}) \tag{3.7}$$

where SL_w is the smallest shelf-life a product can have. λ and δ are given positive constants generally found from historical data and η is the boundary considered for shelf-life reduction. Figure 3.3 represents the variation of the product's shelf-life in function of the machine's age based on Equation (3.7). As we can see, when the machine is new, the shelf-life is at its biggest.

As the machine ages, the shelf-life starts to decrease, and when the system is old, the shelf-life reaches its worst value SL_w. From these observations, SL_w is the worst shelf-life value when the system is old, and (SL_w+ η) represents the biggest shelf-life value, when the system is new. λ and δ are used to change the scale and the shape of the model defined in equation (3.7). The latter is commonly used in the literature (Bouslah et al., 2018; Cheng and Li, 2020) Rivera-Gómez et al., 2020 apply the same model and highlight this ‘‘S’’ shape or, in our case, this ‘‘S reversed’’ shape (Figure 3.3) by drawing it from simulation results. The authors note that this formulation is widely used and is considered general since it can represent many cases. Moreover, this model as well as parameters could be fitted based on historical data using different techniques such as Bayesian approaches and maximum likelihood (Rinne, 2008). Figure .33 shows also the effect of the parameter δ on the shape of the mean of the shelf-life. When δ (Figure 3(a)) or λ (Figure 3(b)) increase, the shelf-life tend to reach its worst value.



(a) Effect of variation of δ ($\lambda = 1.5.10^{-4}$)

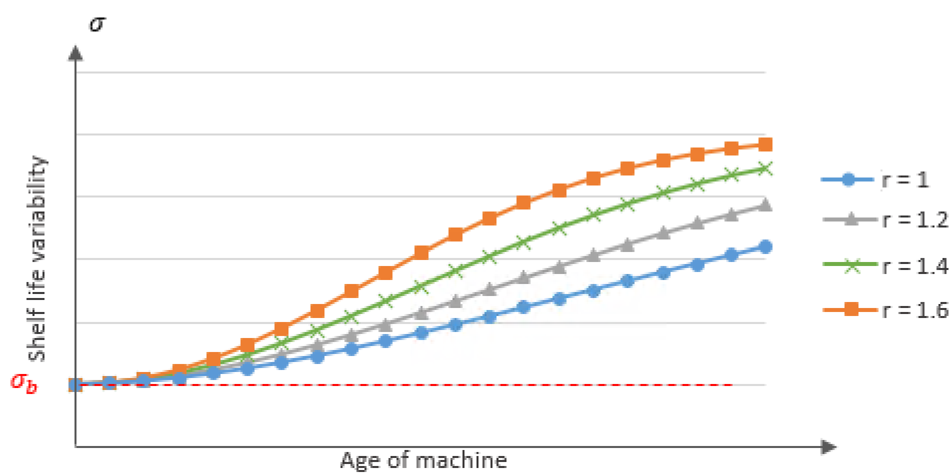
(b) Effect of variation of λ ($\delta = 1.1$)

Figure 3.3 Mean of shelf life decrease with the machine's age

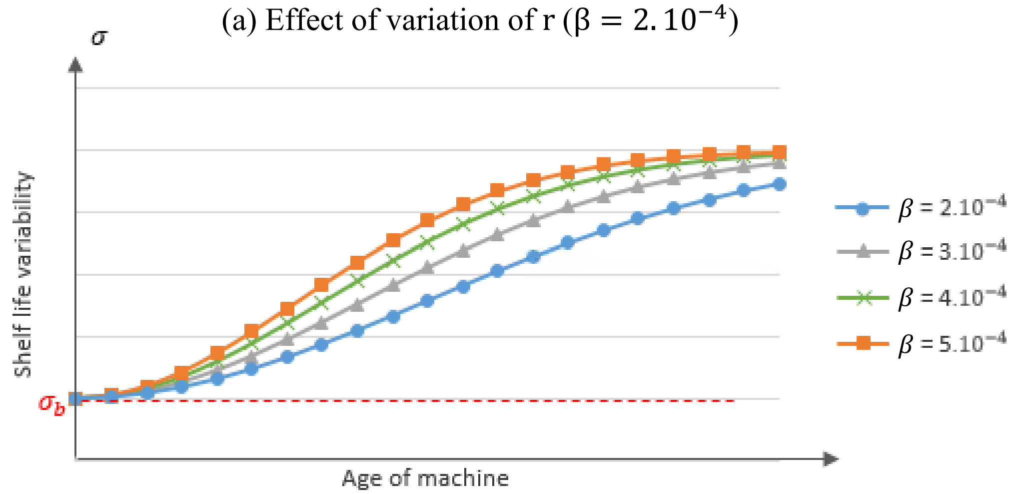
The variability of the shelf-life increases with the increase of machine's age. In the same sense, we model the variability of the shelf-life by the following equation:

$$\sigma(a) = \sigma_b + y\,(1 - exp(-\beta\, a^r)) \tag{3.8}$$

Where σ_b is the smallest shelf-life variability accorded to a product when the machine's age $a(t)$ is low. β and r are given positive constants obtained from historical data and y is the boundary considered in the shelf-life variability increase. We show in Figure 3.4, the effect of machine's age on the shelf-life variability and its variation when varying r (Figure 3.4(a)) and β (Figure 3.4(b)). As we can see, when the age of the machine is small, the variability is at its lowest value, and as the machine ages, it increases. The model described by equation (3.8) is based on the work of (Rivera-Gómez et al., 2020) by using the same "S" shape. By changing the values of β and r, we could change the shape of the model. When r and ω increase, the shelf-life variability increases as well.



(a) Effect of variation of r ($\beta = 2.10^{-4}$)



(b) Effect of variation of β ($r = 1.2$)

Figure 3.4 Shelf-life variability increase with the machine's age

Based on the theory of probability (Ross, 2014), we use the set of equations (3.9) to compute the limiting probability at each mode.

$$\begin{cases}(\pi_1 \;\; \pi_2 \;\; \pi_3).\, Q = 0 \\ \pi_1 + \pi_2 + \pi_3 = 1\end{cases} \tag{3.9}$$

Where π_i is the limiting probability at mode i ($i \in B$) and Q representing the transition rates matrix given by:

$$Q = \begin{pmatrix} -\left(\frac{1}{MTTF(a)} + \omega_p(.)\right) & \frac{1}{MTTF(a)} & \omega_p(.) \\ \frac{1}{MTTR} & -\frac{1}{MTTR} & 0 \\ \frac{1}{MTPM} & 0 & -\frac{1}{MTPM} \end{pmatrix}$$

With $MTTF(a) = q_1 + \; q_2\,(1 - exp(-q_3\, a))$ illustrated in Figure 5 for given positive constants q_1, q_2 and q_3. This model describes the machine degradation as its age increases according to a model often used in the literature (Rivera-Gomez et al. 2016; Polotski et al., 2019).

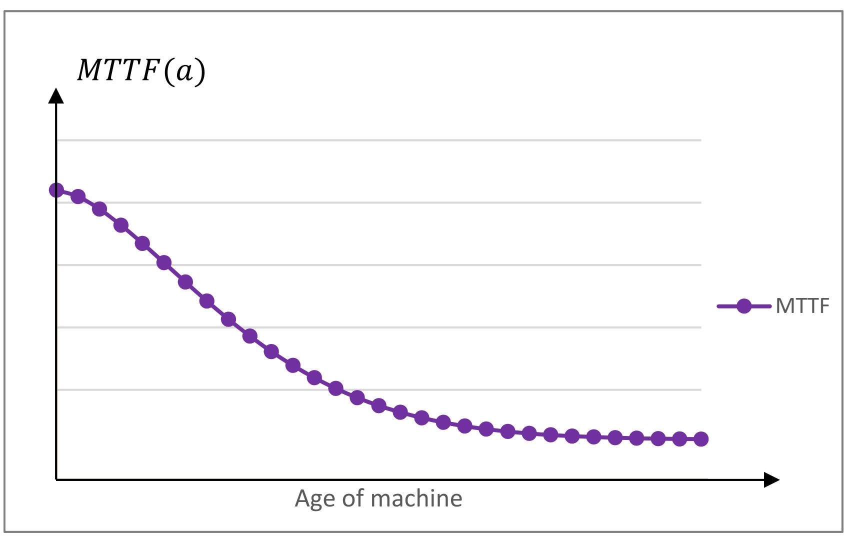


Figure 3.5 Variation of MTTF with the machine's age

Upon resolving equations (3.9), the limiting probability at each mode given by the following expressions:

$$\begin{cases} \pi_1(a) \ = \dfrac{MTTF(a)}{MTTF(a) + MTTR + \omega_p(.)MTTF(a).MTPM} \\ \pi_2(a) = \dfrac{MTTR}{MTTF(a)}\ \pi_1(a) \\ \pi_3(a) = \ \omega_p(.).MTPM.\pi_1(a) \end{cases} \tag{3.10}$$

At any time t, the machine must satisfy the feasibility constraint expressed by the following equation (3.11).

$$U_m * \pi_1(a)\ > D\ +\ u_2^p \tag{3.11}$$

Where u_2^p defines the rate of disposal as expressed in Equation (3.3).

We note that when there is no preventive maintenance ($\omega_p(.)$ = 0), the value of the limiting probability at the operational mode is $\pi_1(a)\ = \frac{MTTF(a)}{MTTF(a)+MTTR}$ (see equation (3.10)) that decreases when the age of the machine increases. We represent in Figure 3.5 the evolution of $MTTF(a)$ when the machine's age increases. We see that MTTF decreases as the machine ages. Consequently, from a certain age, the system may become infeasible according to equation (3.11). That's why PM interventions are needed to restore the manufacturing system to ''as-good-as-new'' condition. Moreover, at the completion of the PM interventions, the shelf-life is restored to its highest value as discussed above.

