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$x(t)$	Niveau d'inventaire
$u(.)$	Taux de production
$u_s(.)$	Taux de sous-traitance
$e(.)$	Niveau d'émission
$\dot{e}(.)$	Taux d'émission
U_{max}	Taux maximum de production
d	Taux de demande constant
L	Limite standard d'émission de polluant imposée par le gouvernement
Y	Limite volontaire d'émission de polluant proposée par l'entreprise
$a(.)$	Age de la machine
q_{ij}	Taux de transition du mode i vers le mode j
i	Période de contrôle de niveau d'émission
$T_{simulation}$	Temps de simulation
N	Nombre de période de contrôle des émissions
MTTF	Temps moyen de panne
MTTR	Temps moyen de réparation
MTTFS	Temps moyen de panne du système manufacturier du sous-traitant
MTTRS	Temps moyen de réparation du système manufacturier du sous-traitant
C^-	Coût unitaire de pénurie
C^e	Coût unitaire de pénalité de dépassement de la limite d'émission L
C_p	Coût unitaire de production
C_s	Coût unitaire de sous-traitance
C_{cor}	Coût unitaire de réparation
C_{over}	Coût unitaire d'overhaul
C_{pm}	Coût unitaire de maintenance préventive
Z	Seuil critique d'inventaire
$g(.)$	Coût total instantané encouru
$J(.)$	Coût total moyen

τ	Délai de livraison
ρ	Taux d’actualisation
θ	Indice d’émission de polluant

INTRODUCTION

Actuellement, la satisfaction des clients, des actionnaires et même des employés est un objectif difficile à atteindre pour les entreprises dans un environnement concurrentiel. Cependant, tout entrepreneur cherche à maximiser ses profits en faisant face aux nouvelles exigences d'un marché très compétitif. Dans ce contexte, l'entreprise moderne doit gérer d'une façon optimale ses ressources et bien adapter ses capacités afin de relever le défi : coût, qualité et délai. En pratique, plusieurs événements internes et externes peuvent affecter l'efficacité économique de la création de valeur du système de production. En effet, les aspects aléatoires des pannes des machines, des réparations, de la dégradation ou de la fluctuation de la demande rendent le contrôle difficile en termes de capacité de production et qualité des produits. Face à cette complexité, l'intérêt des industriels porte sur l'optimisation de leurs ressources et leurs capacités.

Au cours des dernières années, les pressions économiques et surtout sociales ont obligé les entreprises à intégrer, dans leurs stratégies, la dimension environnementale. Plusieurs secteurs industriels tels que l'industrie chimique, pétrolière et l'industrie des mines sont en mesure d'accorder une forte attention aux conséquences environnementales de leurs processus manufacturier. Sur un plan opérationnel, le secteur industriel connait un manque au niveau de développement de stratégies manufacturières pour respecter les normes et les exigences en termes d'émission, des déchets ou des rejets toxiques. Ce manque est accentué par la difficulté de faire des travaux de recherche dans ce sens étant donné le contexte hautement dynamique et complexe qui régit les systèmes manufacturiers.

En forte relation avec le milieu industriel, la recherche scientifique a été en mesure de proposer des méthodes de gestion et de contrôle des systèmes manufacturiers. À travers les années, les méthodes de modélisation et de résolution des problèmes industriels ont beaucoup évolué pour s'adapter à la complexité de plus en plus élevée du milieu manufacturier. Malgré la présence des conditions et des hypothèses simplificatrices dans les approches de résolution, la recherche scientifique ouvre la porte à la résolution des problèmes industriels.

Ce projet de recherche s'inscrit dans ce cadre, l'objectif principal est l'étudier d'un problème de contrôle des systèmes manufacturier en tenant compte des aspects environnementaux. L'originalité de ce projet est qu'il est d'actualité étant donné que le développement durable est un sujet qui a commencé dernièrement à attirer l'attention des industriels ainsi que des chercheurs.

Dans un contexte de la théorie de commande optimale stochastique, nous traitons des problèmes de contrôle de la production et de la maintenance pour des systèmes manufacturiers non- fiables et polluants sous une approche règlementaire de contrôle des émissions. Afin de résoudre ces problèmes, nous procédons par une approche expérimentale en intégrant la simulation et des techniques statistiques d'optimisation.

Ce rapport de mémoire est organisé en 5 chapitres : au début, le Chapitre 1 présente une revue détaillée de la littérature. Dans le même chapitre, nous définissons le cadre générale de ce mémoire : la problématique, la méthodologie ainsi que les objectifs de ce projet de recherche. Le Chapitre 2 est un article scientifique publié dans «International Journal of Production Research», intitulé «Environnemetal hedging point policy to control production rate and emissions in unreliable manufacturing systems». Un deuxième article soumis à «International Journal of Advanced Manufacturing and Technology», intitulé «Environmental issue in an alternative production-maintenance control for unreliable manufacturing system subject to degradation» est présenté dans le Chapitre 3. Les deux derniers Chapitres 4 et 5 présentent également deux articles scientifiques, intitulés respectivement « Production planning and emission control for an unreliable manufacturing system with subcontracting strategy to achieve environmental objectives » et « Emission and production control for unreliable manufacturing system with uncertain subcontractor » et qui ont été soumis, respectivement, à «International Journal of Production Economics» et «International Journal of Production Research».

CHAPITRE 1

REVUE DE LA LITTÉRATURE

1.1 Introduction

Dans ce chapitre, une revue détaillée de la littérature est présentée. Dans un premier temps, nous fournissons une présentation générale des systèmes manufacturiers ainsi que les différentes approches de modélisation. Dans une deuxième partie, nous présentons la théorie de commande optimale stochastique par la recourt à des références incontournables de la littérature. Par la suite, l'aspect environnemental dans les travaux de recherche est abordé en présentant les travaux qui ont proposé des politiques de contrôle et de gestion des systèmes manufacturiers intégrant des aspects environnementaux. On termine par la définition du cadre général du projet : problématique, objectifs de ce mémoire en se basant sur une critique de la littérature afin de montrer ses limites et positionner les contributions de notre travail. Finalement, la méthodologie de recherche adoptée est présentée.

1.2 Les systèmes manufacturiers

1.2.1 Généralité

En général, un système est un ensemble d'éléments coordonnés par une théorie, une loi ou une doctrine. Dans le domaine manufacturier, un système de production est l'ensemble des ressources matériels (machine, matière première…) qui interagissent avec des ressources humaines par l'intermédiaire des flux physiques (produit) et des flux d'information (ordre et plan de production). Son objectif est de transformer la matière première en produits finis conforme aux exigences des clients. Pour plus de détails, on suggère au lecteur la référence suivante (Gershwin, 1994). Les systèmes de production sont sujets à des aléas et des fluctuations qui rendent leur contrôle souvent difficile. En effet, les industriels doivent tenir compte des contraintes internes (capacité, flexibilité…) et externes (approvisionnement, fluctuation de la demande…) pour atteindre les objectifs à court, moyen et long terme. Les systèmes de production peuvent être classés suivant plusieurs critères. Les classifications les plus connues sont :

- Classification selon la quantité produite : d'après Tamani (2008), on peut distinguer trois familles selon la quantité fabriquée : production unitaire, production par lot (Bouslah et al. 2013) et production en série (Sethi et al. 1997).

- Classification selon le mode de gestion de la production : en fonction de la nature de flux de production, on peut parler de la production en flux poussés (production sur stock) (Gharbi et al. 2011) et la production en flux tiré dite aussi sur commande (Lavoie et al. 2010, Agrawal et al. 1996).

Il existe d'autres classifications des systèmes de production comme la classification selon le la nature des processus de production (production en continue et production en discontinue).

1.2.2 Approches de modélisation des systèmes manufacturiers

On distingue trois grandes familles de modèles développés dans la littérature:

- Systèmes de nature discrets : c'est la fabrication de produits sous la forme des pièces distinctes dans un système manufacturier (Elhafsi et Bai, 1996). On parle en mode discret des opérations successives et indépendantes. À titre d'exemple, des travaux ont considéré des systèmes discrets en présence des stocks d'en-cours (Bironneau, 2000).

- Systèmes de nature continus : un système de production est considéré continu dans le cas contraire d'un système discret. Alors, les flux des matières circulent en continu d'un poste de travail à un autre (raffinerie, coulé continue en fonderie…).

- Systèmes de nature hybrides : dans la majorité des cas pratiques, le processus de production de l'entreprise nécessite une configuration mixte : continue/discret. Ce dernier type est appelé système hybride (Bhattacharya et Coleman, 1994). Les systèmes hybrides permettent de gérer un flux de matière continue dans un processus de fabrication (équipements) à état discret. Donc, il ne s'agit ni d'un système continu car certains événements sont discrets, ni d'un système continu. Liberatore et al. (1995) ont considéré l'arrivée d'un client comme un événement discret qui se produit à un instant discret dans le temps. La panne d'une machine, l'achèvement d'une tâche et la mise en service d'un équipement sont aussi des événements discrets (Gharbi et al. (2011); Assid et al. (2014)).

1.2.3 Système de production étudié

Dans ce projet de recherche, on étudie un système manufacturier non- fiable dans un contexte de protection et contrôle environnementale. La figure 1.1 présente la structure de ce système.

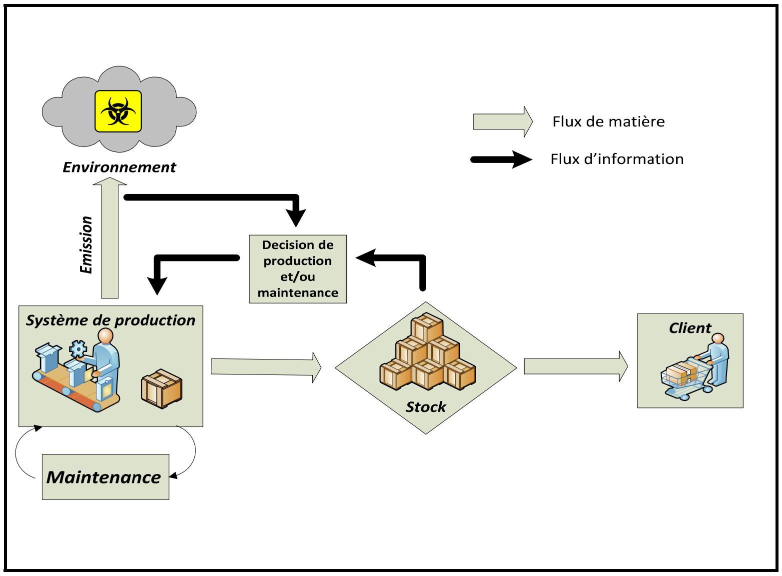

Figure 1.1 Structure du système manufacturier étudié

Dans la Figure 1.1, chaque élément est indiqué par son nom ou sa fonction. Les flèches symbolisent la circulation des flux entre les entités : flux d'information et flux de matière. Le système manufacturier étudié consiste en une unité de production, soumise à des pannes et réparations aléatoires, fabricant un seul type de produit. La maintenance (corrective, préventive,...) est un service indispensable pour maximiser la disponibilité des ressources. La demande des clients est satisfaite à partir du stock d'inventaire. En pratique, la production est souvent en forte relation avec l'environnement. Nous admettons alors que le processus de production engendre des émissions polluantes ce qui peut engendrer des coûts supplémentaires à l'entreprise.

Dans le cadre de ce travail, l'aspect décisionnel est défini au niveau de l'interaction entre le stock des produits finis, le système de production et les émissions générées. En effet, on propose des politiques de production et/ou maintenance qui tiennent compte non seulement du niveau d'inventaire, mais aussi des émissions générés par la fabrication.

1.3 Commande optimale stochastique des systèmes manufacturiers

1.3.1 Commande optimale stochastique : Généralités

C'est une théorie de modélisation qui tient compte de la dynamique discrète ou/et continue des phénomènes pour un système étudié. L'approche a été développée sur la base d'une méthode mathématique. La théorie de la commande optimale a été utilisée dans les domaines d'ingénierie et des mathématiques appliquées, ensuite elle a été introduite pour étudier les systèmes stochastiques en tenant compte de aspect la production, la maintenance, qualité...etc.

Dans le contexte d'un système dynamique, Rishel (1975) a réussi à établir les conditions d'optimalité nécessaires et suffisantes du problème de commande optimale stochastique en rétroaction (feedback control) en utilisant le principe de maximum. Par le biais de la programmation dynamique, Rishel a résolu les équations Hamilton-Jacobi-Bellman (HJB) pour trouver la solution optimale unique du problème. Ces équations permettent de caractériser les conditions optimales du problème de commande stochastique de la production. En se basant sur les résultats des travaux de (Rishel, 1975), Older et Suri (1980) ont modélisé et formulé la structure de la commande optimale stochastique d'un système manufacturier sujet à des pannes et des réparations suivant un processus markovien homogène. Depuis, plusieurs chercheurs ont étudié problème de commande optimale stochastique pour des systèmes manufacturiers non- fiables. Plusieurs méthodes ont été utilisées afin de résoudre ce genre de problème tel que :

- L’intelligence artificielle : (Basnet et Mize (1995); Chiodini (1986)).
- Les heuristiques (Williams et Wirth (1996); Thesen (1999)).
- La simulation (Kenne et Gharbi (2000), Assid et al. (2014)).

1.3.2 Politique de commande à seuil critique

Dans la littérature, les politiques de commande rétroactives (feedback control polices) sont parmi les sujets qui ont attiré beaucoup l’attention des chercheurs. À travers plusieurs travaux de recherches, ce type de politique a montré une grande efficacité à gérer les évènements aléatoires dans un environnement hautement stochastique. Dans ce contexte, Akella et Kumar (1986) ont traité le problème d’une seule machine non- fiable (soumis à des panne et de activités de réparation) produisant un seul type de produit et une demande constante. Les auteurs ont modélisé le système par une chaîne de Markov homogène (taux de transition constants). Leur contribution était très intéressante. En effet, ils ont réussi à résoudre analytiquement les équations HJB. La politique trouvée est optimale et de type seuil critique « Hedging Point Policy» (HPP), qui minimise le coût total (d’inventaire et pénurie) sur un horizon infini. La structure de la politique obtenue est caractérisée par un seuil optimal d’inventaire Z*. La forme de la politique de commande du taux de production est donnée par l’équation (1.1) :

$$u(x(t),\alpha(t)) = \begin{cases} \alpha(t).U_{\max} & if \quad x(t) < Z^* \\ \alpha(t).d & if \quad x(t) = Z^* \\ 0 & if \quad x(t) > Z^* \end{cases} \tag{1.1}$$

Avec :

- *x(t) :* est le niveau instantané d’inventaire;

- $u(.)$: est le taux de production ;
- U_{max} : est le taux de production maximum;
- $\alpha(t)$: est processus stochastique qui décrive l'état du système à un instant t; $\alpha(t) = 1$, si le système est disponible et $\alpha(t) = 0$, sinon;
- d : est le taux de la demande;
- Z^* : est le seuil critique d'inventaire;

L'objectif est de contrôler le taux de production en fonction du niveau d'inventaire en tenant compte de l'état discret du système. Cette politique consiste à produire avec un taux de production maximum lorsque le niveau d'inventaire est inférieur au seuil critique Z^*. Dans le cas où le niveau d'inventaire $x(t)$ est égale au seuil critique Z^*, le système doit produire juste à la demande d. Sinon la production est arrêtée. En conséquence, un stock de sécurité est maintenu pendant les périodes d'excès de capacité qui va servir à prévenir les manques de capacité durant les pannes.