We denote Γ (.) the domain of admissible decisions:

$$\Gamma\ (\alpha) = \{u(a,.), \omega_p(a,.) |\ 0 \leq u \leq U_m\ Ind\ \{\alpha =\ 1\}, \omega_p \in \{0,1\}\} \quad \text{with } \xi(t)\ =\ \alpha \tag{3.12}$$

First, we define the cost rate function $g(.)$ to be able to penalize the costs of inventory holding, disposal, backlog and maintenance (corrective and preventive) as follows:

$$g(\alpha, x_1, x_2, a, u, \omega_p) = C_1^{+}.\ x_1^{+} + C_1^{+}.x_2 + C_1^{-}.\ x_1^{-} + C_p\,.u_2^{p}\,x_2\ + C_{cm}\,.E_{\mathrm{cm}} + C_{pm}\,.E_{\mathrm{pm}} \quad (3.13)$$

Where:

$x_1^{+} = max\ (0, x_1), x_1^{-} = max\ (-x_1, 0)$

And,

$E_{\mathrm{cm}} = \begin{pmatrix} 1\ if\ \xi(t) = 2 \\ 0\ otherwise \end{pmatrix}$, $\qquad E_{\mathrm{pm}} = \begin{pmatrix} 1\ if\ \xi(t) = 3 \\ 0\ otherwise \end{pmatrix}$

Having defined the admissible domain in (3.12) and based on the instantaneous cost defined in equation (3.13), we define the overall cost function $J(.)$ over a finite horizon given in equation (3.14) as in (Polotski et al., 2021).

$$J(\alpha, x_1, x_2, a, u, \omega_p) = \lim_{\mathrm{T}\to\infty} \frac{1}{T} E\left\{\int_0^{\mathrm{T}} g(.)\ \mathrm{dt} \mid x_1(0) = x_1\ , x_2(0) = x_2\ , \xi(0) = \alpha, \right\}, \quad (3.14)$$

$$\forall\ \alpha \in \mathrm{B}$$

The objective is to minimize a long-run average cost $J(.)$ defined in (3.14) over $\Gamma\ (\alpha)$ and under constraints given by equations (3.1) to (3.11). Hence, we have to proceed with the definition of $J^{*}(.)$ as a minimizer of $J(.)$ as follows: $J^{*}(.) = \operatorname*{Inf}_{(u,\omega_p)\ \in\Gamma(\alpha)} J(\alpha, x_1, x_2, a, u, \omega_p)$. The determination of the cost $J^{*}(.)$ and the associated joint optimal policy (u, ω_p) is considered complex in the work of Polotski et al., (2021) with respect to optimization approaches based on stochastic optimal control theory centered on dynamic programming techniques. In their study, the shelf-lives of the products were considered deterministic. However, in this study, we consider a dynamic and stochastic environment: random failures and repair times, random shelf-lives, evolutions of shelf-life variability, interactions between shelf-lives and machine's age. Hence, these factors make the resolution process much more complicated. Therefore, we adopt a resolution approach based on simulation technique, design of experiment and response surface methodology. The resolution approach is detailed in section 3.5.

3.4 Proposed joint production and maintenance control policy (PPMP)

We propose a joint production and maintenance control policy for manufacturing systems subject to random failure and repair times producing perishable products where the shelf-life decreases with the machine's degradation.

3.4.1 Production control policy

The production control policy adopted in this study is inspired from the literature. In fact, the considered manufacturing system is unreliable with random failure and repair times. In this case, the class of the hedging point policies is considered efficient. That's why we propose to extend the classical (HPP) to a Multi-Hedging Point Policy (MHPP) for the case of perishable products. The proposed production control policy is based on the work of (Assid et al., 2015) dealing with a failure prone manufacturing system producing two product types (x_1 and x_2). Ben Salem et al., 2015 also proposed a MHPP for a failure prone manufacturing system respecting environmental regulations. We propose the structure of production control policy described by equations (3.15) -(3.17). It consists of building and maintaining safety stocks of each sub-stock (x_1 and x_2) based on multiple hedging levels. The objective of the proposed production control policy is to allow the system to satisfy demand during the non-operational times of the machine on one hand, and to minimize the number of perished products on the other hand. The production rate in equations (3.15) -(3.17) is determined based on the dynamics of the stock expressed in equation (3.4) and the value of the
demand expressed in equations (3.5) and (3.6).

$\boldsymbol{If\ \ x_2 \geq Y}$

$$u\,(1,.) = \begin{cases} U_{\mathrm{m}} & if \quad x_1\,(t) \; < \; Z_1 \\ u^{P}_{Z_1} & if \quad x_1\,(t) \; = \; Z_1 \\ 0 & if \quad x_1\,(t) \; > \; Z_1 \end{cases} \tag{3.15}$$

Where $u^{P}_{Z_1} = \frac{Z_1}{\alpha_1}$

$\boldsymbol{If\ 0 < x_2 < Y}$

$$u\,(1,.) = \begin{cases} U_{\mathrm{m}} & if\ \ x_1\,(t)\ <\ Z_2 \\ u_{Z_2}^{P} & if\ \ x_1\,(t)\ =\ Z_2 \\ 0 & if\ \ x_1\,(t)\ >\ Z_2 \end{cases} \tag{3.16}$$

Where $u_{Z_2}^{P} = \frac{Z_2}{\alpha_2}$

$\boldsymbol{If\ \ x_2 = 0}$

$$u\,(1,.) = \begin{cases} U_{\mathrm{m}} & if\ \ x_1\,(t)\ <\ Z_2 \\ D & if\ \ x_1\,(t)\ =\ Z_2 \\ 0 & if\ \ x_1\,(t)\ >\ Z_2 \end{cases} \tag{3.17}$$

With α_1 and α_2 positive constants and $Z_1 \leq Z_2$, $u(2,.) = u(3,.) = 0$.

3.4.2 Maintenance policy

As for the maintenance policy, we propose an Age-based PM policy. This choice is motivated by the fact that machine degradation is dependent on its age and the fact that products' shelf-life decreases as the machine degrades. The structure of the maintenance policy is based on the work Rivera-Gómez et al. (2018) and Berthaut et al. (2010) and is governed by two control parameters: A and Z_{PM}. The structure of the proposed maintenance policy is expressed by equation (3.18). In this case, the machine is maintained upon reaching a predetermined age A and when the inventory on hand is bigger than Z_{PM}. Indeed, A is a threshold of cumulative number of produced products called also the critical PM age. Z_{PM} denotes the critical products' threshold that must be in inventory in order to execute PM activities. This parameter aims to minimize the risk of backlog and is based on the work of Berthaut et al. (2010) who deals with the case of a single type of finished product. We propose to use the sum of instantaneous inventories of the two sub-stocks of finished products $(x_1\,(t) + x_2\,(t))$ to control the preventive interventions. Here, the decision variable called $\omega_p(t)$ is defined by a binary function equal to 1 if a preventive maintenance action is performed, and equal to 0 if not.

$$\omega_p(3,.) = \begin{cases} 1 & (if\ a(t) \geq A)\ and\ (x_1(t) + x_2(t)) \geq Z_{PM} \\ 0 & otherwise \end{cases} \tag{3.18}$$

The optimization problem consists of finding the optimal control parameters (Z_1, Z_2, Y, A, Z_{PM}) of the joint production and maintenance control policy called hereinafter Perishable Production Maintenance Policy (PPMP) to minimize the expected total cost expressed by equation (3.14). It includes backlog, inventory holding, disposal and maintenance costs.

3.5 Resolution Approach

This section details the main steps of the resolution approach adopted. We should note that it is difficult to find the analytical solution for complex problem evolving in a dynamic and stochastic context. Therefore, in order to optimize the control parameters that minimizes the total cost in equation (3.14), a simulation-based optimization method is adopted. This method combines simulation modelling, Design of Experiment (DOE) and a Response Surface Methodology (RSM). The adopted method is frequently used in the resolution of complex problems such (Rivera-Gómez et al., 2018). The resolution steps are illustrated in Figure 3.6.

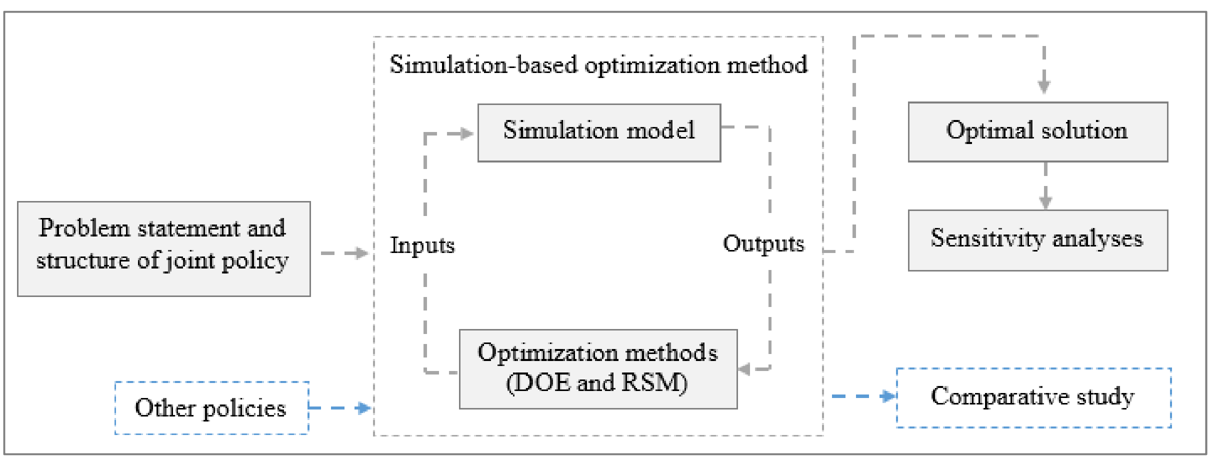


Figure 3.6 Proposed resolution approach

Step 1: Structure of joint policy

In this step, the studied manufacturing system is described, and the problem is formulated. Afterwards the structure of the proposed joint control policy is defined. The control parameters represent inputs of the simulation model (See Sections 3.3 and 3.4).

Step 2: Simulation model

In order to imitate the system dynamics under the proposed joint policy, a simulation model is built. The control parameters of the proposed joint control policy are considered inputs for multiple experiments in order to evaluate the performance of the system (See section 3.6.1).

Step 3: Optimization using Design of Experiment (DOE) and Response Surface Methodology (RSM)

In this step, the objective is to find the optimal control parameters that minimizes the total incurred cost. DOE is used to define the inputs for the simulation runs. RSM is applied on the total cost obtained with the simulation to establish the effect of significant control parameters, their interactions and their quadratic effects on the total incurred cost. The total cost is then minimized to determine the optimal control parameters. Section 3.6.2 details this step.

Step 4: Sensitivity analysis

In this step, multiple sensitivity analyses are conducted for a wide range of cost and system data (backlog disposal variability of shelf-life…) to observe the behavior the proposed joint maintenance and production control policy and to confirm the robustness of the resolution approach (see Section 3.7).

Step 5: Comparative study

This step aims to conduct a comparative study between the proposed joint control policy and other policies. The comparison is carried out for a wide range of system and cost parameters to determine the policy that offers the lowest incurred total cost (See Section 3.8).

Step 6: Implementation of the control policy

In Section 3.9, the implementation of the proposed joint control policy is established. The objective here is to provide the decision maker with insights to help him effectively implement the proposed joint control policy. An example is provided to guide the manager step by step through the implementation process.

3.6 Simulation-based optimization method

The control problem formulated above has constraints and is stochastic. The stochastic events are the correlated shelf-lives of the product with the age of the machine, and the random failure and repair times of the machine. When dealing with complex systems with dynamic and stochastic settings, obtaining analytical solutions is difficult. Therefore, a simulation-based optimization method is used in order to evaluate the economic performance of the proposed joint control policy. It combines simulation, DOE and RSM in order to determine the optimal control parameters. This approach is very commonly used for problem resolution of complex manufacturing systems' problems (Negahban and Smith, 2014; Freitag and Hildebrandt, 2016).