Plus tard, la structure de la politique a été confirmée par Bielecki et Kumar (1988) en utilisant un modèle de file d'attente M/M/1.

À la base de la politique originale (HPP), plusieurs travaux ont proposé des extensions qui sont souvent des politiques à multiples seuils critiques. Cependant, la solution analytique des équations d'HJB n'est possible que dans le cas d'une seul machine et un seul type de produit. C'est alors que Boukas et Haurie (1990) ont utilisé une méthode numérique basée sur l'approche de Kushner (Kushner et Dupuis, 1992) pour résoudre les équations de HJB. Ils ont étudié un système qui fabrique plusieurs produits dans un processus Markovien non-homogène. D'auteurs chercheurs ont réussi à combiner cette approche numérique avec une approche expérimentale basée sur la simulation et les plans d'expériences pour approximer la structure de la politique de commande et trouver la valeur optimale du seuil critique ainsi que le coût total optimal. Dans ce cadre, Kenné et Gharbi (2000) ont traité un système de production non- fiable caractérisé par un processus non-markovien (pannes, réparations et demande suivants plusieurs distributions de probabilité) dans le cas d'une demande aléatoire. Ils ont montré que la politique est de type seuil critique.

Motiver par ces travaux, des extensions ont été développées dans le domaine de la commande des systèmes manufacturiers en s'adressant à des différents aspects. Gharbi et Kenné (2003) ont augmenté la complexité du problème en étudiant un système manufacturier à plusieurs machines qui fabriquent plusieurs types de produit. La politique trouvée est sous optimale. La maintenance des systèmes de production a attiré aussi l'attention de plusieurs chercheurs (Berthaut et al. (2010); Dehayem et al. (2011). Sethi et Zhang (1999) et Gharbi et al. (2006) ont considéré le setup (coût et/ou temps) dans l'optimisation des systèmes manufacturiers stochastiques. D'autres travaux ont mis l'accent sur la fiabilité des fournisseurs dans la chaine d'approvisionnement tel que Hajji et al. (2009**).** Dernièrement, certains chercheurs ont commencé à se rapprocher de plus en plus de l'environnement industriel en traitent des sujets pratiques et complexes comme la qualité. Dans ce contexte, Radhoui et al. (2009) ont abordé l'interaction entre la qualité et la maintenance pour un système de production par lot. Dans un contexte de flexibilité de capacité, une autre étude a été développée par Gharbi et al. (2011). Les auteurs ont traité le cas d'un système de production composé d'une machine centrale qui, dans le cas d'un manque de capacité, fait appel à une machine de réserve afin de satisfaire la demande.
On s'intéresse dans la section suivante à la problématique d'intégration de l'aspect environnemental dans le domaine industriel à travers une revue de la littérature.

1.4 Aspect environnemental dans le milieu industriel

La situation environnementale actuelle est l'un des sujets les plus importants à l'échelle mondiale. La pollution est parmi les principaux facteurs responsables de cette situation. Dernièrement, le réchauffement climatique dû à l'effet de serre, l'augmentation des coûts d'élimination des déchets et l'épuisement des ressources de la matière première ont mis en urgence la nécessité d'agir de la part des gouvernements et les entreprises pour augmenter l'efficacité des politiques et des pratiques de contrôle de pollution. Bien que le secteur des transports et le secteur de l'énergie soient les premiers concernés par ces problèmes, l'industrie manufacturière est, aussi, un domaine d'activité qui doit assumer sa part. Depuis longtemps, les industriels se sont intéressés à l'optimisation des coûts afin de maximiser leurs profits sans considérer les aspects environnementaux. Cependant, de nos jours, les autorités ont commencé à mettre de la pression sur les entreprises pour limiter les dégâts et encourager l'intégration du développement durable au sein de leurs activités.

Il est important de noter que d'après Elkington (1998), l'analyse de la durabilité est basée sur trois axes essentiels : 1) l'environnement, 2) l'économie et 3) la société. Pour connaitre les fondations de la notion de durabilité, on suggère au lecteur de consulter les travaux de Neto et al (2007); Carter et Rogers (2008); Seuring et Muller (2008). Dans ce projet de recherche, nous allons aborder la problématique relative aux deux premiers axes : l'environnement et l'économie.

Dans la littérature, un nombre très limité d'auteurs ont étudié l'aspect de développement durable et son interaction avec le planning de production. Mais, la littérature à ce sujet commence à se développer à cause des pressions économiques et surtout sociales. De manière générale, les travaux de recherche qui ont étudié l'aspect environnemental dans le domaine manufacturier ont considéré deux différentes approches de contrôle et protection de l'environnement : règlementaires et volontaires.

1.4.1.1 Approches règlementaires

Ce sont des approches très connues utilisées par les gouvernements à travers le monde. Elles consistent à établir des normes et des règles afin de contrôler et limiter les émissions toxiques, les polluants ou les déchets des industries (Chen et Monahan, 2010). D'après Lee et Yik (2004), les instruments réglementaires permettent aux gouvernements une intervention sur le marché facilitant la mise en place des changements nécessaires. Dans le cadre de l'« Approche réglementaire de contrôle de l'environnement », différentes outils ont été introduits par les gouvernements en Europe et en Amérique visant la réduction des risques environnementaux et l'amélioration de la gestion des déchets. Dans la littérature, les approches les plus connus à l'égard de la protection de l'environnement sont :

- Approche standard de contrôle et commande : L'approche standard de contrôle et de commande était la méthode la plus utilisée et la plus connue pour le contrôle et la protection de l'environnement (Jain, 1993). Elle consiste à fixer des normes de performance et des moyens pour limiter la quantité de déchet ou d'émission qui peut être générer par les industriels. La norme est une limite maximale de pollution imposée par les autorités. Sous la surveillance du gouvernement, l'entreprise est obligée de limiter ses rejets pour ne pas dépasser en aucun cas la limite. Pearce et Turner (1990) ont jugé que cette approche est facile à apprendre et appliquer. Cependant, la rigidité et le manque de flexibilité est l'inconvénient majeur de cet instrument (Shin et Chen, 2000). Plus récemment, les gouvernements ont pensé à réaliser leurs objectifs environnementaux en utilisant d'autres méthodes à la place des instruments rigides d'interdictions. La solution était d'augmenter le coût relié à l'exercice de l'activité en question (émissions toxiques, pollutions atmosphériques, consommation énergétique ou déchets) (Lee et Yik, 2004). Pour les industriels, ce coût supplémentaire augmente le coût total de production et les oblige, par la suite, à une utilisation plus efficace des ressources. Dans ce contexte, trois instruments ont été développés partout dans le monde :

- La pénalité de pollution : l'idée consiste à donner plus de flexibilité à l'approche standard de contrôle et commende. En effet, un coût de pénalité est imposé lorsque les rejets de l'entreprise dépassent la limite standard fixée par les autorités. (Chen et Monahan (2010); Chen et al. (2013), Jaber et al. (2013)).

- La taxation: similaire à celle de pénalisation, l'approche de taxation oblige les entreprises à payer un coût de taxe suite à une émission, un rejet... Le montant de taxe est lié directement à la quantité de rejets dans l'eau, le sol ou l'air. La taxe peut être liée aux composants du produit ou au produit lui-même. (Jaber et al. (2013); Quirion (2010)).

- Les systèmes de permis échangeables : cet instrument établit un plafond général de rejets, puis donne des permis individuels aux émetteurs potentiels. Dans le cas où les émissions de l'entreprise sont inférieures à la limite autorisée, elle peut vendre la différence entre ces émissions réelles et le plafond fixé sur le marché. Alors, une entreprise dont les émissions dépassent la limite peut acheter (ou échanger) les droits d'émissions pour émettre plus. (Li, 2013).

Par rapport aux réglementations basées sur les normes strictes, les approches réglementaires basées sur le principe « pollueur payeur » donnent aux entreprises une grande flexibilité dans la mesure où ils ne sont pas forcés à installer des équipements de recyclage ou de dépollution qui coûtent cher ou qui sont difficiles à maintenir.

Dans la littérature scientifique, plusieurs travaux de recherche ont considéré une ou plusieurs approches réglementaires afin d'analyser les effets de l'intégration de l'aspect environnemental dans le milieu manufacturier. Une série de travaux de I. Dobos (1998, 1999, 2001) a été développée afin de déterminer l'effet de la stratégie environnementale sur les décisions de production et d'inventaire de l'entreprise. L'auteur s'est basé sur un modèle mathématique dans le but de déterminer la meilleur politique environnementale dans le cadre d'une approche de taxation, pénalité d'émission ou permis d'échange de droit d'émission. En se basant sur ces travaux, Li et Gu (2012) ont comparé la politique de contrôle de production-inventaire avec et sans prise en compte des exigences environnementales. Le phénomène de détérioration des produits a été introduit dans le travail précédent sous une approche de permit d'émission (Li, 2013). Dans le cadre de la théorie de commande optimal, le même auteur Li (2014) a ajouté la maintenance au dernier travail (Li, 2013) dans un contexte de l'approche de taxe d'émission. En plus du taux de production et celui de la maintenance, l'auteur considère le taux d'investissement en pollution R&D comme variable de décision. Drake et al. (2012) ont étudié l'importance du choix de la technologie et la décision de capacité dans un contexte de contrôle d'émission. Parmi les résultats les plus importants, les auteurs ont montré que le choix de la technologie pourrait réduire les émissions.

Jaber et al. (2013) ont été parmi les premiers à considérer « Le système communautaire d'échange de quotas d'émission» (The European Union Emissions Trading System (EU-ETS)) dans gestion de la chaine d'approvisionnement. En ce qui concerne l'axe environnemental, les auteurs ont étudié plusieurs méthodes de contrôle d'émission : taxation du carbone, pénalisation des émissions et permis d'échange des droits d'émission. L'objectif était de trouver le taux de production qui minimise le coût total (coût environnemental et coût de la chaine d'approvisionnement) en prenant le taux de production et le multiplicateur de coordination vendeur-acheteur comme variables de décision.

D'autres travaux ont réussi à introduire la dimension environnementale dans le modèle de quantité économique de commande (EOQ). Bonney et Jaber (2011) sont partis du modèle traditionnel de «EQQ» pour développer un modèle intitulé « Enviro-EQQ». Les auteurs ont considéré, en plus du coût du transport, un coût d'émission et un coût des déchets. Dans le même contexte, Chen et al. (2013) ont étudié un modèle EOQ en considérant des émissions de carbone dans le cadre d'une approche de pénalisation. Ils ont étudié la possibilité de réduire les émissions sans trop augmenter les coûts. Les auteurs ont montré que la modification de la quantité commandée peut réduire les émissions sous certaines conditions. Un modèle de EOQ à multi objectif qui minimise le coût et les dégâts environnementaux a été développé par Bouchery et al. (2012). Les auteurs proposent une révision du modèle EOQ classique pour tenir compte de l'aspect de durabilité.

Tous ces travaux de recherche, parmi d'autres, examinent l'effet de l'intégration de l'aspect environnemental dans l'industrie en présence d'une approche de contrôle réglementaire (taxe, pénalisation, permit d'échange, …). En plus des approches réglementaires de contrôle citées précédemment, d'autres approches dites «Approches volontaires» ont été proposées.

1.4.1.2 Approches volontaires

Récemment, les approches volontaires, provenant des normes internationales (les systèmes de gestion de l'environnement (SGE)) et des programmes volontaires, sont devenus très connus et utilisées en tant qu'outils d'amélioration de l'efficacité environnementale et de réduction des rejets (Brouhle et al., 2009). En 1991, l'Agence américaine de protection de l'environnement (EPA) a mis en place son premier programme volontaire. Depuis, l'utilisation de ces approches a connu une forte hausse en Amérique afin de limiter les problèmes environnementaux (Brouhle et al., 2005). Il s'agit de donner de la place aux considérations environnementales dans l'aspect stratégique et les outils d'aide à la décision (Corbett et Kirsch, 2001). Marcus et Willig (1997) affirment que l'approche volontaire est propre à chaque industrie et permet de s'auto-réglé. D'un point de vue financier, Blackman et Boyd, (2002) ont montré que le recourt aux programmes volontaires aide les entreprises à réduire les coûts. D'autre part, certains auteurs (Arora et Cason (1996), Arora et Gangopadhyay (1995), Khanna et al. (1998)) ont mis l'accent sur le fait qu'une action volontaire permet d'améliorer la réputation environnementale de l'entreprise au regard de ces clients et même ses actionnaires. Brouhle et al. (2009) ont présenté plusieurs autres avantages de l'utilisation d'une approche volontaire afin d'améliorer la stratégie environnementale de l'entreprise. En plus, il est important de savoir que les approches volontaires sont, parfois, plus intéressantes, par rapport aux réglementations, puisqu'ils encouragent l'innovation (Wallace, 1995).

Récapitulons, selon Chen et Monahan (2010), l'approche réglementaire et l'approche volontaire conduisent à deux processus distincts de planification de la production et de gestion des stocks. Dans un contexte de réglementation, l'entreprise est obligée de respecter les normes qui forment, dans la majorité des cas, une contrainte de capacité. Cependant, le contrôle volontaire est un choix interne à l'industrie. Alors, les objectifs environnementaux sont fixés par le système d'aide à la décision. Les auteurs affirment que, généralement, les méthodes volontaires donnent plus de flexibilité au système manufacturier.

1.5 Critique de la littérature

Il est évident que les travaux de recherche, présentés dans la revue de littérature, ont donné naissance à des résultats très intéressants concernant l'intégration de l'aspect environnemental dans le milieu industriel. Malgré la robustesse des modèles développés par les chercheurs, nous présentons dans cette section quelques limites aux niveaux des travaux antérieurs.

D'une part, à notre connaissance, la plupart des travaux ont abordé les problèmes par des méthodes purement mathématiques et avec des approches de résolution basés sur des développements analytiques (Jaber et al. (2013), Chen et al. (2013), Dobos (1998, 1999, 2001), Li (2012, 2013, 2014), Chen et Monahan (2010)). Bien que ces démarches mathématiques ont permis d'avoir des résultats intéressants, les modèles proposés ainsi que certaines hypothèses ne tiennent pas compte des aspects stochastiques et dynamiques dans le milieu manufacturier (pannes, les temps de réparation, délai de livraison…).

D'autre part, plusieurs travaux de recherche dans différents contextes manufacturiers ont prouvé que l'intégration de plusieurs phénomènes et contraintes dans une même approche de modélisation et résolution mène à des meilleurs résultats auxquels le décideur peut ne pas s'attendre. Dans la littérature scientifique, la prise en considération des aspects environnementaux à un niveau opérationnel de prise de décision est relativement nouvelle. D'où le besoin d'approfondir les connaissances des différents phénomènes pouvant influencer le processus de prise de décision. Dans ce contexte, à l'exception du travail de Li (2014) qui a abordé le contrôle de la production en considérant la maintenance, la qualité et les émissions, les autres travaux s'intéressent surtout à l'aspect développement durable dans un contexte bien précis; production (Chen et Monahan, 2010), chaine logistique (Chabaane et al. 2012), chaine d'approvisionnement (Jaber et al. 2013).