3.6.1 Simulation model and its validation

The simulation model developed using Arena software combines discrete and continuous events. The advantage of using simulation modeling technique lies in its capacity to imitate the actual operating conditions under which the manufacturing system evolves. The block diagram of the simulation model is presented in Figure 3.7. The structure of the model consists of several events interacting with each other such as arrival of demand, the control policies, etc.

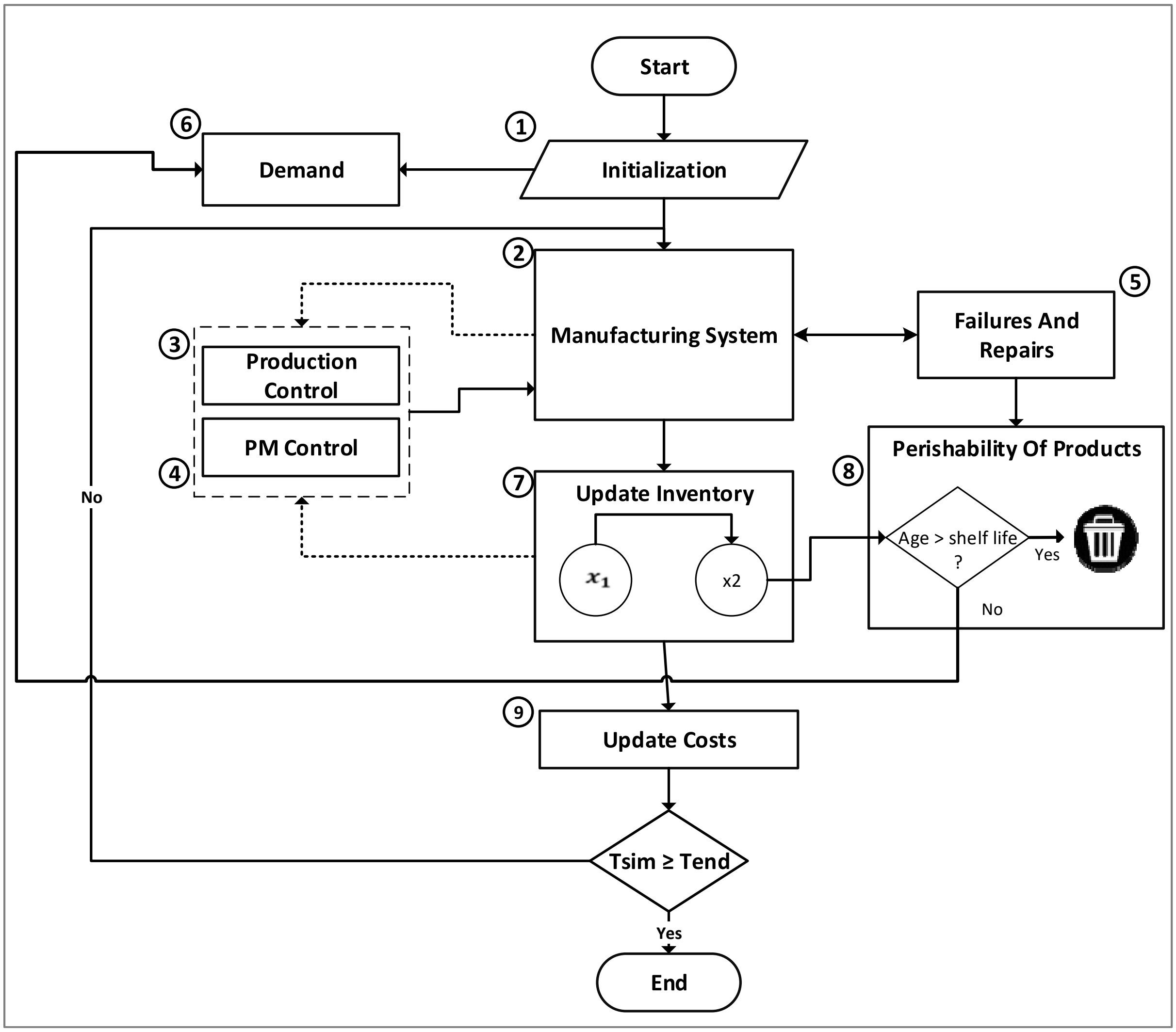


Figure 3.7 Block diagram of the simulation model

The first block (block 1) is the initialization of input variables (demand rate, maximum production rate, shelf-life, control parameters, ...). Then, the manufacturing system (block 2) prone to failure and repair times (block 5) is governed by the joint production and maintenance control policy. The production control policy (block 3) allows the manufacturing system to determine the production rate based on the different inventory levels following equations (3.15) - (3.17). The preventive maintenance control policy (block 4) is responsible for providing changes in the state of the system based on the two control parameters: age of the machine and the level of inventory. The manufacturing system aims to satisfy the demand (block 6) that directly affects the inventory level of both sub-stocks of finished products. Then, the level of inventory (block 7) is updated accordingly. Indeed, the variation in inventories depends on machine production rates, demand rate and the disposal of perished products. (Block 8) represents the evolution of stock due to their perishable nature and is linked to (block 5) since that the value of the shelf-life varies in function of the machine's age. In this step, the age of inventory is checked, if the product exceeds its shelf-life, then it must be disposed and if not, then it satisfies demand (block 6). Before the end of the simulation run, the total cost (block 9) is calculated taking into consideration the cost of disposal of perishable products, backlog, inventory holding and maintenance costs (PM and CM).

To validate the simulation model, a numerical example was executed for a manufacturing system governed by the joint control policy PPMP. We show in Figure 3.8 the variation of different system parameters. Figure 3.8 shows in (arrow ①, Figure 3.8.a) the increase of level of inventory x_1 with a rate ($U_m - u_1^p - D_1$) as the machine operates at maximum capacity. The level of inventory allows demand to be satisfied, and the remaining products are used to build the hedging level Z_2. When reaching Z_2 (arrow ②, Figure 3.8.a), the production rate is set to a value equal to $u_2^p = \frac{Z_2}{\alpha_2}$. Given that the age of products is continuously growing, the level of x_2 increases according to ($u_1^p - u_2^p - D_2$) as shown in Figure 3.8(b). Also, the perishable products increase as well as shown in Figure 3.8(c). When a failure event occurs (Figure 3.8.d), its impact is first seen in inventory x_2 as it decreases until reaching zero (arrow ③, Figure 3.8.b). In fact, since the demand is set in way to follow equations (3.5) and (3.6), products are pulled from the oldest inventory x_2 until it is empty then it starts pulling from x_1. At that time x_1 starts decreasing (arrow ④, Figure 3.8.a) with a rate equal to ($- u_1^p - D_1$). In (arrow ⑤, Figure 3.8.a), backlog occurs and the stock level of x_1 decreases bellows zero, at that time x_2 is equal to zero. In (arrow ⑥, Figure 3.8.b), the inventory level x_2 reaches the threshold Y which means that the system has enough products in stock to reduce the production rate. In such a situation, the threshold level of the sub-stock x_1 decreases to Z_1 (arrow ⑦, Figure 3.8.a) and the production rate is reduced to $u_1^p = \frac{Z_1}{\alpha_1}$. When a failure occurs, the machine undergo repair interventions (Figure 3.8.d), the machine is restored to an ‘‘as-bad-as-old’’ condition (arrow ⑪, Figure 3.8.e). As for the preventive maintenance interventions (arrow ⑧, Figure 3.8.d) when the age of the machine reaches the critical age A (arrow ⑨, Figure 3.8.e), the manufacturing system checks the quantity of inventory on hand and compares it to the critical threshold Z_{PM} and only executes PM interventions if inventory is enough ($x_1(t) + x_2(t) \geq Z_{PM}$). As we explained in previous sections, the shelf life of products is highly dependent on the age of the machine. Upon a PM intervention, the machine is restored to ‘’as-new-condition’’, which means the shelf life increases. That’s why we notice that the slope of the perishable products’ variation (Figure 3.8.c) decreases (arrow ⑩, Figure 3.8.c).

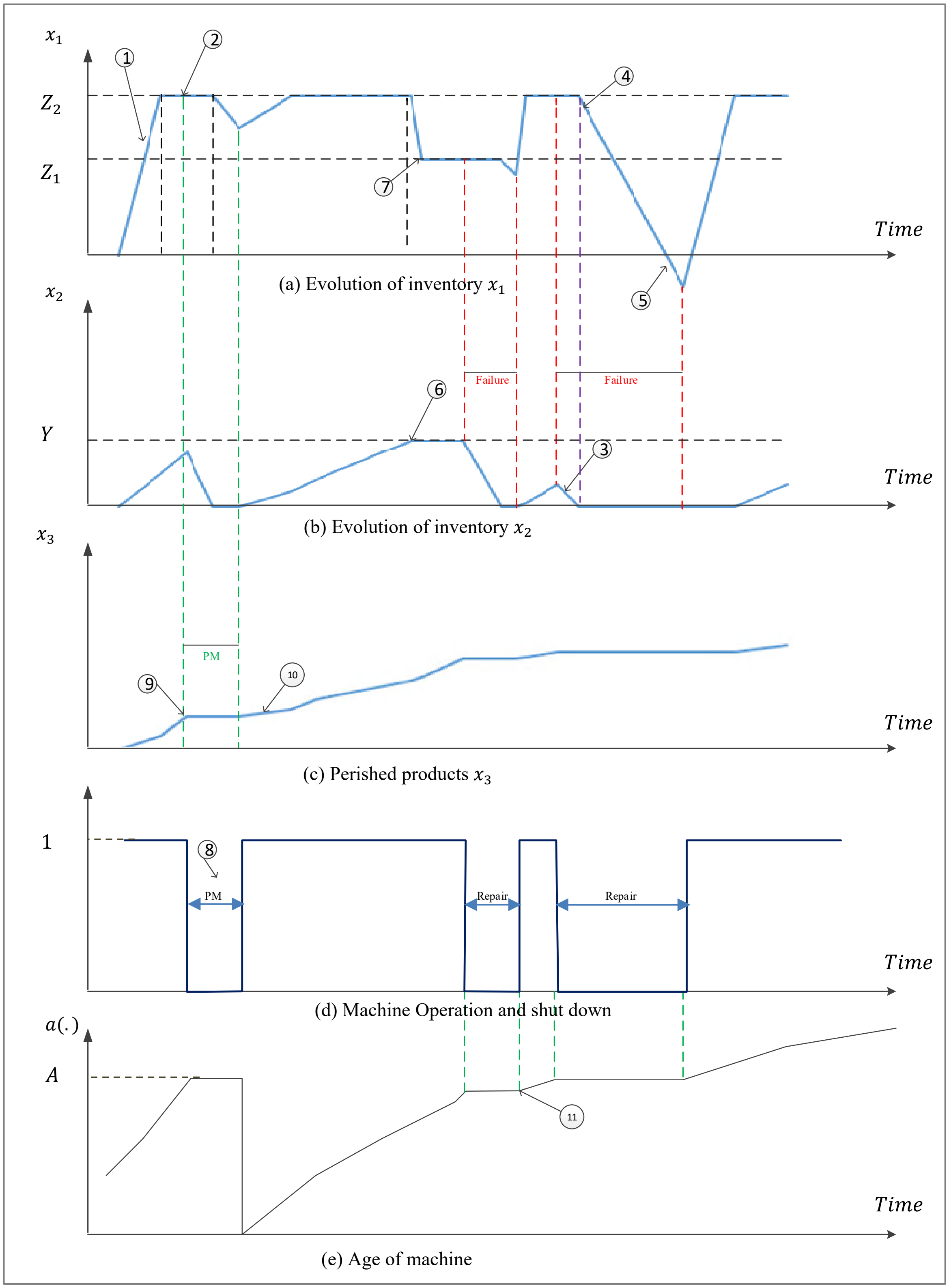


Figure 3.8 Variations of system parameters when PPMP is used

The following section is dedicated to the optimization of the control parameters and the approximation of the total cost incurred.