En ce qui concerne les systèmes manufacturiers non- fiables, les travaux dans la littérature ont montré que la politique de contrôle à seuil critique a donné un meilleur contrôle de systèmes de production, en présence d’une stratégie de setup (Assid et al. 2014), de contrôle de qualité (Bouslah et al. (2013)), de phénomène de dégradation (Rivera- Gomez, 2013). À notre connaissance, sous l’approche de commande optimale, aucune politique de type seuil critique n’a été proposée intégrant l’aspect environnemental.

1.6 Cadre général du projet

Après avoir présenté la revue de la littérature dans les paragraphes précédents, on s’intéresse dans cette section à la définition du cadre général du projet de recherche. En se basant sur l’analyse et la critique de la littérature, on définit la problématique et les objectifs de ce mémoire. Par la suite, la méthodologie de résolution des problématiques est présentée.

1.6.1 Problématique de la recherche

Suite à la critique de la littérature, il est clair que la problématique de la gestion des systèmes manufacturiers dans un contexte de protection de l’environnement n’a pas été suffisamment étudiée d’un point de vue opérationnel. Ainsi, au tour de ce sujet, plusieurs questions se posent actuellement :

- Y-a-il des politiques de commande rétroactifs qui peuvent contrôler adéquatement un système manufacturier dans un contexte stochastique et en considérant l’aspect environnemental ? Quelles sont les effets de la considération de cet aspect sur le planification de la production/inventaire et de la maintenance ?

- Dans un contexte industriel pratique, quelles sont les phénomènes à tenir en compte et qui peuvent avoir une liaison directe avec les rejets de polluant? À titre d’exemple, la dégradation des équipements peut-elle avoir un impact sur les émissions générées par les unités de production ? Quelles sont les décisions au niveau de la production et surtout au niveau de la maintenance à prendre face à tel un phénomène (dégradation) ?

- Dans un contexte stochastique et dynamique, peut-on dépasser les limites des méthodes mathématique de résolution pour se rapprocher plus de la réalité des systèmes manufacturiers ?

Dans le paragraphe suivant, nous allons présenter les objectifs de notre projet de recherche afin de répondre aux questions de la problématique abordée.

1.6.2 Objectifs de la recherche

L'objectif principal de ce travail de recherche est d'étudier des systèmes manufacturiers non-fiables et qui génèrent des émissions dans le cadre d'une approche de control et protection de l'environnement. Sous l'approche de commande optimale stochastique, nous allons proposer des politiques de commande rétroactifs qui tiennent compte des émissions générées dans la décision de production et de la maintenance. Ainsi, ce travail consiste à aborder cette problématique et fournir des études approfondis qui peuvent aider les décideurs, sur le plan opérationnel, à s'adapter aux exigences environnementales.

Étant donné le contexte hautement dynamique et complexe qui régis les systèmes manufacturiers, nous avons choisi de d'aborder le problème étape par étape :

- Dans une première étape, nous allons étudier un système manufacturier non fiable qui génère des émissions sous une approche de plafond d'émissions. En se basant sur la politique de commande à seuil critique (HPP), une nouvelle structure de la politique de commande de la production sera proposée afin d'intégrer le niveau d'émission dans la décision de production. L'objectif de ce modèle est de fournir une étude qui considère l'environnement dans un contexte des politiques de type HPP.

- Dans la deuxième étape, nous allons intégrer le contrôle de la maintenance au premier modèle dans un contexte de dégradation de l'équipement. Ce travail permettra d'établir une relation entre la dégradation de la machine et la quantité d'émission générée. Trois politiques de contrôle de la production et de la maintenance seront développées et comparées.

- Dans la troisième étape, nous allons étudier un système manufacturier non- fiable et polluant en présence d'un sous-traitant caractérisé par un délai de livraison et un coût. Ce travail va combiner l'aspect environnemental dans le contrôle des systèmes manufacturiers avec la notion de sous-traitance dans un contexte stochastique. L'objectif est de mesurer l'efficacité du recourt à un sous-traitant fiable pour améliorer la stratégie environnementale et économique de l'entreprise.

- Le dernier travail est une extension du troisième. Dans le cas d'un sous-traitant non-fiable, nous allons proposer une politique de commande de la production et de la sous-traitance et étudier l'effet de la disponibilité du sous-traitant sur la décision de l'entreprise. Des outils d'aide à la décision pour sélectionner le sous-traitant seront développés dans le cadre de deux derniers travaux.

Pour résoudre la problématique dans chacun des travaux cités ci-dessus, nous avons adopté une approche expérimentale de résolution décrite en détail dans la section suivante.

1.6.3 Approche de résolution

Dans la littérature, plusieurs approches ont été développées afin de proposer un meilleur contrôle et gestion des systèmes manufacturiers non- fiables. Les politiques de commande rétroactives (feedback policies) sont parmi les sujets qui ont attiré l'attention des plusieurs chercheurs. Tel qu'il a était indiqué à la revue de la littérature, Akella et Kumar (1986) ont montré l'optimalité de la HPP analytiquement. Ensuite, le concept de la politique HPP a évolué afin d'étudier des systèmes plus complexes (plusieurs machines, plusieurs produits…) ce qui rend la résolution analytique très difficile. Alors, pour trouver la politique optimale, différentes approches de résolution ont été proposées. Boukas et Haurie (1990) ont utilisé une approche numérique basée sur la méthode de Kushner (Kushner et Dupuis, 2001) pour résoudre le problème lorsque les états du système sont décrits par des processus Markoviens non-homogènes. Kenné et Gharbi (2000) ont pour leur part proposé une approche expérimentale basée sur la simulation pour déterminer le seuil critique de la HPP dans le cas où les pannes et les réparations sont non markoviens et/ou la demande est aléatoire. Kenné et Gharbi (2001) ont aussi proposé une nouvelle approche de résolution combinant les deux méthodes : numérique et expérimentale. Cette approche a été utilisée dans les travaux de Gharbi et al. (2011). Plus tard, Berthaud et al. (2011), Bouslah et al. (2013) et Assid et al. (2014) ont adopté une approche purement expérimentale en proposant de politiques heuristiques basées sur les anciens travaux. L'approche a montré une efficacité à traiter les problèmes de contrôle des systèmes manufacturiers non- fiables lorsque la résolution analytique et/ou numérique sont difficiles à appliquer. Dans le même contexte, on propose dans ce projet de recherche une approche de résolution expérimentale combinant la simulation, le plan d'expérimental et la méthodologie de surface de réponse. Les différentes étapes de l'approche sont les suivantes :

- Étape1 : Politique de commande

  La structure de la politique de commande à appliquer pour le système manufacturier sera présentée, analysée et exprimée par des équations mathématiques. Ainsi, les paramètres de la politique seront décrits.

- Étape 2 : Modèle de simulation

  Un modèle de simulation sera développé en utilisant le langage SIMAN sous le logiciel «ARENA» avec des routines C++. Il s'agit d'un modèle combiné discret-continue qui présente le système étudié. Lavoie et al. (2010) ont montré l'avantage de de l'utilisation cette combinaison en terme de temps de simulation et reproductivité de la dynamique du système étudié. Le modèle de simulation utilisera la structure de la politique de commande définie dans l'étape précédente comme entrée pour mener des expériences afin d'évaluer rendement du système de production. Ainsi, pour des valeurs données des facteurs de contrôle, le coût total sera obtenu.

- Étape 3: Démarche de conception expérimentale

  Elle va définir le nombre d’expérience (le plan d’expérience) et le domaine expérimental des variables indépendantes (paramètres de la politique). Ensuite, l’analyse de la variance ANOVA permettra de déterminer les effets principaux des facteurs, leurs interactions et leurs effets quadratiques sur le coût moyen (variable dépendante) d'un ensemble minimal d'expériences de simulation.

- Étape 4 : Surface de réponse

  La méthodologie de la surface de réponse sera alors utilisée pour obtenir la relation entre les coûts, les principaux facteurs et les interactions significatives donnée dans l’étape précédente. Le modèle obtenu va être optimisé pour déterminer la meilleure combinaison des paramètres de la politique de commande qui minimise le coût total.

1.7 Conclusion

Dans une première partie de ce chapitre, nous avons présenté les approches de modélisation de systèmes manufacturiers ainsi que le système étudié dans ce projet de recherche. Ensuite, nous avons passé à la présentation de la théorie de commande optimale stochastique de systèmes manufacturiers et la politique de commande à seuil critique. Nous avons abordé aussi la problématique de l’intégration de l’aspect environnemental dans l’industrie à travers les travaux de recherche. Cette première partie est une étape indispensable dans un projet de recherche. En effet, en se basant sur les limites des anciens travaux constatés à partir de la revue de la littérature, nous avons défini le cadre général de notre projet. Ainsi, la problématique de la recherche, les objectifs à atteindre dans ce mémoire et la démarche de résolution des problèmes abordés ont été décrits.

Dans les quatre prochains chapitres, nous allons présenter les détails des modèles décrits dans ce chapitre.

CHAPITRE 2

ARTICLE 1: ENVIRONEMENTAL HEDGING POINT POLICY TO CONTROL PRODUCTION RATE AND EMISSIONS IN UNRELIABLE MANUFACTURING SYSTEMS

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Abstract: This paper proposes a new hedging point policy which integrates environmental concerns into the optimal control of unreliable manufacturing systems. The considered system is composed of a production facility subjects to random failures and producing a product family intended for a given market with stable demand. The manufacturing facility's operations cause harmful emissions to the environment, and may incur sanctions in the form of an environmental tax imposed by the relevant authorities. Given the significant compromise that must take place between inventory, backlog and taxes costs, the main objective of this paper is to propose a feedback adaptive control policy which provides a better control of the production rate and the emissions generated. Under the hedging point policies (HPP) category, a new structure called the Environmental Hedging Point Policy (EHPP) is proposed. To illustrate the effectiveness of the proposal, an experimental approach based on simulation modelling, variance analysis and response surface methodology (RSM) is applied. The results show a significant gain in terms of incurred costs compared to those incurred when the system is governed by a classical HPP. An improved version of EHPP is also proposed for systems with high emission rates. Several sensitivity analyses are conducted to illustrate the robustness and effectiveness of the proposed policies.

Keywords: Unreliable manufacturing systems, hedging point, emission, production control, simulation, RSM.

2.1 Introduction

During the past 20 years, the social and economic pressures have led manufacturing firms to pay more attention to the environmental consequences of the products and services they offer and to the processes they deploy (Brandenburg et al. 2014). This reality has brought a new dimension, namely, environmental performance, to the efficiency and traditional performance measures of a business. Therefore, operational strategies must be able to adapt to market changing conditions, react to unforeseen events, and solve such difficulties by collaborating, even while integrating environmental concerns.

From an operational point of view, industrial facilities are facing a lack of strategies developed to meet waste and toxic emissions standards and requirements while maintaining high economic efficiency (Bonney and Jaber, 2011). This lack of strategies is accentuated by the highly dynamic and complex context that governs manufacturing systems. There is obviously a significant gap when it comes to strategies or standards independently addressing both economic and environmental problems.

In the scientific literature, when environmental aspects are ignored, most efforts tend to be focused on monitoring and improving management processes giving rise to several theories. In a dynamic stochastic context, optimal control theory is one of the most contributory in the development of operational manufacturing strategies.

In the context of manufacturing system, feedback control policies are among the most effective strategies in a stochastic dynamic environment. One of the most cited and employed class of strategy in manufacturing systems facing random events (e.g., breakdowns, random demand, etc.), is the Hedging Point Policy (HPP) (Kenne and Gharbi, 2000). In its simplest form, for an M1P1 (one unreliable machine (M) producing one product type (P)), aiming to minimize a long-term discounted cost, HPP acts as a feedback strategy to control the production rate as a function of the state of the system, and calls for a safety stock (threshold) to be built during excess capacity periods in order to be able to meet demand during failure periods. Based on the concept of HPP, many others applied the same formalism to extend this control policy to other manufacturing contexts. Hajji et al. (2011) and Gharbi, Hajji, and Dhouib (2011) developed the Multiple HPP (MHPP) for multiple state systems. Berthaut Berthaut, Gharbi, and Dhouib (2011), Rezg, Chelbi, and Xie (2005) and Ayed, Dellagi, and Rezg (2012), among others, considered a joint implementation of a corrective and preventive maintenance strategy and production rate control. For systems producing multiple part types, Bai and Elhafsi (1997) developed Hedging Corridor Policy (HCP), adapted to this context. Based on this work, Gharbi et al. (2006) extend the problem to a multiple-machine context. Hajji, Gharbi, and Kenne (2009) considered joint replenishment and production control in a two-stage stochastic manufacturing system and developed a state-dependent HPP including feedbacks on the raw material and finished products inventories. Recently, process and product quality considerations have been integrated into production planning (Radhoui, Rezg, and Chelbi 2009; Bouslah, Gharbi, and Pellerin 2013).

All the aforementioned works – in addition to many others – have considered important aspects of manufacturing system control. However, the integration of the environmental dimension when controlling manufacturing systems in a dynamic stochastic context remains an open problem, and needs to be addressed. In fact, this need is due mainly to the reality faced by the industrial sector, which must combine its economic efficiency goals with environmental standards requirements.

In the literature, few authors address production control activities jointly with environmental aspects at the operational decision level. Some such contributions, cited below, are clearly responding to an urgent need highlighted by a significant increase in environmental legislation and in waste disposal costs (Porter and Linde, 1995). Papers that address the environmental aspect jointly with production planning decisions mainly consider two different approaches, namely, RCA and VA.

Regulatory control approach (RCA): This is a well-known approach used by authorities worldwide to establish standards and rules for controlling and reducing toxic emissions, pollutants and wastes (Chen and Monahan, 2010). Regulatory instruments allow necessary interventions through higher standards and/or taxation to reduce environmental risks (Lee and Yik, 2004).

Bonney and Jaber (2011) were among the first to integrate the environmental dimension into inventory management models. They proposed an extension of the lot sizing model called the "Environ-EQQ". In addition to transportation costs, this model integrates emissions and waste costs. Jaber et al. (2013) addressed the problem within the European Union Emissions Trading System (EU-ETS). They studied and proposed several schemas for emission quota exchange. The principal objective of their work was to find the best production plan that minimizes the total, environmental and supply chain incurred costs.

Voluntary approaches (VA): Also known as self-regulation, these approaches are mainly inspired from international EMS (Environmental Management System) standards (Simonet, 2003). These voluntary approaches have become widely known and used as tools for improving efficiency, reducing emissions (Brouhle et al., 2009) and allowing industries to self-regulate (Marcus and Willig, 1997).

According to Chen and Monahan (2010), regulatory and voluntary approaches lead to two distinct processes of production planning and inventory management. In a regulatory context, the company is required to meet standards that most often constitute a capacity constraint for it. However, voluntary control is an internal choice in which environmental objectives are set by the decision support system. Generally, voluntary approaches provide more flexibility for manufacturing systems in terms of capacity management.

In the light of this new reality and the increasing needs, the main contribution of this paper is to provide decision makers with manufacturing strategies that incorporate both economic and environmental visions. Thus, a stochastic optimal control problem of a manufacturing facility emitting pollutants is considered. The objective is to develop a control policy falling under the class of HPPs that provide the best way to manage incurred costs and generated emissions within an environmental control approach.

The paper is organized as follows. Section 2.2 presents a description of the system and the stochastic optimal production control problem considered. In the same section, a description of the system's dynamic evolution and the structure of the proposed control policy are presented. Section 2.3 introduces the proposed resolution approach and presents the simulation model. The other steps are applied in section 2.4 to solve the problem under a linear relationship between the emission and production rates. Section 2.5 extends the problem analysis for a case of an exponential form of emission. Section 2.6 concludes the paper.

2.2 Problem statement

2.2.1 Notations

The following notations are used:

$x(t)$	Finished product inventory/backlog level
$u(t)$	Production rate
$e(t)$	Emission level
U_{max}	Maximum production rate
d	Finished product demand rate
L	Standard permitted limit of emission
Y	Voluntary limit of emission
θ	Emission index
P_{er}	Length of emission control period

N	Number of periods in the planning horizon
ρ	Discount rate
$\alpha(t)$	Discrete variable describing the manufacturing system state
MTTF	Mean Time To Failure
MTTR	Mean Time To Repair
C^+	Finished product holding cost/Unit/Time unit (TU)
C^-	Finished product backlog cost/Unit/TU
C^e	Penalty cost for emissions/Unit
Zi	Finished product Hedging level, i =1, 2.

2.2.2 Problem description

The manufacturing system under study (Figure 2.1) consists of an unreliable production facility producing one product family type to satisfy a constant demand directly from a finished product *(FP)* stocking area. The manufacturing system is unreliable, which causes periods of unavailability (failures) requiring repairs to restore the system. Failure events and repairs duration are assumed to evolve according to a stochastic process. Due to the unavailability periods of the system, unsatisfied demands are backlogged, with a penalty cost. The manufacturing facility's operations cause harmful emissions to the environment and may incur sanctions in the form of an environmental tax imposed by the relevant authorities. We assume that there is no emission caused by the products in work in process (WIP). Given the significant compromise that must take place between inventory, backlog and emissions penalty costs, the main objective of this paper is to propose a feedback adaptive policy which provides a better control of the production rate and the emissions generated.

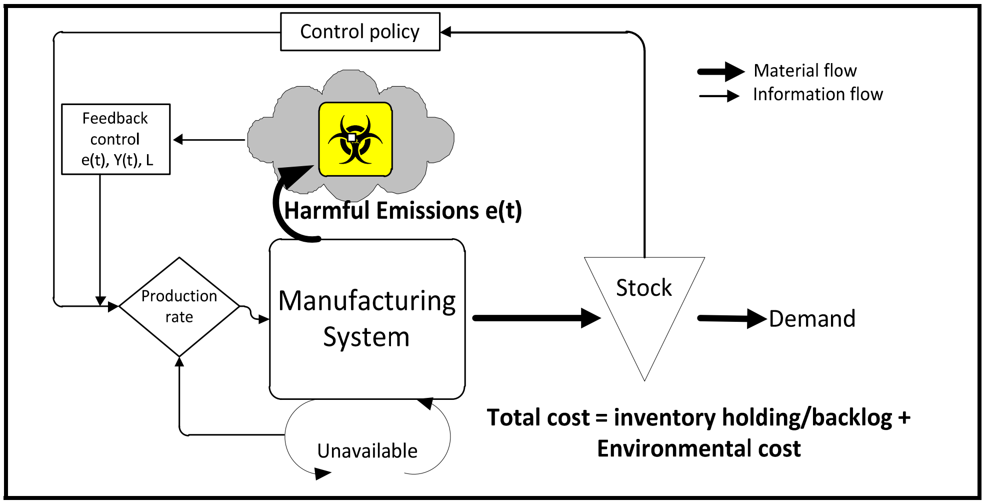


Figure 2.1 System under study

For the considered manufacturing system, *x(t)* and *u(t)* denote the inventory/backlog level of *FP* and the production rate of the system.

For any specific time t, the state of the system has two components: a continuous component denoted *x(t)* describing the cumulative surplus level, and a discrete component denoted *α(t)* describing the manufacturing system state. *α(t)* is a continuous- time discrete space stochastic process taking value: 0 if the system is under repair and 1 if it is operational. Hence, the dynamic behaviour of the system can be modelled by the state variables *(x(t), α(t))*, where $x(t) \in R, \alpha(t) \in M = \{0,1\}$. The dynamic behaviour of the *FP* surplus is given by the following differential equation:

$$\dot{x}(t) = u(t) - d, \quad x(0) = x_0 \tag{2.1}$$

where x_0 denotes the initial surplus level.

The production rate at any given time must satisfy the capacity constraint of the system given by equation (2.2):

$$0 \le u(t) \le U_{\max} \tag{2.2}$$

When processing parts at a fixed rate *u(t)*, the system is constrained to emit a quantity of harmful pollutants for each part produced. Let θ be the emission index expressed as the quantity of pollutants per unit produced. The dynamic behaviour of the quantity of emissions is given by equation (2.3):

$$\dot{e}(t) = u(t) \times \theta, \quad t \in [t_i, t_{i+1}[, e(t_i) = 0, i = 0,..,N \tag{2.3}$$

Where *N* denotes the number of periods in the planning horizon.

Following the aforementioned *Regulatory control approach (RCA)*, the manufacturing facility under study must comply with the standards and rules that stipulate that in each reference period *i*, if the quantity of emissions exceeds a standard level L fixed by the relevant authorities, the excess quantity is penalized with an environmental cost C^e (Jaber et al. 2013). At the end of the reference period, the emission counter is reset to zero.
For a better comprehension of the emission indices θ, we refer the reader to the work of Chen and Manahan (2010).

The decision variable of the control policy we are seeking is the production rate *u(t)* which can have tree values; *u(t)=0* if the system is shut down; *u(t)=d* or $u(t)=U_{max}$ if the system is available.

The decision made by the manager is strongly conditioned by the involved costs defined in the following equations.

At time t, we calculate the inventory and backlog cost according to the inventory level *x(t)*. The instantaneous cost function $g(.)$ is given by the following equation:

$$g(x(t)) = C^{+}x^{+} + C^{-}x^{-} \tag{2.4}$$

Where $x^{+} = \max(0, x)$, $x^{-} = \max(-x, 0)$, C^{-} is the *FP* backlog cost and C^{+} is the *FP* inventory cost.

The penalty emission cost at the end of reference periods *i* is given by the following equation:

$$EC(t_i) = C^{e} \times \max(0, e(t_i) - L), i = 0,.., N \tag{2.5}$$

Using equations (2.4) and (2.5), the total cost *J(.)* can be defined by the following equation:

$$J(x,\alpha) = \int_0^{\infty} e^{-\rho t} g(x(t))dt + \frac{\sum_{i=1}^{N} C^{e} \times \max(0, e(t_i) - L)}{N \times P_{er}} \tag{2.6}$$

The production planning problem considered here is to find an admissible decision or control policy *u(.)* that minimizes *J(.)*, given by (2.6) subject to equations (2.1) to (2.3). Such a feedback control policy, as illustrated in Figure 2.1, determines the production rates as a function of *x(t)*, *α(t)* and *e(t)*.

In the following section, an extended version of HPP is proposed to control such a system.

2.2.3 Environmental Hedging Point Policy (EHPP)

Recall that the classical HPP doesn't consider the emission costs. The control of the system under study will confront the manager with the need for an important trade-off between backlog costs, if the produced quantity is not sufficient, and the inventory and emission cost, if the produced quantity is very significant. The simplest way to tackle the problem will be to never exceed the permitted limit L. Unfortunately, in an unreliable manufacturing context, the manager, in order to remain competitive in the market, cannot afford to permanently limit production and ignore the possibility of an occasional emissions overflow. In the light of this reality, starting from the classic HPP, which requires production to be carried out at the maximum rate to reach a hedging level Z_1, an additional feedback information from the emission level *e(t)* is needed in order to improve production planning decisions. In this context, the manager should have an adapted emission control level beyond which he can decide to stop production if the emission cost rises. This decision cannot be taken independently of the inventory level, and thus a coupled feedback control should be considered. This could be inspired from the multiple HPP (MHPP), in which case the manager could decide to stop production if the emission level becomes high and the inventory level is judged sufficient ($\geq Z_2$), in order to minimize backlog risks. Based on HPP and MHPP, a new control policy called the Environmental Hedging Point Policy (EHPP) is proposed. This policy is a voluntary commitment which consists in setting a specific limit that controls the production rate, based on the inventory and emission levels.

The following equations (2.7) and (2.8) summarize the EHPP policy:

$$\begin{cases} if\ e(t) \leq Y : apply\ HPP\ with\ a\ hedging\ Level\ Z_1 \\ \\ u(x,\alpha) = \begin{cases} U_{\max} & if \quad x(t) < Z_1 \quad and \quad \alpha(t) = 1 \\ d & if \quad x(t) = Z_1 \quad and \quad \alpha(t) = 1 \\ 0 & if \quad x(t) > Z_1 \quad or \quad \alpha(t) = 0 \end{cases} \end{cases} \tag{2.7}$$

$$\begin{cases} if\ e(t) > Y : apply\ HPP\ with\ a\ hedging\ Level\ Z_2 \\ \\ u(x,\alpha) = \begin{cases} U_{\max} & if \quad x(t) < Z_2 \quad and \quad \alpha(t) = 1 \\ d & if \quad x(t) = Z_2 \quad and \quad \alpha(t) = 1 \\ 0 & if \quad x(t) > Z_2 \quad or \quad \alpha(t) = 0 \end{cases} \end{cases} \tag{2.8}$$

Where Z1 ≥ Z2.

Figure 2.2, presents a hypothetical evolution of the finished product inventory level and the way in which EHPP decisions should be taken following equations (2.7) and (2.8).

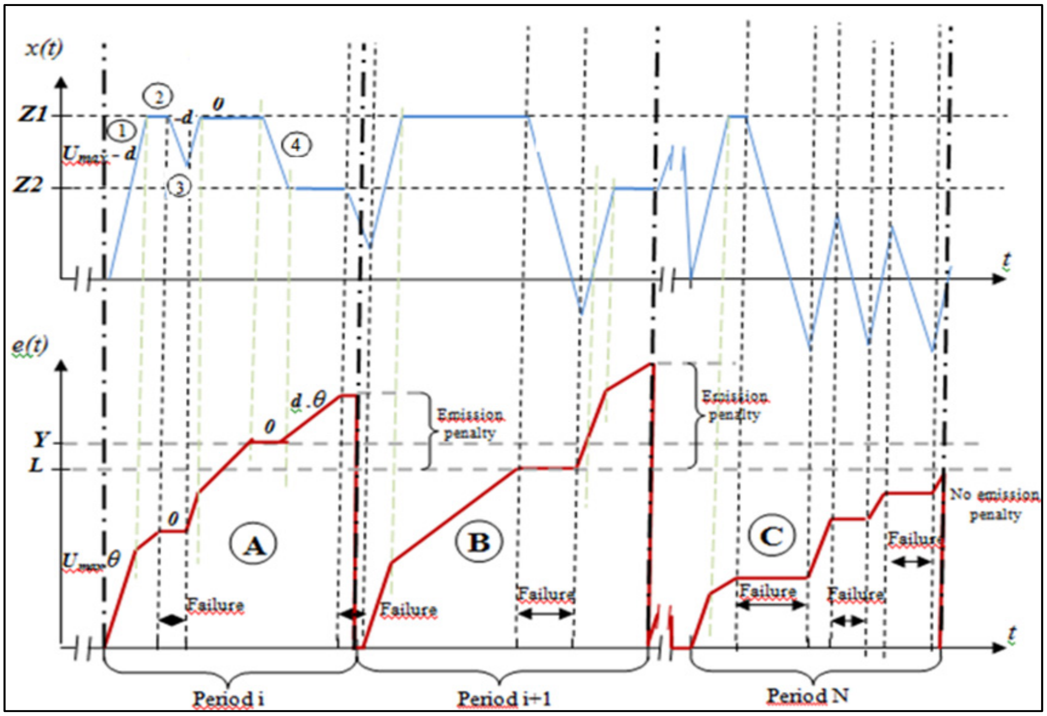


Figure 2.2 Inventory and emission levels evolution under EHPP

①: When producing at a maximum rate, the inventory level *x(t)* rises according to a rate equal to (U_{max} - d); the level of production allows demand to be satisfied, and the remaining products are stocked and used to build the hedging level *Z1*. Given that the emission rate is synchronized with the production rate, the level of the emission rises according to $U_{max} \times \theta$.

②: When *x(t)* reaches *Z1*, the production rate is set to the demand rate *d*, and consequently, the emission rate is decreased to $\dot{e}(t) = d \times \theta$.

③: When a failure event occurs, production processing and emission are stopped (u(t)= 0), and consequently, the inventory level decreases according to (*–d)*, while the emission level remains stable.

Ⓐ and Ⓑ : During a given reference period, the cumulative quantity of emissions may exceed the standard limit *L* set by the relevant authorities. This is the case for periods *i* and *i+1* in Figure 2.2. In such situations, a penalty must be paid for every excess unit of emission. When the emission level exceeds the voluntary limit *Y*, the hedging level becomes *Z2*, which is lower than *Z1* ④. In this case, reaching the security level *Z2* is enough to reduce production, and consequently, the emissions. At the end of each reference period, the emission counter is reset to zero.

Ⓒ : When a failure event occurs, production and emissions are stopped, the inventory level decreases with the possibility of backlogs, as shown for period *N*. In this case, if the emission level is lower than L, no penalty is imposed.

In comparison with the Hedging Point Policy HPP, EHPP allows the manager the ability to adapt the production policy according to environmental and system constraints. In the following sections, the proposed policy is implemented and several experiments and comparative studies are developed to show its effectiveness.

2.3 Resolution approach

2.3.1 Resolution approach steps

To solve the problem and optimize the policies parameters, an experimental approach integrating simulation, design of experiment (DOE) and RSM is adopted as in Berthaut et al. (2011). The main steps of the experimental resolution approach are:

- Step 1: Establishing of the control policies

In section 2.2, the structure of EHPP is presented, analysed and expressed by mathematical equations. Regarding HPP, we refer the reader to Kenne and Gharbi (2000). These policies will govern our simulation models.

- Step 2: Simulation models

  Each simulation model (see Section 3.2) is designed to reflect the system dynamics governed by one of the control policies considered (HPP and EHPP) in order to compare each one to the other. These policies are used as an input to conduct several experiments, and thus evaluate their costs.

- Step 3: Experimental design and response surface methodology

  The experimental design approach defines the number of experiments, the experimental space of the independent variables considered, and the variation extent of each factor. The analysis of variance (ANOVA) is subsequently used to determine the main factors and their interactions which have a significant effect on the cost (dependent variable). Then, the RSM allows us to determine the relationship between the cost and the significant factors. The resulting model is then optimized in order to determine the best combination of factors which minimizes the total cost.

2.3.2 Simulation models

Using the simulation language SIMAN under «ARENA» software, a combined discrete-continuous model is developed with C++ routines. This type of modeling has showed an advantage in terms of shorting simulation run time (Lavoie et al. (2010)). Figure 2.3 illustrates the simulation model diagram under the control policy EHPP. Under the control policy HPP the same diagram illustrates the simulation model, but with $Z_1 = Z_2$.