3.6.2 RSM model and optimization

We present in this section the optimization step of the control parameters for the proposed joint policy to minimize the total cost incurred. The objective is to obtain the equation of the optimal total cost and the control parameters and see their interaction and effect on the total cost. In this sense, a numerical example is considered in order to illustrate the experimental approach combining simulation, DOE and RSM. The data used are summarized in Table 3.2 and are fixed based on the literature related to maintenance strategies and control policies. For instance, the TTF, TTR and TPM are chosen based on the work of (Rivera-Gomez et al., 2013) following a log-normal distribution.

Table 3.2 Parameters for the numerical example

Parameters	U_m	D	C_1^-	(C_1^+, C_2^+)	C_p
Values	*60*	*20*	*30*	*(1, 1)*	*15*
Parameters	C_{cm}	C_{pm}	TTF	TTR	TPM
Values	*5000*	*1000*	LogN (120, 24)	LogN (10, 1.6)	LogN (5,1)
Parameters	SL_w	η	λ	δ	β
Values	*2*	*40*	0.00015	*1*	5.10^{-5}
Parameters	k	σ_b	y	β	r
Values	*1.2*	*0.2*	*0.8*	3.10^{-6}	1.2
Parameters	$\alpha_1 = \alpha_2$				
Values	$Norm(24, 6)$				

Here, it's important to mention that Z_{PM} must be smaller than Z_2. In fact, Z_{PM} represents the threshold of the total inventory and Z_2 represent the highest threshold the inventory can reach. In this case we can say that Z_{PM} can be written as a function of Z_2: $Z_{PM} = \tau\ Z_2$ with $0 \leq \tau \leq 1$. In this case, the control parameters to optimize (Z_1, Z_2, Y, A, τ).

For the proposed policy PPMP, a dependent variable (total cost) and five independent variables (Z_1, Z_2, Y, A, τ) are considered. In this sense, we adopt the full factorial designs at threei levelsi

3^5 for the PPMP control policy. This kind of designs allows that each interaction is estimated separately which leads to more accurate results (Montgomery, 2017). Given the number of independent variables (n = 5), 2 replications were executed for each factor's combination, involving the performance of 486 ($3^5 * 2$) simulation runs. Regarding the duration of the simulation model, it is fixed at 500,000 U.T in order to reach steady state.

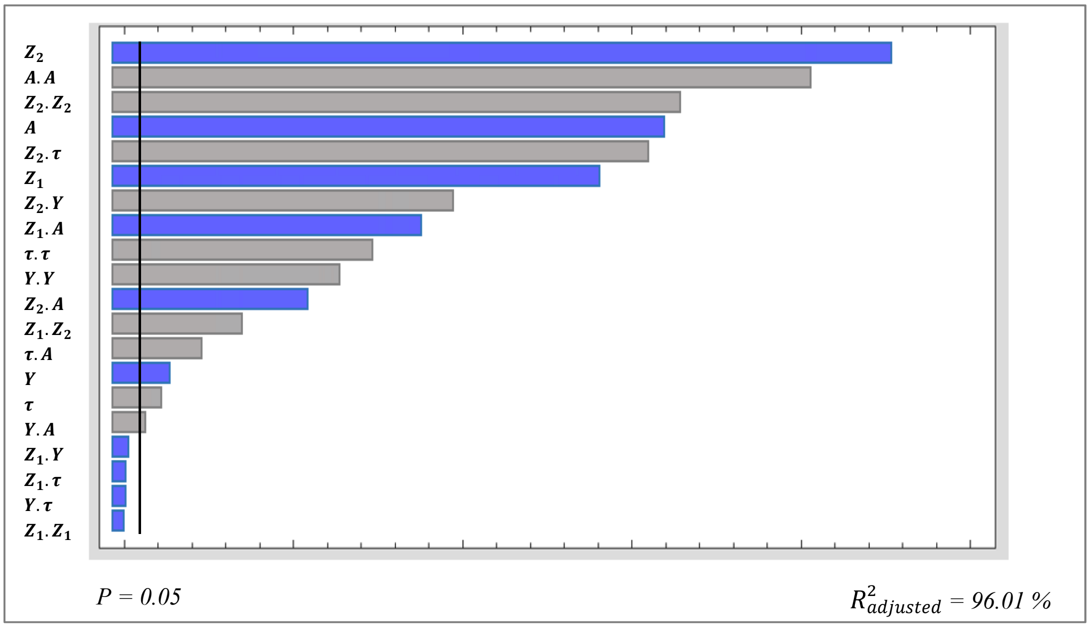


Figure 3.9 Standardized Pareto plot for the proposed policy

The effect of each independent variables (Z_1, Z_2, Y, A and τ), their interactions and their quadratic effect on the total cost are obtained using a multifactorial ANOVA. Figure 3.9 represents the pareto plot of the proposed policy. It shows the level of significance of each control parameters, their interactions and their quadratic effect as well as $R^2_{adjusted}$ (the adjusted correlation coefficients). Figure 3.9 shows that at the exception of the interactions $(Z_1 * Y, Z_1 * \tau, Y * \tau)$ and the quadratic effect Z_1^2, all the main factors (Z_1, Z_2, Y , A and τ), the other interactions and quadratic effects are significant at a level of significance of 95%.

Also, we see that the correlation coefficient $R^2_{adjusted}$ is equal to 96.01%. We can say that the simulation model explains more than 95% of the variability observed on the total estimated cost (Montgomery, 2008). Also, Statgraphics software allowed us also to perform other statistical analysis such as the homogeneity of the variance and the analysis of the normality of the residuals which allowed us to verify the conformity of our model.

A response surface methodology is carried out to find the optimal control parameters and the total cost function. The cost function is given by equation (3.19).

$$
\begin{aligned}
\widehat{Cost_{PPMP}} = {} & 1164.49 - 585.61\ 10^{-2}.Z_1 - 826.29\ 10^{-2}.Z_2 - 121.28\ 10^{-2}.Y \\
& - 65.9\ 10^{-2}.A - 593.24\ .\tau + 206.32\ 10^{-5}.Z_1\ Z_2 - 99.80\ 10^{-5}.Z_1.Y - \\
& 82.27\ 10^{-5}.Z_1.A - 61.6\ 10^{-2}.Z_1.\tau + 76.36\ 10^{-4}.Z_2.Y - 19.2\ 10^{-5}.Z_2.A \\
& + 714.69\ 10^{-2}.Z_2.\tau + 8.2\ 10^{-5}.Y.A - 36.2\ 10^{-2}.Y.\tau + 21.7\ 10^{-2}.A.\tau - \\
& 31.88\ 10^{-5}\ Z_1^2 + 762.18\ 10^{-5}\ Z_2^2 + 109\ 10^{-4}\ Y^2 + 15.1\ 10^{-5}\ A^2 + \\
& 603.3\ 10^{1}\ \tau^2 + \varepsilon
\end{aligned}
\tag{3.19}
$$

The obtained results are as follows: $Cost^*_{PPMP}$ = 4608.60, Z_1^* =419, Z_2^* =802, Y^* =358, A^* = 5711, τ = 0.53 (Z_{PM} = 425). Figure 3.10 represents the estimated total cost contour plot.

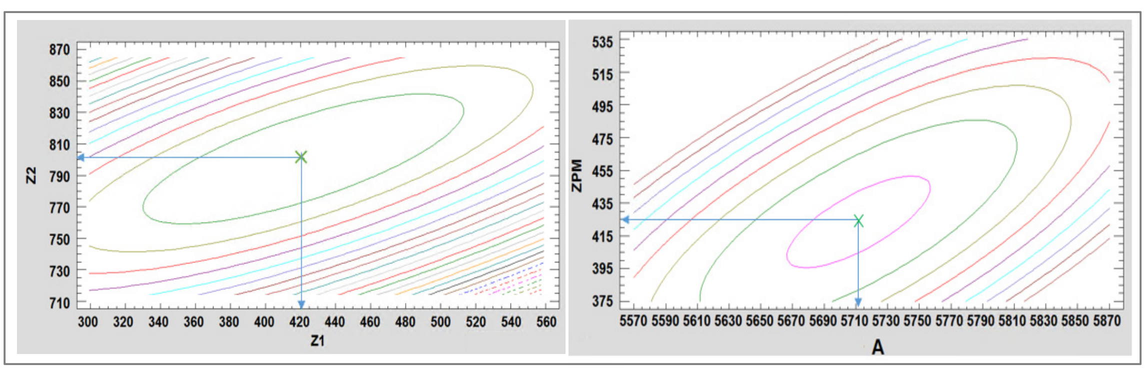


Figure 3.10 The estimated total cost contour surface plot

The response surfaces corresponding to the total cost function (Equation 3.19) are presented in Figure 3.10. In addition, to cross-check the validity of the developed model, we compute the confidence interval that is obtained based on an additional 50 simulation runs using as input the optimal parameters. Results confirm that the optimal total cost approximated $Cost^{*}_{PPMP} = 4608.60$ falls within the 95% confidence interval [4589.18, 4659.27].

3.7 Sensitivity analyses

The effectiveness of the proposed joint policy PPMP is verified by examining the effect of different system and cost parameters on the control policy parameters and on the total cost incurred.