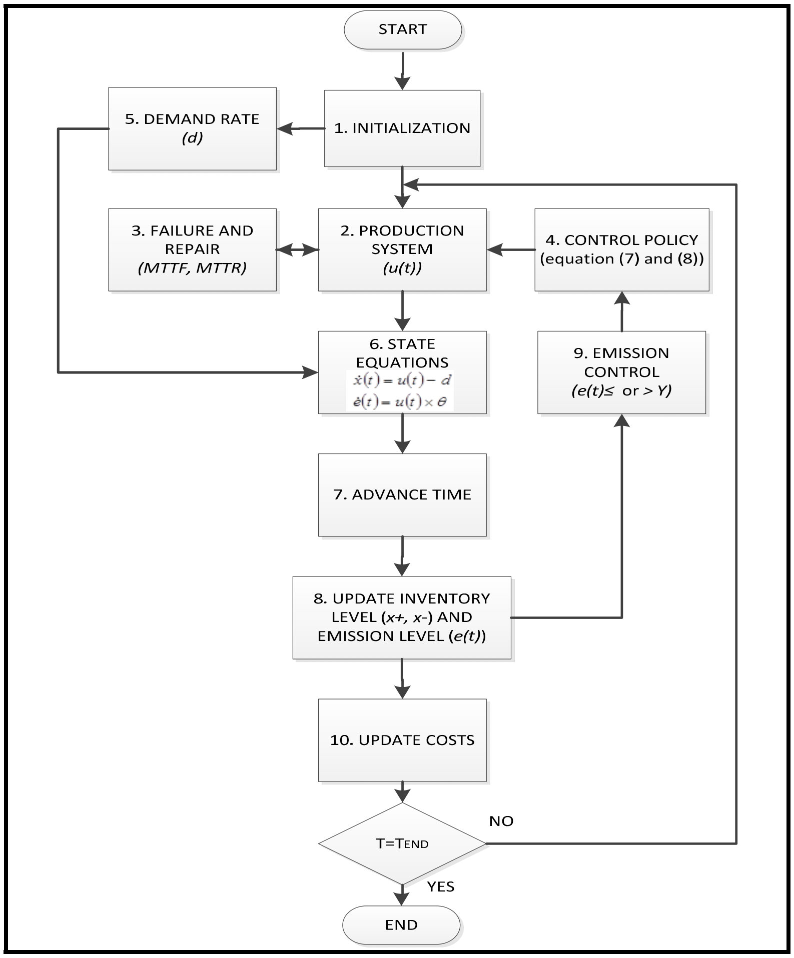


Figure 2.3 Diagram of the simulation model

According to Figure 2.3, after initializing the model with the necessary simulation parameters and inputs (Z, U_{max}, d, simulation time ...) (block 1), the production system (block 2), subject to random failures and repairs activities (block 3), allows to produce according to the control policy (block 4) described by equations (2.7) in order to meet the demand (block 5). The state equations (block 6), which are defined using C++ routines, describe the variation of inventory levels $x(t)$ and the emission levels $e(t)$ according to the equations (1) and (3). The simulation time advance (block 7) and the model updated the level of surplus inventory and the emission level generated (block 8). The control of the emission level, in a reference period i (block 9), allows to check the condition ($e(t) > Y$). When $e(t)$ exceeds the level Y, production control policy (block 4) changes and the system produces according to the equation (2.8). Finally, a calculation of each cost (inventory, backlog, and emission cost) is executed (block 10).

2.4 Numerical examples: Linear emission rate case study

This section uses the resolution approach adopted in order to calculate the optimal total cost and optimal values of parameters defining the control policies. It is followed by a sensitivity analysis and a comparison of the HPP and EHPP. Regarding the emissions aspect, we consider a random emission index θ varying uniformly in a given interval [a, b] as in Chen and Monahan (2010). Table 2.1 summarizes the considered system parameters for the first numerical example.

Table 2.1 Values of the system parameters

Parameters	**d**	**U_{max}**	**MTTF**	**MTTR**		
Values	100	130	Exp (7 TU)	Exp (0.4 TU)		
Parameters	**L**	**C^+**	**C^-**	**C^e**	**P_{er}**	**[a, b]**
Values	650000	1	25	5	5760 TU	[0.5, 2]

2.4.1 RSM model and optimization

Regarding HPP, we use a polynomial regression model in order to optimize its unique parameter (Z) (Kenne and Gharbi, 2000). A polynomial regression is performed using the statistical software STATGRAPHICS. The results of this analysis are presented in Table 2.2.

Table 2.2 Polynomial regression results for HPP

Parameter	*Estimate*	*S. Error*	*T. Statistic*	*P-Value*
CONSTANT	228,676	2,35342	97,1677	0,0000
Z	-0,839675	0,0373857	-22,4598	0,0000
Z^2	0,00479738	0,000134017	35,7969	0,0000

The model which respects the convexity property of the cost function is given by equation (2.9). The results show that the adjusted correlation coefficient R^2_{adjusted} is equal to 98.22%. This means that more than 98% of the observed variability of the expected total cost is explained by the model (Montgomery, 2005). In the same direction, an analysis of the residual normality and of the homogeneity of variance was also carried out to check the conformity of the models.

$$\widehat{Cost}_{HPP} = 228.67 - 0.839675 \times Z + 0.00479738 \times Z^2 \tag{2.9}$$

The minimum total cost is observed at point $Z^* = 87.51$, with a value of $\text{Cost}^*_{\text{HPP}} = 191.93$. On the other hand, for the EHPP policy, we select a full factorial design with 3 factors, at 3 levels each. The full factorial of such a plan is often used because it gives more accurate results since each interaction is estimated separately. Five replications were performed for each combination of factors, meaning therefore that a total of 135 ($3^3 * 5$) simulation experiments were performed. For both simulation models, the simulation length was set to 500.000 units of time. That is long enough to reach the steady state. Regarding the design factors of EHPP, several preliminary simulation experiments were performed to set their levels, as detailed in Table 2.3. To ensure the constraints ($Z_2 \leq Z_1$), a substitute parameter $r = Z_2/Z_1$ is introduced, with $0 \leq r \leq 1$.

Table 2.3 Experimental domain

Factor	*Low*	*Medium*	**High**
Y	600000	725000	850000
Z1	35	67.5	100
r	0.01	0.5	0.99

The effects of independent variables (Z_1, r, Y), their interactions, and their quadratic effect on the response variables (cost) were obtained thanks to a multi-factorial ANOVA. The results of this analysis summarized in Table 2.4 show that all the main factors, their interaction (except ($Y \times Z_1$) and ($Z_1 \times r$)) and their quadratic effects are significant at a 95% level of significance. The adjusted correlation coefficients ($R^2_{adjusted}$) equal to 97.18% show that more than 97% of the variability is explained by the RSM model given by equation (2.10):

$$\widehat{Cost}_{EHPP} = 557.474 - 0.00057944 \times Y - 2.84992 \times Z1 - 89.3766 \times r + 3.3918\ 10^{-10} \times Y^2 + 0.0000989915 \times Y \times r + 0.0162262 \times Z1^2 + 10.0495 \times r^2 \qquad (2.10)$$

Table 2.4 ANOVA results for EHPP

Source	***Sum of Squares***	***Df***	***Mean Square***	***F-Ratio***	***P-Value***	***Signification***
A:Y	2025,92	1	2025,92	167,61	0,0000	S
B:Z_1	41332,0	1	41332,0	3419,43	0,0000	S
C:r	1234,46	1	1234,46	102,13	0,0000	S
AA	843,214	1	843,214	69,76	0,0000	S
AB	17,405	1	17,405	1,44	0,2324	N.S
AC	2205,76	1	2205,76	182,49	0,0000	S
BB	8812,29	1	8812,29	729,05	0,0000	S
BC	25,0528	1	25,0528	2,07	0,1525	N.S
CC	174,661	1	174,661	14,45	0,0002	S
Total error	1510,92	125	12,0874			
Total (corr.)	58181,6	134				

The projections of the cost response surfaces on two-dimensional planes are presented in Figure 2.4:

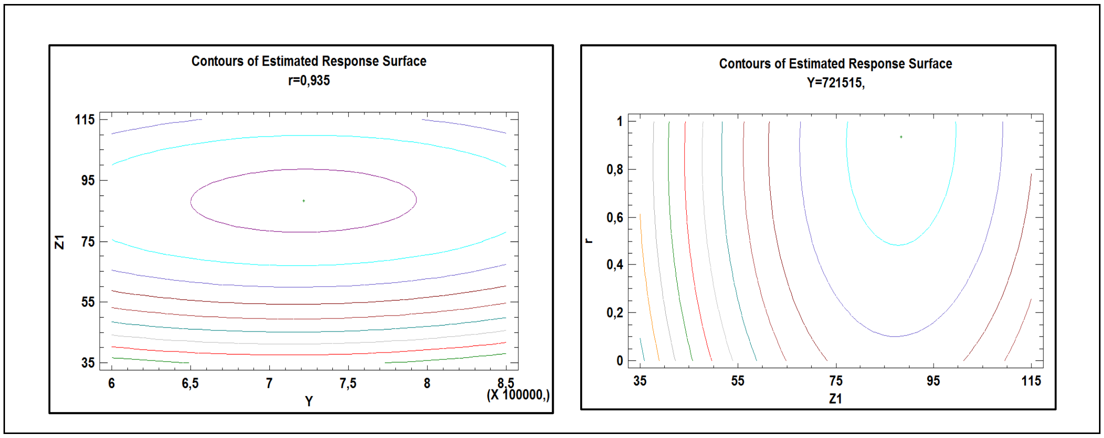


Figure 2.4 Response surfaces contour plots for the total cost

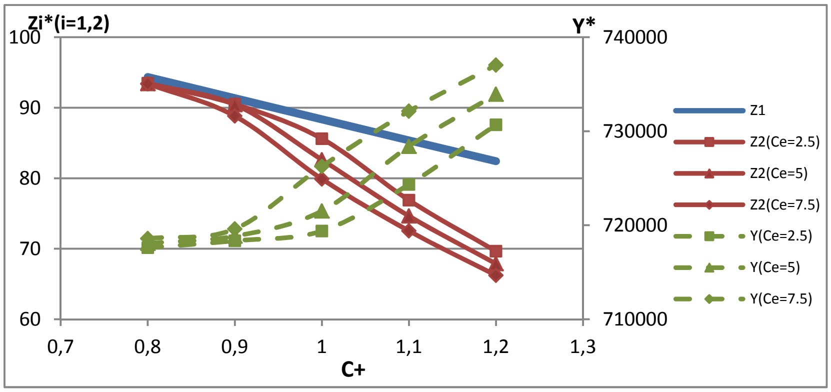
The minimum total cost obtained is equal to $\text{Cost}^*_{\text{EHPP}} = 182.54$ which corresponds to the optimal control parameters, Z1*= 88.35, r*= 0.935 (Z2*= 82.61) and Y*= 721515.

The optimization results obtained for HPP and EHPP show that for selected system parameters (Table 2.1), EHPP is more advantageous in terms of cost than the classical HPP, with a 4.89% reduction. This improvement is mainly due to the ability of EHPP to better control the production rate and the generated emissions such as to arrive to better compromise of costs. To cross-check the validity of the models represented by equations (2.9) and (2.10), we confirm that the optimal cost for each control policy falls within the confidence interval at the 95% level; [181.85, 183.4] and [191.31, 193.37] for EHPP and HPP, respectively.

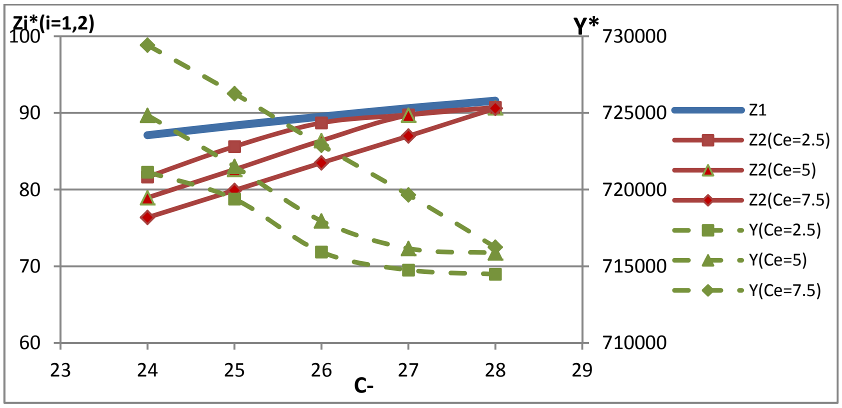
2.4.2 Sensitivity analysis: (C^+, C^- and C^e)

In order to confirm the robustness of the resolution approach employed as well as the advantage of EHPP compared to HPP in different scenarios, an extensive sensitivity analysis was conducted. The results of this analysis are presented in the next subsections.

Figure 2.5 shows the variation of the three design parameters of EHPP when C^+ varies from 0.8 to 1.2 (respectively C^- varies from 24 to 28). When C^+ increases (respectively C- decreases), the system reacts by decreasing the values of the optimal hedging levels. Thus, Z_1 and Z_2 decrease. When C^+ decreases (respectively C- increases), the opposite occurs. The same figure also shows the effects of the “penalty cost for emissions” C^e on the optimal hedging levels. Thus, when C^e decreases, Z_2 tends to approach Z_1. For low values of C^+ (respectively for high values of C^-), this trend is accelerated and Z_2 tends to get too close to Z_1. At the limit, when C^e is negligible, EHPP becomes equal to HPP, given that Z_2 tends to be equal to Z_1.



a: (C^+)



b: (C^-)

Figure 2.5 Variation of Zi*(i=1,2) and Y* when varying C^+, C^- (EHPP)

With respect to the variation of Y in Figure 2.5, we can observe that it is the opposite of that of Z_1 and Z_2. In fact, when the costs (C^+ or C^-) lead to high values of Z_1 and Z_2, it means that the system will produce more at the maximum rate, a situation which leads to more emissions. To limit this increase, the system reacts by reducing the values of Y, leading to an earlier stoppage of production. This reaction is also a function of the “penalty cost for emissions” C^e. From Figure 2.5, we can also observe that when C^e increases, Z_2 decreases, leading to a higher risk of backlogs. Thus, higher values of Y are required to maintain the inventory level longer at Z_1.

Figure 2.6 show that when varying C^e no effect is observed on Z_1. This makes sense since the hedging level Z_1 mainly governs the production rate, and is mostly sensitive to C^+ and C^-. However, the variation of C^e mainly affects the hedging level Z_2. As explained in the last paragraph, when C^e increases, the system reacts by limiting emissions through a reduction of the level of Y from which production is stopped. When C^e decreases, the gap between the two hedging levels is reduced, leading to the classical HPP for negligible C^e.

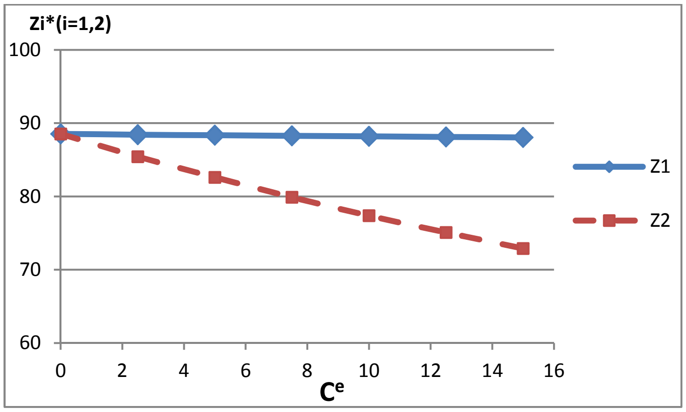


Figure 2.6 Variation of Zi (i=1, 2) when varying C^e (EHPP)

The same sensitivity analysis was conducted for the HPP. In this context, the variations of the design parameter Z when varying the cost parameters are the same as Z_1 for EHPP. It is also interesting to note that for all cases, we observed an average gain equal to 4% for the total cost under EHPP compared to that under HPP.

2.4.3 Improved HPP and EHPP: Production rate optimisation

In the literature of optimal control (see Section 2.2.1), few works consider the maximum production rate as a design parameter to be optimized as in Sana and Chaudhuri (2010) and Giri and Dohi (2005). Whether or not the maximum production rate is considered as a design parameter is directly dependent on whether or not the production rate is penalized in the objective function. In the case of HPP, only inventory and backlog costs are penalized. It is always in the interest of the system to produce at high rates U_{max} in order to quickly reach the security hedging level. Recall that in our case, when emission limit is exceeded, an emission tax is added. This cost indirectly penalizes the production rate, given the relationship (2.3). Thus, we argue that the optimization of the production rate within HPP and the proposed EHPP could improve performance.

In the literature, Jaber et al. (2013) were among the first who considered the production rate as a design parameter to optimize in a context including environmental aspects. However, the problem considered in Jaber et al. (2013) did not take into account the operational activities at the manufacturing level. In this section, we discuss the situation in which the production rate is considered as a decision variable, in addition to the decision variables (Z_1, Z_2 and Y) for EHPP, and Z for HPP.

Considering the same system parameters (see Table 2.1), the maximum production rate should be set to meet the feasibility constraint given by formula (2.11). Thus, the maximum production rate should be at least equal to 105.72, given that the system is available 94.59% of the time, and the demand rate is equal to 100.

$$U_{max} \times \frac{MTTF}{MTTF + MTTR} \geq d \tag{2.11}$$

The experimental domain of the decision variable U_{max} is given in Table 2.5. The improved proposed policies, named HPPU and EHPPU, are represented by the same equations (2.7) and (2.8), but U_{max} should be optimized together with (Z_1, Z_2 and Y).

Table 2.5 Experimental domain of U_{max}*

Factor	**Low**	**Medium**	**High**
U_{max}	110	120	130

Following the same approach (Section 2.4.1), and for the same set of system parameters (Table 2.1), the results obtained showed that the RSM models have very good adjusted correlation coefficients $R^2_{adjusted}$, equal to 98.88% for HPPU and 98.57% for EHPPU. These models are given by equations (2.12) and (2.13) for EHPPU and HPPU, respectively.

$$\begin{aligned}\widehat{Cost}_{EHPPU} = {} & 32569.9 - 0.00025806 \times Y - 33.1701 \times Z1 - 238.334 \times r - 484.796 \\ & \times U_{max} + 0.0000418142 \times Y \times r + 0.00000124433 \times Y \times U_{max} \\ & + 0.0198931 \times Z1^2 + 0.230125 \times Z1 \times U_{max} + 1.4625 \times U_{max} \times r \\ & + 1.8241 \times U_{max}^2\end{aligned} \tag{2.12}$$

$$\begin{aligned}\widehat{Cost}_{HPPU} = {} & 16165.9 - 26.0288 \times Z1 - 235.284 \times U_{max} + 0.0191186 \times Z1^2 \\ & + 0.17877 \times Z1 \times U_{max} + 0.868991 \times U_{max}^2\end{aligned} \tag{2.13}$$

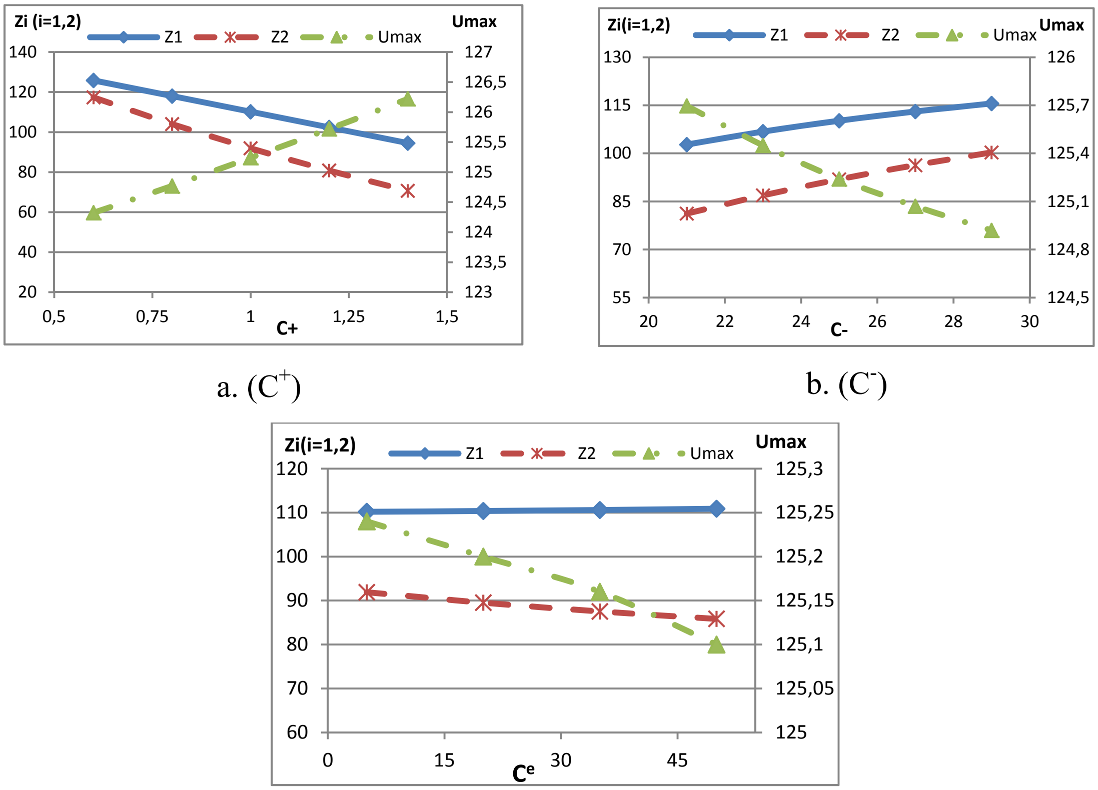
Table 2.6 gives the optimal design parameters and costs for HPPU and EHPPU. The results obtained clearly show a marked improvement. The production rate optimization led to an average cost reduction equal to 18.9% and 21.9% compared to HPP and EHPP, respectively (see Section 2.4.1). In conclusion, the EHPPU policy is the best policy to consider in our case.

Table 2.6 Optimization results for HPPU and EHPPU

Model	**Z_1**	**Z_2**	**Y**	**U_{max}**	**Total cost ***	**Confidence interval (95%)**
HPPU	92.06	-	-	125.91	155.65	[155.22, 156.42]
EHPPU	110.18	91.9	1061520	125.24	142.57	[141.86, 143.07]

2.4.4 Sensitivity analysis

In Section 2.4.2, we studied the effect of the holding and backlog costs on the critical thresholds (Z1 and Z2). In the same vein, from Figure 2.7a and 2.7b, we note that when the parameter C^+ increases (respectively C^- decreases), Z1 and Z2 decrease. Thus, the maximum production rate increases because a high production rate allows to quickly build the comfortable thresholds. Regarding the emissions, the increase in Z1 and Z2 increase the emissions (see Section 2.4.2), and consequently, the production rate decreases in order to limit this increase.



a. (C^+)

b. (C^-)

c. (C^e)

Figure 2.7 Variation of Zi* (i=1, 2) and U_{max}* when varying C^+, C^-, C^e (EHPPU)

Regarding the penalty cost, Figure 2.7c shows that the optimal production rate decreases when C^e increases, leading to a decrease in the emission rate. This result, together with the explanation of Figures 2.7a and 2.7b, can be supported by the fact that the system must adjust its maximum production rate to avoid exceeding the permitted emission level.

2.5 Numerical example: Nonlinear emission rate case study

In the previous sections, we considered a linear relationship between the emission and the production rates. This assumption could be unrealistic in some practical situations. Consequently, the exploration of other modes of emissions seems appropriate in order to study the robustness of the proposed policies.

In the literature, Jaber et al. (2013) adopted a quadratic expression given by Bogaschewsky (1995) to describe the relationship between the emission rate and the production rate.

In our case, we propose a more general expression which gives more flexibility to the emission model. This expression is given by equation (2.14):

$$\dot{e}(t) = \theta \times [u(t) + e^{k(u(t)-d)}] \tag{2.14}$$

Where k is a given parameter allowing the adjustment of the shape of the relationship. Note that k and θ are two parameters characterizing the manufacturing system and can be found based on its history. Figure 2.8 illustrates the emission rate as a function of the production rate under equation (2.14) for different values of k and a fixed value of θ =1.1.

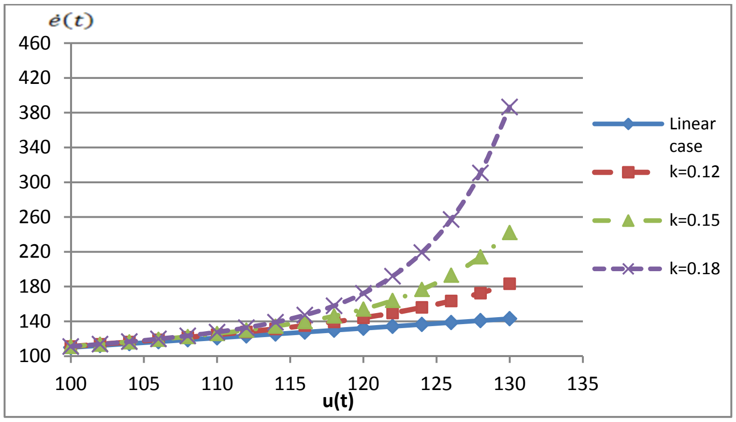


Figure 2.8 Emission rate evolution function of the production rate

Using the exponential form leads to study the case where the emission rate increases in a more pronounced way as the production rate increases. We use the same simulation model, and introduce the new relationship between $\dot{e}(t)$ and *u(t)*. For k=0.15 and θ =1.1, the results show that the EHPP is better than the classical HPP in terms of incurred total cost. The average value of the gain remains around 4% as in the case of a linear emission rate.

Recall that the optimization of the production rate, in the case of a linear relationship between $\dot{e}(t)$ and $u(t)$, accentuates the gain in EHPPU and HPPU as compared to EHPP and HPP. When the relationship between $u(t)$ and $\dot{e}(t)$ is exponential, our experimental results show that the economic gain provided by the optimization of U_{max} is much more significant compared to the case of a linear emission rate. Indeed, for k=0.15, the improvements in HPPU and EHPPU compared to HPP and EHPP are more than 22% and 29%, respectively. This result is clearly logical since the penalization of the production rate by the penalty cost (C^e) is very strong in the case of an exponential relationship.

2.5.1 Effect of the trajectory of the emission rate

The parameter k in equation (2.14) measures the intensity of the relationship between $\dot{e}(t)$ and $u(t)$. At this point, it is interesting to note that the effect of the variation of k on the variables defining the control policies is the same as that of the cost parameter C^e. This is explained by the fact that the variation of these two parameters (k and C^e) has the same consequences on the total emission cost. Indeed, if k increases, the emission quantity increases, and consequently, the total emission cost increases. Similarly, increasing C^e also leads to an increase of the total emission cost.

From Table 2.7, it is important to note that the gain of HPPU and EHPPU compared to HPP and EHPP, respectively, is accentuated when k increases. In fact, with higher emission quantities, the production rate is greatly penalized. Therefore, the optimization of $u(t)$ becomes more profitable.

The key observation in this section is that the new policy, EHPPU, is the best policy and shows its advantage compared to the classical HPP with an economic gain of more than 46% in some cases (k = 0.18).

Table 2.7 Effect of the variation of k on the total costs of policies

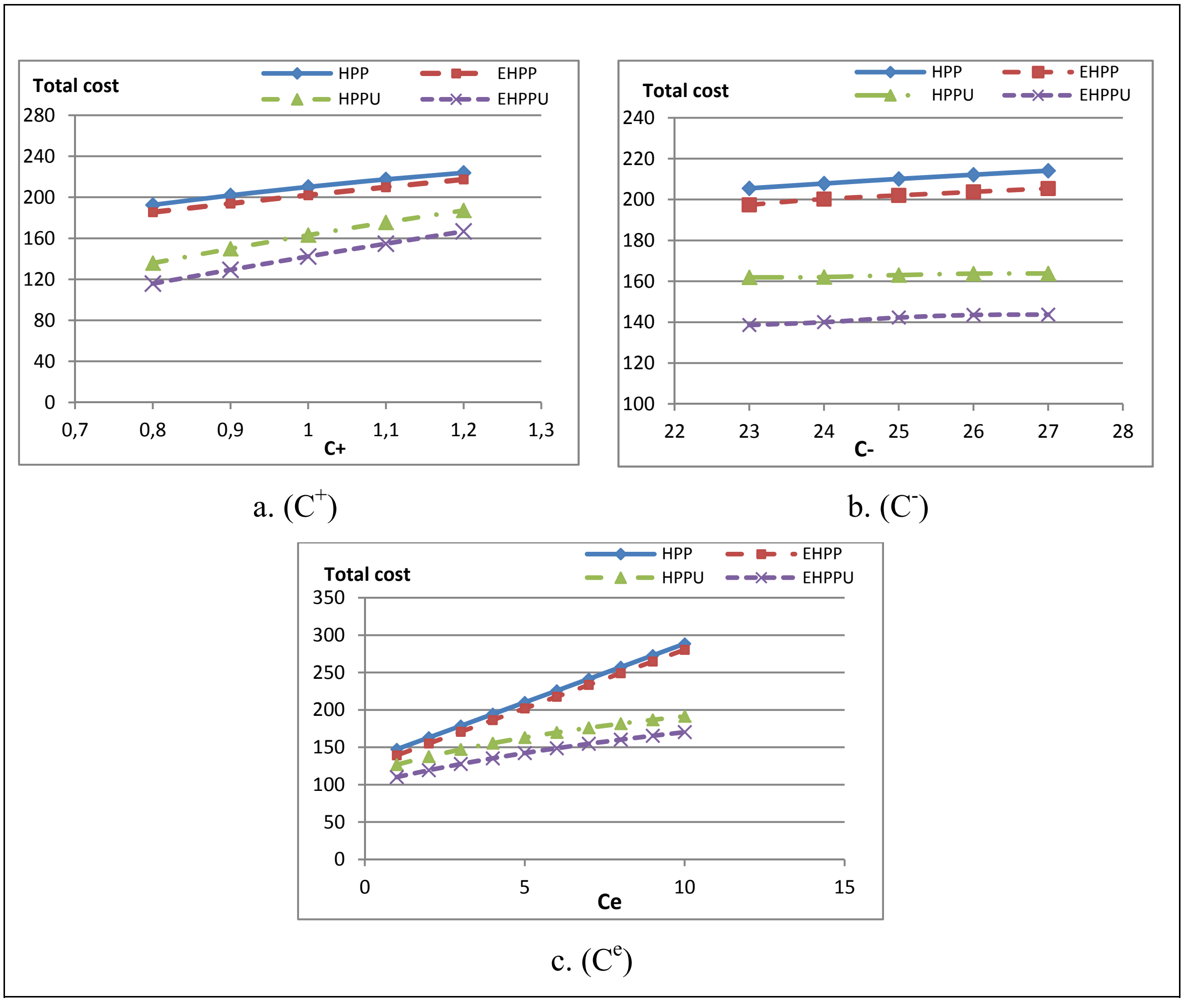
	HPP	HPPU		EHPP	EHPPU	
K	**Cost***	**Cost***	**Gain/HPP**	**Cost***	**Cost***	**Gain/HPP**
0.12	157.66	129.74	17.71%	150.45	116.71	25.97%
0.15	210.08	163.06	22.38%	202.03	142.28	32.27%
0.18	339.01	197.37	41.78%	329.32	179.72	46.98%

2.5.2 Influence of cost parameters on the control policies

In this section, a comprehensive study of the influence of cost parameters on the total incurred cost of the control policies is performed. The main objective is to identify and analyze the evolution of these policies compared to one another in the case of an exponential emission rate.