3.7.1 Effects of cost variation

In Table 3.3, we present different cases of cost parameters variations and their effect on the control parameters (Z_1, Z_2, Y, A, Z_{PM}). We did not include the holding costs ($\boldsymbol{C_1^+}, \boldsymbol{C_2^+}$) because it has no significant effect on the control policy parameters.

- *Effect of the Backlog cost* $\boldsymbol{C_1^-}$: By increasing the backlog cost C_1^-, the manufacturing system reacts by increasing the hedging levels Z_1, Z_2 and Y which allows a higher stock level in the system, thus, minimizing the risk of backlog. Here, we notice an increase of the level of inventory of the second sub-stock. In fact, by increasing Y, the model guaranties that the level of inventory of the first sub-stock is maintained at the highest threshold Z_2 for a longer time, so the system has more inventory, and this decreases the risk of backlog. When the thresholds increase, the machine produces more which means that the age of the machine increase. This leads to an increase in the frequency of PM by decreasing the critical age A and the critical threshold Z_{PM} in order to minimize the occurrence of failures. In this case, the non-operational times of the machine are shorter, so the system risks less backlog. Also, by executing more PM actions, each time the mean value of shelf-life increases, and the variability decreases so less perished products, and the system risks less backlog.

- *Effect of the Disposal cost* $\boldsymbol{C_P}$: In the case of disposal cost variation, we can observe two different and opposite phenomena. First, for the case study 3 and 4, the variation of C_p affects mainly the hedging level Z_1 that decreases when C_p increases. Here, the system tries to minimize the risk of having perishable products by reducing the value of Z_1 related to the first sub-stock. As for the variation of Z_2, it decreases as well but slowly compared to Z_1. However, the risk of backlog becomes higher since there are not enough products to satisfy demand. That's why we observe a relatively small increase for the value of Y to serve against backlog. In the same sense, to hedge against this backlog, the system reacts by increasing the PM parameters (A, Z_{PM}) in order to increase the operational time of the machine. In this case, the control parameters are set in a way to avoid a more expensive cost of backlog. However, we can observe another system behavior if we set a high value of the disposal cost (case 5). Here, the manufacturing system behave in a way to minimize the more expensive cost of disposal. First, we observe that the system wants to execute more PM interventions by reducing Z_{PM} and A in order to increase the shelf-life of the products. Also, to avoid the risk of disposal, the production control parameters Z_1, Z_2 and Y decreases.

Table 3.3 Sensitivity analysis for the proposed policy

Optimal control Parameters			Z_1^*	Z_2^*	Y^*	A^*	Z_{PM}^*	
Basic Values			419	802	358	5711	425	Remarks
1	$\boldsymbol{C_1^-}$	20	402	711	289	6012	451	$Z_1^* \downarrow Z_2^* \downarrow Y^* \downarrow a^* \uparrow Z_{PM}^* \uparrow$
2		40	431	914	429	5141	379	$Z_1^* \uparrow Z_2^* \uparrow Y^* \uparrow a^* \downarrow Z_{PM}^* \downarrow$
3	$\boldsymbol{C_p}$	10	439	811	344	5537	409	$Z_1^* \uparrow Z_2^* \uparrow Y^* \downarrow a^* \downarrow Z_{PM}^* \downarrow$
4		20	381	793	369	6022	459	$Z_1^* \downarrow Z_2^* \downarrow Y^* \uparrow a^* \uparrow Z_{PM}^* \uparrow$
5		60	302	612	241	4879	347	$Z_1^* \downarrow Z_2^* \downarrow Y^* \downarrow a^* \downarrow Z_{PM}^* \downarrow$
6	$\boldsymbol{C_{pm}}$	500	394	722	311	4931	378	$Z_1^* \downarrow Z_2^* \downarrow Y^* \downarrow a^* \downarrow Z_{PM}^* \downarrow$
7		1500	463	891	409	6232	481	$Z_1^* \uparrow Z_2^* \uparrow Y^* \uparrow a^* \uparrow Z_{PM}^* \uparrow$
8	$\boldsymbol{C_{cm}}$	4000	478	701	311	6107	497	$Z_1^* \uparrow Z_2^* \downarrow Y^* \downarrow a^* \uparrow Z_{PM}^* \uparrow$
9		6000	457	867	384	4925	383	$Z_1^* \uparrow Z_2^* \uparrow Y^* \uparrow a^* \downarrow Z_{PM}^* \downarrow$

- *Effect of the PM intervention cost* $\boldsymbol{C_{pm}}$: When the cost of PM increases, the critical age A and the threshold Z_{PM} to execute PM interventions increase to avoid PM actions that cost more. In this case, the risk of failures increases, hence the need to increase the threshold levels Z_1, Z_2 and Y to avoid backlog.

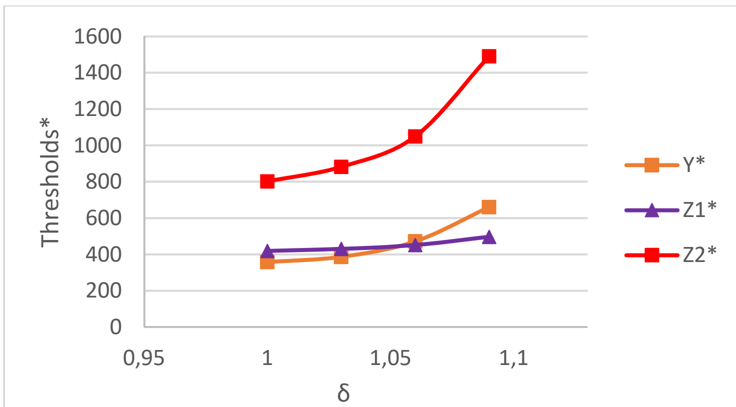
- *Effect of the CM intervention cost* $\boldsymbol{C_{cm}}$: Compared to the variation in the cost of PM, the influence of the cost of corrective maintenance C_{cm} has the opposite effect on the control parameters. Indeed, when C_{cm} increase, the system tends to execute more PM interventions by reducing the critical A and the threshold Z_{PM} in order to avoid more CMs over time. In this case, the system risks more backlog hence the increase of the thresholds Z_1, Z_2 and Y.

3.7.2 Effect of shelf-life parameters

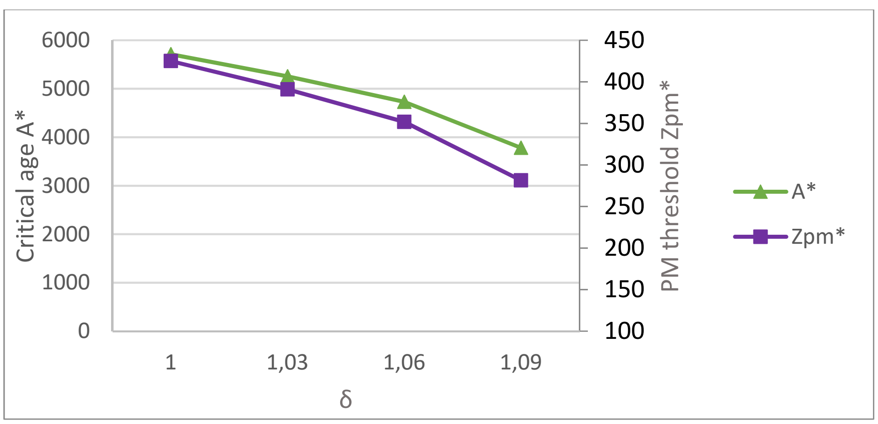
The lognormal distribution is widely used to approximate the shelf-life of many perishable products. For this section, we are interested in varying the mean value of the shelf-life by varying δ in equation (3.7). Also, we studied the effect of shelf-life variability on the control parameters by varying r in equation (3.8).

We show in Figure 3.11 the effect of varying δ on the control policy parameters (Z_1, Z_2, Y,A, Z_{PM}). As we presented in Section 3.3, when δ increase, the mean value of the shelf-life decreases faster in function of the machines' age.

We notice that the variation of δ affects significantly the values of the control parameters. The threshold Z_1, Z_2 and Y (Figure 11.a) increase as δ increases. In fact, when the mean value of the shelf-life value decreases (as δ increases), the number of perished products increases as well and so does the corresponding cost component. Moreover, when the number of perished products increase, the less there is to satisfy demand which means more backlog. In this case the system find itself increasing the value of the control parameters to protect itself from high costs especially those due to backlog. The opposite effect is observed on the PM parameter. The critical age A to execute PM interventions decreases when δ increases (Figure 3.11.b). In this case, the system reacts in way to execute more PM actions in order to restore the machine to ''As-good-as-New'' condition thus increasing the shelf-life. That's why we also observe a decrease in the value of the threshold Z_{PM} (Figure 3.11.b). This decrease gets gradually higher as δ increases in order to guaranty a more frequent PM interventions that restore the shelf-life to its best value.



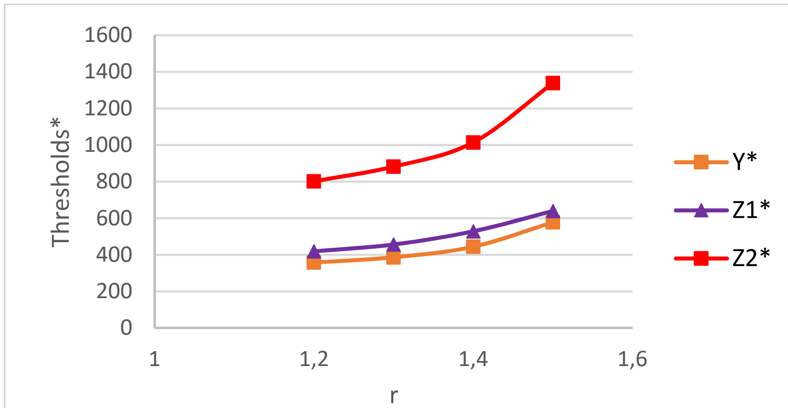
(a) Variations of the thresholds (Z_1, Z_2, Y)



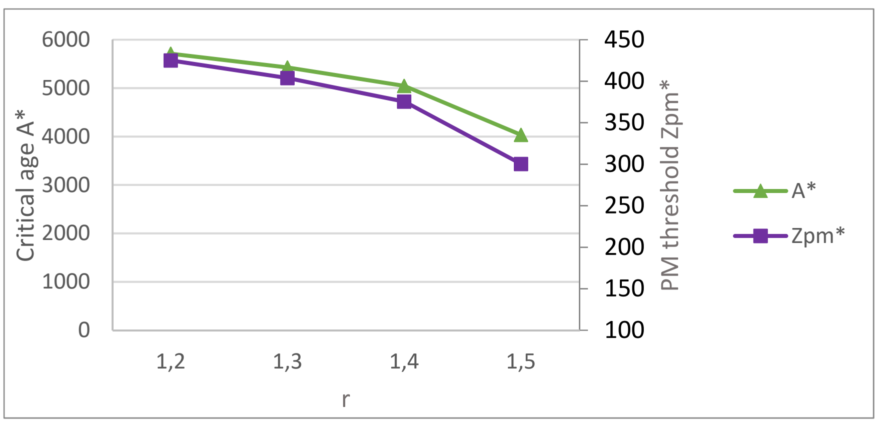
(b) Variation of the critical age A and the threshold Z_{PM}

Figure 3.11 Effect of the variation of shelf life mean on the optimal control parameters (variation of δ)

We show in Figure 3.12 the effect of varying r on the control policy parameters (Z_1, Z_2, Y, A, Z_{PM}). As we presented in Section 3.3, As r increase, as the shelf-life variability increase faster in function of the machines' age. Here we draw the same conclusions as in Figure 3.11. The threshold Z_1, Z_2 and Y (Figure 3.12.a) increase as r increases. As for the parameters of the PM strategy, we see that the value of the critical age A and the threshold Z_{PM} (Figure 3.12.b) decrease aiming to increase PM interventions.