From Figure 2.9a (respectively Figure 2.9b), when C^+ decreases (respectively C- increases), the difference between the policies (HPP, HPPU) and between (EHPP, EHPPU) increases because the production threshold Zi* (i=1,2) increase. Thus, the system produces more at U_{max} for (HPP, EHPP) and more at U_{max}* (≤ U_{max}) in the case of (HPPU, EHPPU). As a result, the optimization of the production rate becomes more interesting. An opposite effect is observed when increasing C^+ (respectively C^- decreases).

From Figure 2.9c, when increasing C^e, the advantage of the production rate optimization increases, leading to a higher difference in total cost between (HPP, HPPU) and between (EHPP, EHPPU).



a. (C^+) b. (C^-)

c. (C^e)

Figure 2.9 Variation of total costs of policies

Note that the same results were observed in the case of a linear emission rate, except that the gap between the costs of policies is accentuated when the emission rate is exponential.

2.6 Conclusion

In this paper, a new control policy called the Environmental Hedging Point Policy (EHPP), characterized by two hedging levels and the voluntary emission limit, which integrates environmental concerns in the production rate control of unreliable manufacturing systems, is proposed. The results obtained show that EHPP is more advantageous in terms of incurred costs compared to the classical HPP, with an average gain of around 4%. To ensure the effectiveness of the proposal, several sensitivity analyses are conducted. To enhance the obtained gain, an improved version of EHPP, called EHPPU, which optimizes the maximum production rate, is proposed. As expected, this control policy improved the incurred total cost compared to EHPP, with an average gain of around 20%. The gain of EHPPU reaches 46% compared to HPP when the emission rate evolves exponentially with respect to the production rate.

In conclusion, in a context where the relevant authorities are becoming increasingly strict about manufacturing facility operations generating harmful emissions to the environment, the proposed policies give managers valuable feedback adaptive strategies for a better control of the production rate and the emissions generated, as well as a better cost compromise.

Considered among the first works treating this type of problem in a complex environment of manufacturing systems, this work will have a significant impact on future studies in this context. Indeed, several aspects can be addressed in the next work by integrating maintenance, quality, etc.

References

Ayed, S., Dellagi, S., Rezg, N., 2012. Joint optimisation of maintenance and production policies considering random demand and variable production rate. International Journal of Production Research, 50 (23), 6870–6885.

Bai, S.X. and Elhafsi, M., 1997. Scheduling of an unreliable manufacturing system with non-resumable set-ups. Computers Ind. Eng., 32, 909-925.

Berthaut, F., Gharbi, A., Dhouib, K., 2011. Joint modified block replacement and production/inventory control policy for a failure-prone manufacturing cell. Omega, 39, 642-654.

Bonney, M. Jaber, M.J., 2011. Environmentally responsible inventory models: Non-classical models for a non-classical era. International Journal of Production Economics, 133 (1), 43–53.

Bogaschewsky, R., 1995. Natürliche Umwelt und Produktion [Natural Environment and Production]. Wiesbaden: Gabler-Verlag.

Bouslah, B., Gharbi, A., Pellerin, R., 2013. Joint optimal lot sizing and production control policy in an unreliable and imperfect manufacturing system. Int. J. Production Economics, 144, 143-156.

Brandenburg, M., Govindan, K., Sarkis, J., & Seuring, S., 2014. Quantitative models for sustainable supply chain management: Developments and directions. European Journal of Operational Research, 233(2), 299-312.

Brouhle, K., Griffiths, C., Wolverton, A., 2009. Evaluating the role of EPA policy levers: An examination of a voluntary program and regulatory threat in the metal-finishing industry. Journal of Environmental Economics and Management, 57, 166–181.

Chen, C. and Monahan, G.E., 2010. Environmental safety stock: The impacts of regulatory and voluntary control policies on production planning, inventory control, and environmental performance. European Journal of Operational Research, 207, 1280–1292.

Gharbi, A., Kenne, J.P., Hajji, A., 2006. Operational level-based policies in production rate control of unreliable manufacturing systems with setups. International Journal of Production Research, 44 (3), 545–567.

Gharbi, A., A. Hajji, and K. Dhouib. 2011. Production Rate Control of an Unreliable Manufacturing Cell with Adjustable Capacity. International Journal of Production Research 49 (21): 6539–6557.

Giri, B. and Dohi, T., 2005. Computational aspects of an extended EMQ model with variable production rate. Computers & Operations Research, 32(12), 3143–3161.

Hajji, A., Gharbi, A., Kenne, J.P., 2009. Joint Replenishment and Manufacturing Activities Control in a Two Stage Unreliable Supply Chain. International Journal of Production Research, 47 (12), 3231–3251.

Hajji, A., Gharbi, A., Kenne, J.P., Pellerin, R., 2011. Production control and replenishment strategy with multiple suppliers. European Journal of Operational Research, 208, 67–74.

Jaber, M.Y., Glock C.H., El Saadany A.M.A., 2013. Supply chain coordination with emissions reduction incentives. International Journal of Production Research, 51 (1), 69–82.

Kenne, J. P., & Gharbi, A., 2000. Production planning problem in manufacturing systems with general failure and repair time distributions. Production Planning & Control, 11(6), 581-588.

Lavoie, P., Gharbi, A. and Kenne, J.-P., 2010. A comparative study of pull control mechanisms for unreliable homogenous transfer lines. International Journal of Production Economics, 124 (1), 241-251.

Lee W.L. and Yik, F.W.H., 2004. Regulatory and voluntary approaches for enhancing building energy efficiency. Progress in Energy and Combustion Science, 30, 477–499.

Marcus, P.A. and Willig, J.T., 1997. Moving Ahead with ISO 14000: Improving Environmental Management and Advancing Sustainable Development. John Wiley & Sons, New York.

Montgomery, D.C., 2005. Design and analysis of experiments. New York: John Wiley & Sons.

Porter, M.E. and Van der Linde, C., 1995. Green and competitive: Ending the stalemate. Harvard Business Review, 73 (5), 120–134.

Radhoui, M., Rezg, N., Chelbi, A., 2009. Integrated model of preventive maintenance, quality control and buffer sizing for unreliable and imperfect production systems, International Journal of Production Research, 47 (2), 389–402.

Rezg N, Chelbi A, Xie X., 2005. Modeling and optimizing a joint inventory control and preventive maintenance strategy for a randomly failing production unit: analytical and simulation approaches. International Journal of Computer Integrated Manufacturing, 18(2-3), 225–35.

Sana, S. S. and Chaudhuri, K., 2010. An EMQ model in an imperfect production process. International Journal of Systems Science, 41(6), 635–646.

Simonet, E. 2003. Les Systèmes De Management Environnemental – Synthèse [The Environmental Management Systems – Summary]. Association LaPlateforme [The Platforme Association]. Accessed February 20, 2014. www.Laplateforme.org.

CHAPITRE 3

ARTICLE 2: ENVIRONMENTAL ISSUE IN AN ALTERNATIVE PRODUCTION-MAINTENANCE CONTROL FOR UNRELIABLE MANUFACTURING SYSTEM SUBJECT TO DEGRADATION

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Abstract: This article addresses the problem of joint production, maintenance and emissions control for an unreliable manufacturing system subject to degradation. The manufacturing system is composed of a production unit producing one product type. The production operations generate harmful emissions to the environment and may be sanctioned by an environmental penalty imposed by the relevant authorities under the emission cap approach. Due to degradation phenomena, the availability of the machine decreases and the emission rate increases continuously over time. This paper aims to propose a feedback strategy to simultaneously control production rate, emission rate as well as maintenance rate in order to mitigate the effect of the degradation of the system. The objective is to minimize the total cost over an infinite horizon. In this article, we propose three different control policies HPP1, HPP2 and HPP3, which are analyzed and compared. Each control policy is characterized by a production and/or maintenance strategy different from the others policies, with or without the consideration of the emission aspect in the structure of the policy. An experimental resolution approach based on experimental design, simulation and response surface methodology is applied in order to determine the optimal control policies parameters. The results show that the proposed HPP3, which integrates the emission control in the production and maintenance strategy, gives a significant gain in term of total cost compared to HPP1 and HPP2. In addition, we integrate a preventive maintenance strategy to HPP3 in order to investigate a more general case. To illustrate the robustness of the proposed policies, several sensitivity analysis are presented to show the effect of system parameters on the structures of each policy. This analysis allows defining an overhaul and a preventive maintenance zones from the interactions between the parameters of HPP3.

Keywords: unreliable manufacturing system, degradation, emission, experimental approach, production, overhaul, preventive maintenance.

3.1 Introduction

The domain of manufacturing systems has undergone several changes over the years. Lately, in addition to economic requirements, social and environmental aspects are increasingly present. Production planning and control is among the topics that have received the attention of many researchers (Fernandes et al. 2009, Mckay 2003).

A detailed review of the literature shows that the problem of production control has been considered by several authors. A significant branch of research has formulated the problem as an optimal control model based on the work of Kimemia and Gershwin (1983). They suggested a retroactive formulation of the control problem for a flexible manufacturing system. Policy founded had a specific structure called Hedging Point Policy (HPP) whose purpose is to control the production rate based on inventory level taking into account the state of the system. In the same direction, Akella and Kumar (1986) have succeeded in developing the analytical solution of the problem for a single machine producing a single type of product. Motivated by this work, many extensions have been developed in this area of research addressing the management of production planning from different perspectives. Caramanis and Sharifnia (1991) have increased the complexity by studying a multiple-part-type problem. A number of studies extended the control problem to investigate the maintenance of production unit (Berthaut et al. (2011), Chelbi and Ait-Kadi (2004)). Sethi and Zhang (1999), Bai and Elhafsi (1997) and Gharbi et al. (2006) considered the setup (cost and / or time) in the optimization of stochastic control problems. Other works focused on the reliability of suppliers in the supply chain such as Hajji et al (2009, 2011) and Parlar and Perry (1995). Radhoui et al (2009) and Rivera-Gómez et al. (2013a, 2013b) discussed the interaction between quality, maintenance and production control. In the context of flexible capacity, another study was developed by Gharbi et al. (2011); the authors treated the case of a production system consisting on a central machine which, in the case of a lack of capacity, has to use a reserve machine to meet the demand.

Despite the diversity of all these research studies, the environmental aspect (industrial discharges, pollutant emissions ...) and its influence on the production and maintenance planning in a dynamic stochastic context is not yet largely studied. However, in practice, the major problem for companies is to minimize costs through the best management of their production system and at the same time meets the environmental requirements regulated increasingly by the majority of industrialized countries. Today, for example, the consideration of harmful emissions in the industry represents a great ambiguity. Given the lack and the great need to focus on introducing the constraints dictated by the environmental requirements in the management of manufacturing systems, some researchers have begun to get closer to the industrial environment addressing a complex and practices issues. A series of contributions of Dobos (1998, 1999, 2001) has been developed to determine the effect of environmental policy on production and inventory decisions. All these studies are based on a mathematical formalism in order to determine the environmental policy in the context of environment control approaches: taxes, emission penalty or trading permits. In these works, the author considers a production system which meets a demand rate. The control and state variables are the production rate and inventory level, respectively, in order to minimize the total cost function. Based on this work, Li and Gu (2012) compared the production-inventory control policy with and without the environmental requirements. Later, Li (2013) has introduced quality issue in the context of trading permit. On the other side, some studies have introduced the environment aspect in the economic order quantity EOQ model (Battini et al. (2014); Bouchery et al. (2012)). Chen et al. (2013) proposed an EOQ model considering emissions. Using an analytical approach, they provided the conditions in which the relative emission reduction is greater than the relative cost increase. Moreover, a few numbers of authors has studied the interaction between maintenance planning and environmental issue. Among these, Li (2014) proposed an alternative production-maintenance policy with deteriorating items with the consideration of an emission tax and pollution R&D investment. Chouikhi et al. (2012) considered a production system subject to failures which can cause demand backlog and have a negative effect on the environment. They determined the optimal maintenance period in order to optimize the maintenance cost and reduce environment discharges.

While all these papers study the effect of introducing the environmental aspect in the production and /or maintenance planning, to the best of our knowledge, no study has addressed the phenomena related to the equipment that may affect the emissions as the degradation in the context of production and maintenance control.

In an industrial environment, manufacturing systems are always subject to a gradual degradation over the time due mainly to the use of the system or a lack to make perfect maintenance activities (reset the system as good as new after corrective or preventive maintenance). In the literature, the manufacturing systems subject to gradual degradation over time has attracted the attention of many researchers. Based on the fact that machine availability decreases over time (Dhouib et al. 2008), different approaches have been developed to find a relationship between the availability and degradation of manufacturing equipment. More specifically, several studies have modeled the degradation of the machine considering the number of failure as an indicator of the degradation state (Lam (2004), Deyahem et al. (2011), Rivera-Gómez et al. (2013a)). Another approach consists on the use of the age of the machine to characterize degradation. In this sense, Love et al (2000) formulated the problem of a manufacturing system with a repair/replacement policy. They considered that corrective action can reduce partially the state of degradation. Recently, Rivera-Gómez et al. (2013b) have established a relationship between the quality and the degradation of a production system that can produce non-conforming parts. The authors presented the rejection rate based on the level of the equipment degradation. By referring to the latter work, the degradation phenomenon affects the performance and effectiveness of the system. Note that degradation has an impact on the availability of the system (Deyahem et al. (2009, 2011)) and even on the quality of products (Rivera- Gómez et al. 2013a, 2013b), thus, we can assume that this degradation can have an effect on emissions generated by the production unit.

Actually, consideration of environmental issues at the operational level of decision-making is relatively new in the literature. Despite the existence of some progression, the interaction of the environmental aspects together with the increasing complexity and dynamic behaviour of manufacturing systems (degradation, maintenance...) is still an open subject in the scientific literature. In the same way, even international standards, such as ISO14000, provide targets and general objectives to achieve in term of environmental management but without too much detail on the operational level (Chen and Monahan, 2010). Hence, we need to expand our understanding of various phenomena that can influence the process of decision making. This paper aims to propose a new control policy that takes into account simultaneously the production and maintenance control of a manufacturing system which generates emissions. We will focus on the interaction between environmental issue and machine deterioration in a stochastic dynamic context. The problem is to determine the joint production, witch integrate emission, and overhaul policy that minimizes the incurred total cost: inventory, backlog, emission and maintenance cost.