(a) Variations of the thresholds (Z_1, Z_2, Y)



(b)Variation of the critical age A and the threshold Z_{PM}

Figure 3.12 Effect of the shelf life variability on the optimal control parameters (variation of r)

3.8 Comparative Study

We apply the simulation-based optimization approach described in section 3.5 to compare between the optimal total cost of the proposed joint control policy PPMP and three other policies. The first policy used for comparison is the proposed production control policy without the preventive maintenance control MHPP described by equations (3.15) - (3.17). The second policy considered is from the literature and is a joint control policy that combine the classical

HPP for production control and the age based preventive maintenance (Berthaut et al., 2011) we note HPP_PM.

The third joint policy used for comparison, it combines EPQ policy and the age based preventive maintenance control policy we note EPQ_PM (Widyadana et al., 2012). We consider the same parameters used in previous sections.

Figure 3.13 show a comparison of the optimal total cost of the policies used for comparison (PPMP, MHPP, HPP_PM and EPQ_PM) while varying cost and system parameters. First thing to notice is that the optimal total cost incurred when applying the proposed joint control policy PPMP is lower than that of the other policies. And the policy that represents the highest incurred total cost is MHPP since it does not integrate PM actions. In this case, the non-operational times of the machine increase so does the CM costs and the backlog costs.

From Figure 3.13.a, as the backlog cost C_1^-increases, PPMP allow the system to minimize the number of perished products since it integrates the age of inventory into production control. This phenomenon is due to the advantage of multiple hedging levels provided by PPMP to monitor different sub-stocks with different ages. Unlike the other policies that doesn't take into consideration the evolution of the age of a product.

From Figure 3.13.b, as the disposal cost C_p increases, PPMP allow the system to be more protected against backlog since the demand is satisfied in a certain order by pulling from the oldest stock before pulling from the new stock. This kind of queuing policy allow the system to minimize the risk of disposal and backlog by minimizing the number of perished products. Also, when applying PPMP, the execution of the PM interventions, increases the shelf-life value thus minimizing the risk of perishability.

From figure 3.13.c we notice that the cost gap between MHPP and the other policies integrating PM interventions increase C_{cm} increases. In fact, MHPP becomes less interesting as C_{cm} increases because it leads to more risks of failures.

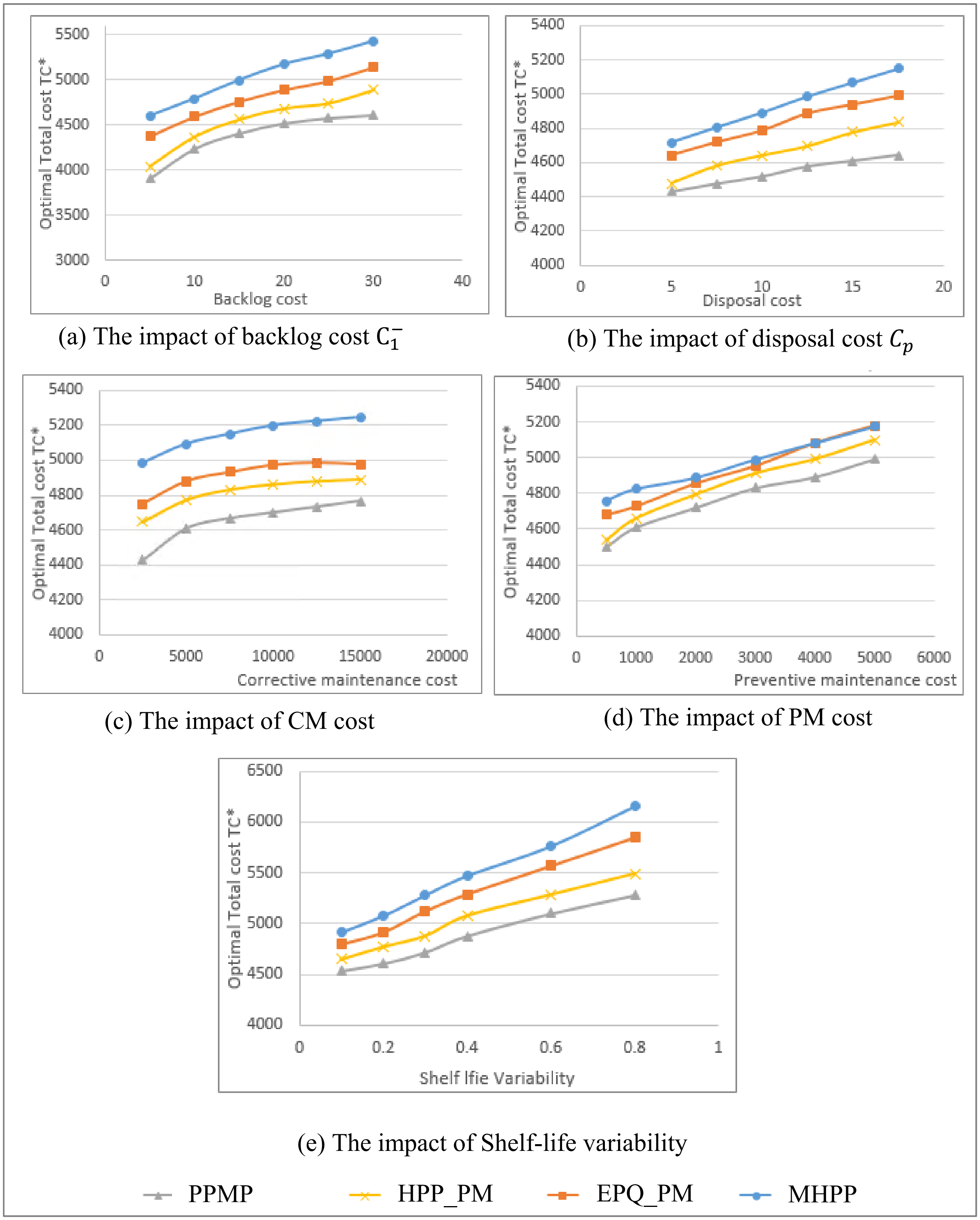


Figure 3.13 Variation of the optimal total cost for PPMP, HPP_PM, EPQ_PM and MHPP in function of cost and system parameters

Figure 3.13.d shows the impact of varying the preventive maintenance cost C_{pm} on the total incurred cost of the considered policies. We notice that when C_{pm} increases, the PM control policy become more expensive to execute. This explains the overrun of the total cost of the policy MHPP and EPQ_PM as MHPP becomes more interesting than EPQ_PM for high values of C_{pm}.

Figure 3.13.e shows the impact of varying shelf-life variability. We notice that the cost advantage of PPMP gets higher as the variability increases. In fact, when the variability increases, the number of perished products increases and so does the costs for backlog and disposal. So, when applying PPMP, a better control is provided since it allows the system to track the quantity of each sub-stock at each age and adjust the production rate accordingly to minimize the risk of disposal and backlog. Also, the PM actions are executed in order to reduce this variability.

To sum up, the comparative study of the considered policies in terms of total incurred cost shows that the PPMP gives better results than the other policies for a wide range of system and cost configurations. This is due to its ability to avoid unnecessary interventions of PM on one hand and avoid backlog cost since it offers multiple hedging levels to control different stock with different ages on the other hand. Moreover, the PPMP minimize the risk of perishability since it ensures a certain priority rule that ensures that products having the shortest remaining shelf-lives satisfy demand first.

3.9 Managerial insights and implementation

Manufacturing systems dealing with products with a limited shelf-life face major challenges in terms of finding the best control policy that take into consideration the age of a product and the degradation of the machine to minimize the total cost. By implementing the proposed joint control policy, the manager is capable of deciding simultaneously on the production rate as a function of the quantity of inventory on hand and on when to execute PM actions in order to minimize the total cost. Since, the shelf-life of the products increase as the machine degrades, the PM interventions allow on one hand to restore the machine to ‘‘as good as new state’’ and, on the other hand restoring the shelf-life of the products to their best value. To implement the proposed joint control policy, the manager is required to monitor the different inventory levels and the state of the machine (operational, under repair or under PM interventions).

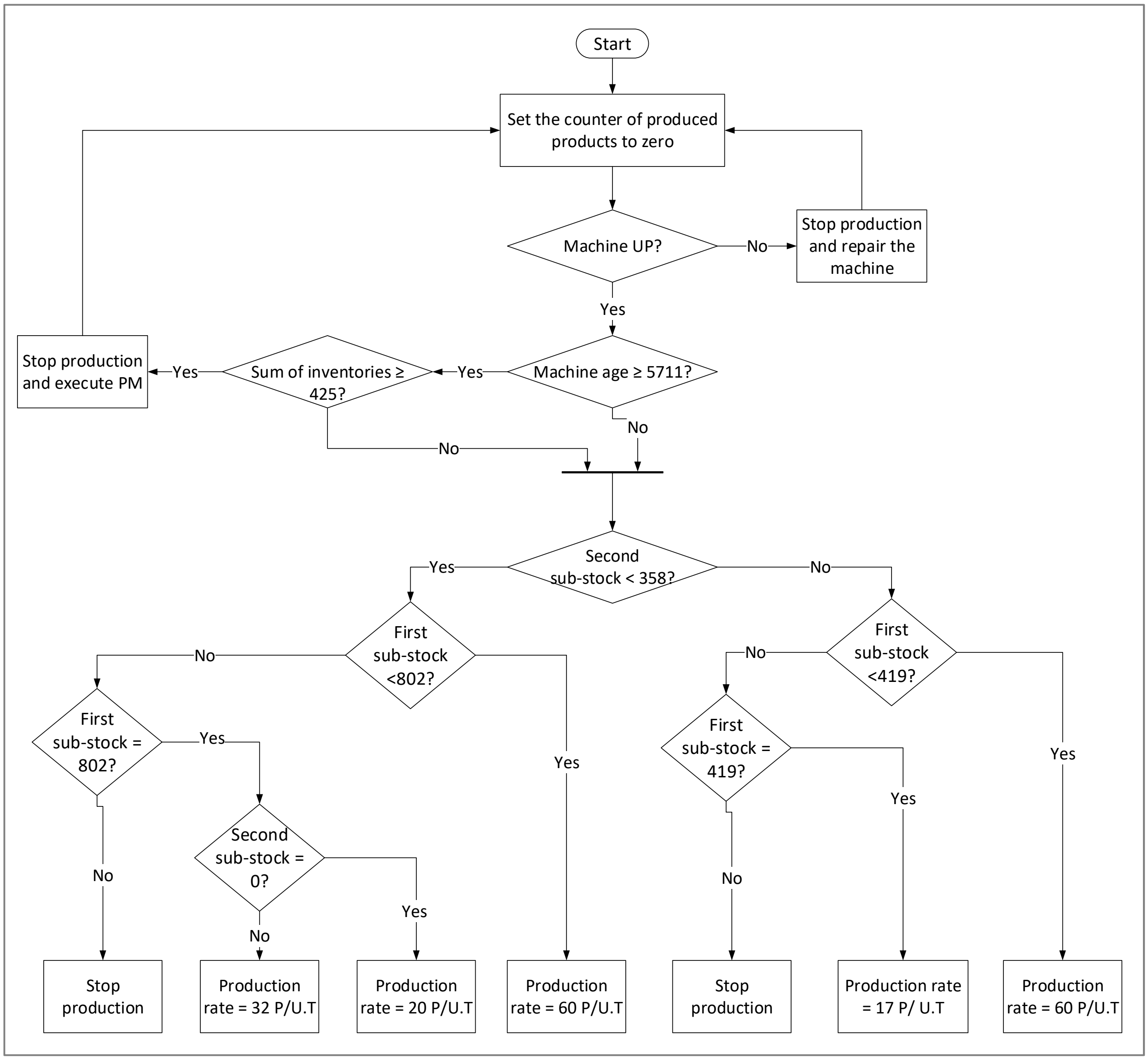


Figure 3.14 Implementation logic chart for PHPP

Figure 3.14 illustrates a logic chart that serves to guide decision makers throughout the implementation for the proposed joint control policy PPMP for the basic case studied. The manager has to track the stock level, monitor the machine mode and its age. The latter is set to zero at the end of each maintenance intervention. Then, according to the PM optimal control parameters (A^*=5711, Z_{PM}^*= 425), if the machine is operational, PM interventions are executed, and the machine's age must be reset to zero.

As for the production control policy, the manager should be able to regulate the production rate knowing the different values of the thresholds with Z_1^* =419, Z_2^* =802 and Y^* =358. The production rate can be set to its maximum level (60 products/U.T), ${u_{Z_1}^P}^*$(~17 products/U.T), ${u_{Z_2}^P}^*$(~32 products/U.T), demand rate (20 products/U.T) or zero, based on the inventory level of each sub-stock. Accordingly, if the level of the second sub-stock is less than the threshold Y^* =358, then the manager has to regulate the production rate using the threshold Z_2^* = 802. Meaning if the inventory level in the first sub-stock is lower than 802, the production rate must be set 60 products/U.T, if it is higher, then the machine must stop producing, and if it is equal to it, then the production rate is either set to the demand rate D (20 products/U.T) if the second sub-stock is equal to zero or the production rate is set ${u_{Z_2}^P}^*$(~32 products/U.T) if not (the second sub-stock is greater than zero). However, if the level of inventory of the second sub-stock is higher than Y^* = 358, then the manager must regulate the production rate using the threshold Z_1^* = 419. In this case, for instance, if the inventory level in the first sub-stock is higher than 419, the machine stops producing. If it is lower than 419, then the production rate is set to 60 products/U.T. Otherwise, if the inventory level is equal to 419, then the production rate must be set to ${u_{Z_1}^P}^*$(~17 products/U.T).

Our proposed joint control policy has a wide range of applications for different types of industries looking to establish an effective and dynamic plan for their maintenance and production activities under which the shelf-lives of the products is depend on the machine's age. By implementing our cost-effective proposed joint control policy, the manufacturers are able to minimize the total incurred cost composed of backlog, holding, disposal and maintenance (corrective and preventive).

3.10 Conclusion

In this paper, we address a production-planning and maintenance control problem for unreliable manufacturing systems producing perishable products and subject to random breakdowns and repairs. Given that the objective is to minimize a total cost composed of backlog, inventory holding, disposal and maintenance, we propose a structure of a joint production and maintenance control policy. Based on the literature we propose an integrated production maintenance policy called Perishable Production Maintenance Policy (PPMP) that combines a production control policy of feedback nature with multiple hedging levels and, an Age-Based Replacement policy for maintenance control. This policy considers the effect of machine degradation on the mean value of shelf-life and on the shelf-life variability. In fact, the increase of the machine's age results in a reduction of the mean value of the shelf-life and an increase of shelf-life variability. This phenomenon is often studied in the literature but only in qualitative way. In this paper, we propose a qualitative relationship between the shelf-life of the products and the age of the machine. In order to solve the problem, a simulation-based optimization approach was adopted. It combines simulation techniques, Design of Experiment and Response Surface Methodology.

Sensitivity analyses were conducted in order to observe the behavior of the system governed by the proposed joint control policy. It is seen that the backlog cost and the disposal cost have opposite effects on the control parameters. Also. The preventive maintenance cost and the corrective maintenance cost have opposite effects on the control parameters. When, the disposal cost is high, the systems tend to execute more PM interventions to restore the shelf-life values to its highest. Results also reveals the important effect of machine degradation on the shelf-life reduction and on the decision-making process and how it affects the PM interventions This consideration could lead to better managerial decisions to reduce the optimal total cost.

Afterwards, a comparative study is established between the proposed joint control policy and other policies from the literature. Results show that the proposed control policy PPMP gives the best results in terms of minimizing the total cost. This is due to its capacity to integrate the age of inventory as it evolves in time and to determine the production rate accordingly. The comparative study carried out demonstrates the advantage of the PPMP policy which allows executing PM actions to reduce the risk of backlog and disposal by increasing the shelf-life mean value and reducing shelf-life variability.

Future research could be explored based on this work. For example, this study can be studied in the case of multiple-type products. Moreover, a future study can incorporate random disposal costs depending on the shelf-life of the products. Also, as we established in the literature review that there is a relationship between quality loss and products perishability, which means that this study can be utilized in the configurations of quality control policies.

CONCLUSION

Dans le cadre de ce travail, nous nous sommes intéressés à étudier l'intégration des produits périssables ayant une durée de vie limitée et aléatoire dans le contrôle et la gestion des systèmes manufacturiers non fiables. Dans ce contexte, nous avons pu traiter deux problématiques. La première est dédiée à la commande optimale de la production. La deuxième problématique est dédiée à trouver une politique combinée de contrôle de la production et de la maintenance. Les deux problématiques sont traitées dans le contexte d'un système manufacturier non fiable sujet aux temps de pannes et réparation aléatoires et produisant des produits finis de nature périssable. La motivation principale pour le choix de ce sujet est née suite à un manque constaté dans les anciens travaux. D'ailleurs, nous expliquons dans la revue de littérature faite qu'il y a un manque de politique de contrôle de production et des activités de maintenance qui sont dédiées aux produits périssables et qui tiennent en considération la spécificité de l'âge du produit.

Le chapitre 2 représente la problématique de base où nous étudions un système manufacturier se composant d'une seule machine non fiable fabriquant un seul type de produit périssable. L'objectif est de trouver une politique de commande de la production en considérant la durée de vie aléatoire des produits qui minimise le coût total se composant du coût de possession de stock, de pénurie et de rejet des produits périmés. L'approche de résolution utilisée est basée sur la théorie de la commande optimale stochastique pour déterminer la structure de la politique de contrôle optimale. Les conditions d'optimalité sous forme d'équations de Hamilton - Jacobi - Bellman (HJB) sont formulées afin de vérifier l'optimalité de la politique de contrôle proposée. Par la suite, nous adoptons une approche expérimentale basée sur une combinaison de la simulation, l'analyse de la variance et la méthodologie de surface de réponse. Cette approche nous permet d'optimiser les paramètres de décisions. L'utilisation de cette approche est due à la complexité du système qui évolue dans un contexte dynamique et stochastique (pannes, réparations, durées de vie).

Une nouvelle politique de commande de type seuil critique (PHPP) est déterminée en se basant sur la théorie de commande optimale stochastique. Une analyse de sensibilité sur les paramètres du coût et du système est menée pour tester la robustesse de la politique ainsi que l'approche de résolution utilisée. Nous avons également examiné l'effet de la variabilité de la durée de vie du produit simultanément avec les paramètres de coût sur le coût total optimal. Les résultats révèlent l'effet important de la variabilité de la durée de vie et comment le fait de la prendre en considération pourrait conduire à de meilleures décisions de gestion pour réduire le coût total optimal. En fait, lorsque la variabilité de la durée de vie est élevée, il existe des possibilités d'améliorer considérablement le coût total et le gestionnaire devrait procéder à des ajustements afin de réduire cette variabilité. Ensuite, une étude comparative entre la politique proposée avec d'autres politiques de la littérature est exécutée. Les résultats confirment que pour le cas des produits périssables ayant une durée de vie aléatoire, la politique proposée donne le coût total optimal le plus bas. Cela est dû à sa capacité à intégrer l'âge de l'inventaire au fur et à mesure de son évolution dans le temps et à déterminer le taux de production en conséquence.

Quant au Chapitre 3, il représente une extension du Chapitre 2 en ajoutant le contrôle de la maintenance pour le même modèle établi dans le Chapitre 2. D'ailleurs, le fait d'intégrer les activités de la maintenance préventive est crucial pour un système manufacturier non fiable afin de diminuer la fréquence des pannes. Dans ce chapitre, nous nous intéressons à étudier l'effet de la dégradation de la machine sur la durée de produit et sur la variabilité de cette durée de vie. En fait, quand la machine se dégrade, elle peut influencer la durée de vie des produits périssables en la réduisant et en contrepartie elle peut augmenter sa variabilité. Pour minimiser cet effet, nous proposons une politique combinée de contrôle de la production et de la maintenance qui tient en compte de la durée de vie limitée des produits et cette influence de la dégradation de la machine. Une étude comparative a été effectuée en variant plusieurs paramètres de coût et de système. Les résultats montrent qu'en combinant la politique de contrôle déterminée dans le chapitre 2 avec la stratégie de maintenance de type Âge, nous obtenons les meilleurs résultats en termes de minimisation des coûts.

Dans le cadre de ce projet de recherche, nous avons abouti à plusieurs résultats en ce qui concerne la problématique de l'intégration des produits périssables à durées de vie aléatoires dans le domaine d'industrie manufacturière. Malgré la complexité de l'implantation des politiques de commande ainsi que la difficulté entourant la démarche d'optimisation (choix des plages expérimentales, nombre de réplications et durée de simulation, plusieurs facteurs, choix de plans d'expériences), les analyses de sensibilité exécutées ont montré la robustesse de l'approche utilisée et des résultats trouvés.

Finalement, dans le cadre de ce mémoire, nous avons pu rédiger deux articles. Le premier est présenté dans le Chapitre 2, et a été soumis dans « International Journal of Production Economics ». Le deuxième article a été soumis dans « International Journal of Advanced Manufacturing Technology » et est présenté dans le Chapitre 3.

Ce travail peut être exploité pour servir plusieurs travaux futurs. Par exemple, traiter le cas de plusieurs produits, car dans de nombreux domaines, il est plus probable de trouver des politiques de contrôle de la production portant sur plus d'un type de produit. Dans ce cas, il faut faire avec plusieurs durées de vie aléatoires. De plus, en ce qui concerne l'effet de la variabilité de la durée de vie, nous avons trouvé des études qui examinent comment elle peut être capturée à l'aide des capteurs temps-température. Dans notre étude, la variabilité de la durée de vie n'est pas contrôlée et, par conséquent, des travaux futurs pourraient se servir de cette étude en combinant les politiques de contrôle proposées avec ces capteurs pour contrôler la variabilité de la durée de vie. Cela offrirait des possibilités de minimiser les coûts. Autre possibilité, c'est d'étudier la relation entre la perte de la qualité et la périssabilité des produits, ce qui signifie que cette étude pourrait être utilisée dans les configurations des politiques de contrôle qualité.

ANNEXE I

NUMERICAL METHODS

The optimality conditions are a set of coupled partial derivatives equations called HJB. These equations are difficult to solve analytically. In this appendix, we develop the numerical methods for solving the optimality conditions. These methods are based on Kushner's approach (Kushner and Dupuis, 1992). The principle of the approach is to use an approximation for the gradient of the function value $V(\alpha, x_1, x_2)$. Let h_i denote the lengths of the finite difference interval of the variable x_i ($i \in \{1, 2\}$). Therefore, we are able to approximate the value function $V(\alpha, x_1, x_2)$ using $V^h(\alpha, x_1, x_2)$. We have:

$$\frac{\partial V\ (\alpha, x_1, x_2)}{\partial x_i} = \begin{cases} \frac{1}{h_i}(V^h(\alpha, x_\mathrm{i} +\ h_\mathrm{i}, .) -\ V^h(\alpha, x_1, x_2))\ if\ \dot{x}_i\ > 0 \\ \frac{1}{h_i}(V^h(\alpha, x_1, x_2) -\ V(\alpha, x_\mathrm{i} -\ h_\mathrm{i}, .))\ otherwise \end{cases} \qquad \forall\ i \in \{1,2\} \qquad \text{(A I-1)}$$

We add equation (2.A.1) into the HJB equation and we get:

$$\rho V^h(\alpha, x_1, x_2) = \min_{\mathrm{U} \in \Gamma(\alpha)} \Bigg\{ g(\alpha, x_1, x_2) + \lambda_{\alpha\alpha} V^h(\alpha, x_1, x_2) + \sum_{\alpha \neq \beta} \lambda_{\alpha\beta}\, V^h(\beta, x_1, x_2) \qquad \text{(A I-2)}$$
$$+ \sum_{i=1}^{2} \frac{\dot{x\imath}}{h_i} [(V^h(\alpha, x_\mathrm{i} +\ h_\mathrm{i}, .) -\ V^h(\alpha, x_1, x_2)] \cdot Ind\{\dot{x}_i \geq 0\}$$
$$+ \sum_{i=1}^{2} \frac{\dot{x\imath}}{h_i} [(V^h(\alpha, x_1, x_2) -\ V^h(\alpha, x_\mathrm{i} -\ h_\mathrm{i}, .)] \cdot Ind\{\ \dot{x}_i < 0\} \Bigg\}$$

By isolating $V^h(\alpha, x_1, x_2)$ in the left side, it results in:

$$\left(\rho + |\lambda_{\alpha\alpha}| + \frac{|\mathrm{U} - q_{12}\, x_1^+ - D_1|}{h_1} + \frac{|q_{12}\, x_1^+ - q_{23}x_2 - D_2|}{h_2}\right) \cdot V^h(\alpha, x_1, x_2)$$
$$= \min_{\mathrm{U}\in\Gamma(\alpha)} \left\{ g(\alpha, x_1, x_2) + \sum_{\alpha\neq\beta} \lambda_{\alpha\beta}\, V^h(\beta, x_1, x_2) \right. \tag{A I-3}$$
$$+ \frac{\mathrm{U} - q_{12}\, x_1^+ - D_1}{h_1} [V^h(\alpha, x_1 + h_1, x_2) \cdot Ind\{\mathrm{U} - q_{12}\, x_1^+ - D_1 \geq 0\}$$
$$+ V^h(\alpha, x_1 - h_1, x_2) \cdot Ind\{\mathrm{U} - q_{12}\, x_1^+ - D_1 < 0\}]$$
$$+ \frac{q_{12}\, x_1^+ - q_{23}x_2 - D_2}{h_2} [V^h(\alpha, x_1, x_2 + h_2) \cdot Ind\{q_{12}\, x_1^+ - q_{23}x_2 - D_2 \geq 0\}$$
$$\left. + V^h(\alpha, x_1, x_2 - h_2) \cdot Ind\{q_{12}\, x_1^+ - q_{23}x_2 - D_2 < 0\}] \right\}$$

Suppose that:

$$\Omega_h^\alpha = \rho + |\lambda_{\alpha\alpha}| + \frac{|\mathrm{U} - q_{12}\, x_1^+ - D_1|}{h_1} + \frac{|q_{12}\, x_1^+ - q_{23}x_2 - D_2|}{h_2}$$

$$\rho^\beta(\alpha) = \frac{\lambda_{\alpha\beta}}{\Omega_h^\alpha}$$

$$P_{x_1}^+(\alpha) = \begin{cases} \dfrac{\mathrm{U} - q_{12}\, x_1^+ - D_1}{h_1 * \Omega_h^\alpha}, & \mathrm{U} - q_{12}\, x_1^+ - D_1 > 0 \\ 0 & O.W \end{cases}$$

$$P_{x_1}^-(\alpha) = \begin{cases} \dfrac{-(\mathrm{U} - q_{12}\, x_1^+ - D_1)}{h_1 * \Omega_h^\alpha}, & \mathrm{U} - q_{12}\, x_1^+ - D_1 < 0 \\ 0 & O.W \end{cases}$$

$$P_{x_2}^+(\alpha) = \begin{cases} \dfrac{q_{12}\, x_1^+ - q_{23}x_2 - D_2}{h_2 * \Omega_h^\alpha}, & q_{12}\, x_1^+ - q_{23}x_2 - D_2 > 0 \\ 0 & O.W \end{cases}$$

$$P_{x_2}^-(\alpha) = \begin{cases} \dfrac{-(q_{12}\, x_1^+ - q_{23}x_2 - D_2)}{h_2 * \Omega_h^\alpha}, & q_{12}\, x_1^+ - q_{23}x_2 - D_2 < 0 \\ 0 & O.W \end{cases}$$

This system can be in mode α or β ∈ B = {1, 2}

$$V^h(\alpha, x_1, x_2) = \min_{U\in\Gamma(\alpha)} \left\{ \frac{g(\alpha, x_1, x_2)}{\Omega_h^\alpha + \rho} \right. \tag{A I-4}$$

$$\left. + \frac{\Omega_h^\alpha}{\Omega_h^\alpha + \rho} \begin{pmatrix} P_{x_1}^+(\alpha) \cdot V^h(\alpha, x_1 + h_1, x_2) + P_{x_1}^-(\alpha) \cdot V^h(\alpha, x_1 - h_1, x_2,) + \\ P_{x_2}^+(\alpha) \cdot V^h(\alpha, x_1, x_2 + h_2) + P_{x_2}^-(\alpha) \cdot V^h(\alpha, x_1, x_2 - h_2) + \\ \sum_{\alpha \neq \beta} \rho^\beta(\alpha) \cdot V^h(\beta, x_1, x_2) \end{pmatrix} \right\}$$

This equation will result in two following equations, each of them corresponds to one mode of $\alpha = \{1, 2\}$:

- For α = 1: Machine is operational

$$V^h(1, x_1, x_2) = \min_{U\in\Gamma(\alpha)} \left\{ \frac{C_1^+ x_1^+ + C_1^+ x_2 + C_1^- x_1^- + Cp\, q_{23} x_2}{\Omega_h^1 + \rho} \right. \tag{A I-5}$$

$$\left. + \frac{\Omega_h^1}{\Omega_h^1 + \rho} \begin{pmatrix} P_{x_1}^+(1) \cdot V^h(1, x_1 + h_1, x_2) + P_{x_1}^-(1) \cdot V^h(1, x_1 - h_1, x_2) + \\ P_{x_2}^+(1) \cdot V^h(1, x_1, x_2 + h_2) + P_{x_2}^-(1) \cdot V^h(1, x_1, x_2 - h_2) + \\ \rho^2(1) \cdot V^h(2, x_1, x_2) \end{pmatrix} \right\}$$

- For α = 2: Machine is under repair

$$V^h(2, x_1, x_2) = \min_{U\in\Gamma(\alpha)} \left\{ \frac{C_1^+ x_1^+ + C_1^+ x_2 + C_1^- x_1^- + Cp\, q_{23} x_2}{\Omega_h^2 + \rho} \right. \tag{A I-6}$$

$$\left. + \frac{\Omega_h^2}{\Omega_h^2 + \rho} \begin{pmatrix} P_{x_1}^-(2) \cdot V^h(x_1 - h_1, x_2, 0) + P_{x_2}^+(2) \cdot V^h(x_1, x_2 + h_2) \\ P_{x_2}^-(2) \cdot V^h(x_1, x_2 - h_2, 0) + \\ \rho^1(2) \cdot V^h(1, x_1, x_2) \end{pmatrix} \right\}$$

In order to implement the successive approximation technique detailed above, we need to use a finite grid we denote G_h, where h represents the length of the finite difference interval of both variables x_1 and x_2. In order to do that, it is essential to define boundary conditions to describe the behaviour of the studied system at the borders of the grid G_h. The computation domain CD is defined as follows: $CD = \{(x_1, x_2) : -x_1^{Inf} \leq x_1 \leq x_1^{Sup}, 0 \leq x_2 \leq x_2^{Sup}\}$, with x_1^{Inf}, x_1^{Sup}, and x_2^{Sup} are given positive constants.

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