The rest of the paper is organized as follows. In section 3.2, the description of the system under study and the formulation of the control problem are defined. The proposed control policies are presented in section 3.3. Sections 3.4 and 3.5 present, respectively, the resolution approach and the simulation model developed. A numerical example is illustrated in section 3.6, and sensitivity analysis is presented for various system parameters. In section 3.7, we propose an extension of HPP3 by considering a preventive maintenance policy. Conclusions are given in Section 3.8.

3.2 Problème formulation

3.2.1 Description of the manufacturing system

The manufacturing system under study consists on a single manufacturing facility subject to random failures, repairs and maintenance activities, which produces to meet the constant demand of a single product type. Among the characteristics of the manufacturing system under study, harmful emissions are generated during the production. We consider that the production of one item causes the release of a quantity of pollutant θ called emission index. The purpose of the production facility is to provide goods in order to satisfy the customer demand while respecting the environment requirements. Among these requirements, the emission cap approach where authorities can impose a standard emission limit L per period i and at each exceeding of L, a penalty should be paid for each emission unit (Chen and Monahan, 2010).

Figure 3.1 presents the manufacturing system considered:

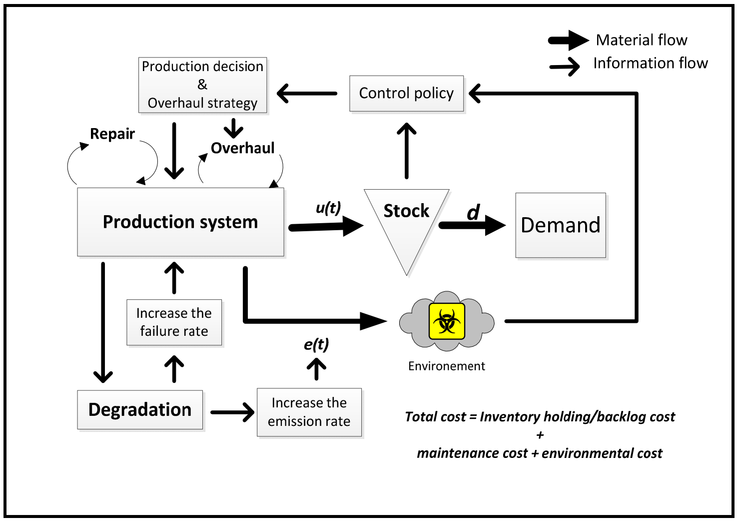


Figure 3.1 Manufacturing system under study

We note that the production system degrades progressively over time which decreases its availability. We consider also that the degradation affects the emission rate $\dot{e}(t)$. In fact, many industries are facing this type of problem. We can take the example of the chemical or pharmaceutical industry; purification facility (Zhang and al., 2011) or filters (e.g. activated carbon filters) are used for the treatment of gases before emitting into the environment (Przepiórski (2006)). The principle of these filters consists on pollutant absorption to reduce the concentration of hazardous gases. However, their absorption characteristic decreases with the use over time. As result of this filter degradation, the emission rate increases. More specially, for carbon filters, when carbon is saturated (not able to absorb pollutants), the filter becomes inefficient, and a maintenance operation is required. At this level, we consider that maintenance activities are necessary to reduce the effects of degradation. Overhaul operation is a long and costly action which completely restores the machine (reliability and emission rate), to the initial conditions (as good as new AGAN). In the other hand, the corrective maintenance operation CM; less expensive, make the machine return to produce after the failure, but without any effect on its degradation (as bad as old ABAO). For a more general case, preventive maintenance PM can be defined between these two extreme maintenances (CM and overhaul) as an activity that reduces proportionally the degradation of the machine. For a more general case, preventive maintenance PM can be defined between these two extreme maintenances (CM and overhaul) as an activity that reduces proportionally the degradation of the machine.

3.2.2 Control problem formulation

3.2.2.1 Problem statement

The manufacturing system studied is subject to random events (failures and repair duration) and maintenance activities. Therefore, the system evolves through three discrete modes according to continuous time discrete state stochastic process described by the random variable $\{\xi(t), t > 0\}$; the machine is available when $\xi(t) = 1$, it produces items and generates emissions. However, when the machine is down $\xi(t) = 2$, a corrective maintenance CM operation is carried out. This type of minimal repair restores the system to the same state as before failure (ABAO as-bad-as-old) since the CM has no influence on the degradation state of the system. Then the emission and the failure rate remain at the same values as before repair. When ξ(t)=3, perfect maintenance (overhaul) restores the degradation effects and makes the system as new (as-good-as-new (AGAN)). After overhaul, the system parameters θ and q_{12} are returned to their initial values. During the maintenance operations, the manufacturing system doesn't emit pollutant since the production has been stopped.

We define q_{ij} *(.)* as the transition rate from the state i to j, i ≠ j; i, j = {1, 2, 3}, ω_0 (.) a decision variable which controls the transition to the overhaul, ω_0 (.) = q_{13}. We assume that the transition to overhaul can be done only if the machine is operational (ξ (t) = 1).
Let *u(t)* denote the production rate and *d* the constant demand rate at time t. The production rate, at any instant, must satisfy the capacity constraint of the machine given by the following equation:

$$0 \leq u(t) \leq U_{max} \tag{3.1}$$

Where U_{max} is the maximum production rate.

The dynamics of the production surplus can be presented by the differential equation (3.2):

$$\dot{x}(t) = u(t) - d\ ,\ x(0)=x_0 \tag{3.2}$$

Where *x(t)* denote the inventory level and x_0 its initial value.

We define the age *a(t)* as the number of products which characterize the machine's history by an increasing function of the production rate since the last operational state of the machine. The cumulative age is presented by the differential equation (3.3):

$$\dot{a}(t) = k_1 \times u(t),\ a(t_r) = 0 \tag{3.3}$$

Where t_r represents the last restart time of the machine after an overhaul, k_1 is a given positive constant.

The emission rate $e(t)$ can be defined by equation (3.4):

$$\dot{e}(t) = u(t) \times \theta(a), \quad t \in [t_i, t_{i+1}[, e(t_i) = 0, i = 0,..,\infty, \tag{3.4}$$

Where $\theta(a)$ is the emission index (units of emission / unit produced) which is defined in our problem as a function of the age of the machine $a(t)$. Under the emission penalty approach, in each reference period i, if the quantity of emissions exceeds a standard limit L fixed by the relevant authorities, the excess quantity is penalized with an environmental cost. At the end of the reference period i, the emission counter is reset to zero.

3.2.2.2 Degradation model

The literature shows that several degradation models were used. In our case, we assume that the machine availability decreases (the failure rate q_{12} increases) due to degradation. The failure rate of the machine can be expressed by the following expression:

$$q_{12}(a) = q_1 + q_2\,(1 - e^{-k_2 \frac{a(t)^3}{k_3}}) \tag{3.5}$$

The failure rate of the machine is an increasing function of the age. Note that q_1 is the value of q_{12} at the initial conditions, q_2 is the limit considered of deterioration, k_2 ($0 \leq k_2 \leq 1$) is an adjustment parameter of the failure rate and k_3 is a positive given constant. The key idea is to relate the failure rate to the age. Initially, when $a(t) = 0$, the machine breaks down with rate $q_{12}(a) = q_1$. Increasing the age, failure becomes more frequent ($q_{12}(a)$). Ultimately, at an advanced age, the failure rate reaches its maximum value $q_{12} = q_1 + q_2$.

These article lead to found a relationship between the age of the machine and the emissions index. In this way, the emission index is defined as an increasing function of the age of the machine. This relationship can be expressed by the following formula:

$$\theta(a) = \theta_0 \times e^{k_4 \alpha\, a(t)} \tag{3.6}$$

Where θ_0 the value of θ at the initial conditions, α an adjustment parameter of the emission index ($0 \leq \alpha \leq 1$) and k_4 a positive given constant.

Figure 3.2 shows the trajectory of the emission index and the failure rate as function of the age for different value of α and k_2, respectively:

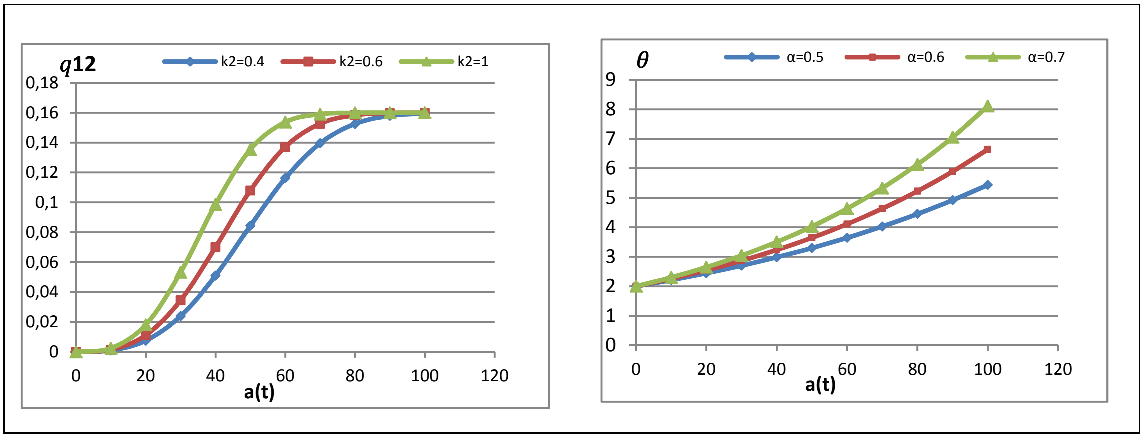


Figure 3.2 Effect of the degradation

3.3 Cost function and control policy

3.3.1 Cost function

The instantaneous inventory, backlog and maintenance cost function g(.) is given by the following equation:

$$g(x(t)) = C^{+}x^{+} + C^{-}x^{-} + C_{\mathrm{Cor}}.\mathrm{Ind}\{\xi(\mathrm{t}) = 2\} + C_{Over}.\mathrm{Ind}\{\xi(\mathrm{t}) = 3\} \tag{3.7}$$

Where $x^{+}= max\ (0,\ x)$, $x^{-}= max\ (-x,\ 0)$, C^{+} and C^{-} are positive constants used to penalize, respectively, the positive inventory and backlog. C_{cor} and C_{over} represent the CM and overhaul cost, respectively.

The penalty emission cost at the end of reference periods *i* is given by the following equation:

$$EC(t_i) = C^{e} \times \max(0, e(t_i) - L), i = 0,..,\infty \tag{3.8}$$

Using (3.7) and (3.8), the total cost function *J(.)* can be defined by the following equation:

$$J(x,e,\alpha,a) = \int_{0}^{\infty} e^{-\rho t} g(x(t))dt + \sum_{i=1}^{\infty} C^{e} \times \max(0, e(t_i) - L) \tag{3.9}$$

The decision variables for this problem are (u^*, ω_0^*). The objective is to minimize the cost function (3.9) and simultaneously define the production and overhaul rates, as a function of the state of the system, the inventory level, the emission level and the age of the machine.

3.3.2 Proposed control policies

In this section, we present three joint production and overhaul policies. First, the equations defining the policies are presented. Then, we explain the structure of each policy through its parameters and present the reasons for proposing these control policies:

- HPP1 policy: over time, the manufacturing system production is controlled by a buffer stock control policy inspired from the well-known hedging point policy. The production policy is defined by the following equation:

$$u(t) = \begin{cases} U_{\max} & if \quad x < Z1 \\ d & if \quad x = Z1 \\ 0 & if \quad x > Z1 \end{cases} \tag{3.10}$$

The manufacturing system is controlled over time by a classical Hedging Point Policy (HPP), as presented in the equation (3.10) where Z1 is the buffer stock capacity. The objective is to control the production rate depending on the inventory level and taking into account only the system state. This policy (HPP) allows better production control for unreliable manufacturing system in addition to the ease of implementation. For more details about this policy, we suggest the reader to consult the work of Akella and Kumar (1986).

The overhaul policy is defined by the following equation:

$$\omega_0(.) = \begin{cases} 1 & if \quad a(t) > Ca \\ 0 & else \end{cases} \tag{3.11}$$

Where *Ca* denotes the critical age level at which an overhaul is required. The overhaul policy consists in doing the major repair only when the age of the machine reaches a critical value *Ca*. Recall that the machine is subject to degradation that affects not only the failure rate, but also the emission rate. The idea is to eliminate the effect of this degradation when the age of the machine reaches a critical value as in Rivera-Gómez et al. (2013b).

- HPP2 policy: for HPP2, we kept the same structure of the production policy which is presented in equation (3.10). However, the overhaul policy is different as presented in the following equation:

$$\omega_0(.) = \begin{cases} 1 & if \quad a(t) > Ca \quad and \quad x(t) \geq Xs \\ 0 & else \end{cases} \tag{3.12}$$

Where $Xs \leq Z1$.

Compared to HPP1, in the second policy (HPP2), the overhaul activity requires the presence of a comfortable inventory level *Xs*, otherwise overhaul is delayed until the inventory level exceeds the value *Xs*. Recall that the overhaul needs a high duration which increases the risk of backlog. The level *Xs* is defined as a safety stock in order to avoid additional backlog cost. In the same direction, several studies have proposed a maintenance strategies governed by inventory levels (Berthaut et al. (2010), Dhouib et al. 2012). The aim of this second policy is to improve the overhaul policy compared to HPP1.

- HPP3 policy: in the previous section, the production control policy described in equation (3.10) is the classical HPP. This policy control the production rate according to only the inventory level *x(t)*. However, in the context environment control and protection, the manager should take into account the emission aspect in the production and maintenance planning. Thus, we consider that an adapted emission control level is beyond which he can decide to stop production if the emission cost rises. This decision cannot be taken independently of the inventory level, and thus a coupled feedback control should be considered. In light of this discussion, the HPP3 structure is defined by the following equations:

$$\begin{cases} if\ e(t) \leq Y : apply\, HPP\, with\ a\ hedging\ Level\ Z1 \\ \\ u(x,\alpha) = \begin{cases} U_{\max} & if \quad x(t) < Z1 \\ d & if \quad x(t) = Z1 \\ 0 & if \quad x(t) > Z1 \end{cases} \end{cases} \tag{3.13}$$

$$\begin{cases} if\ e(t) > Y : apply\ HPP\ with\ a\ hedging\ Level\ Z2 \\ \\ u(x,\alpha) = \begin{cases} U_{\max} & if \quad x(t) < Z2 \\ d & if \quad x(t) = Z2 \\ 0 & if \quad x(t) > Z2 \end{cases} \end{cases} \tag{3.14}$$

We define *r = Z2 / Z1, 0 < r ≤ 1* to respect the condition *Z1 ≥ Z2.*

Considering the importance and dangers of industrial discharges into the environment, the third control policy HPP3 is a multi-hedging point policy that takes into account the evolution of the emission level *e(t)* over time. We propose to put another emission limit *Y* (different from the standard emission limit *L* imposed by the authorities) at which the production is reduced in order to minimize the emission cost. Production is continued at a slower rhythm when the backlog risk became too high.

The structure of the overhaul policy is presented by the equation (3.15):

$$\omega_0(.) = \begin{cases} 1 & if \quad a(t) > Ca \quad and \quad x(t) \geq Z2 \\ 0 & else \end{cases} \tag{3.15}$$

For HPP3, the structure of overhaul policy defined in equation (3.15) is substantially the same as in HPP2 policy. However, in the case of HPP3, the threshold Z2, defined in the production policy, is considered as the comfortable inventory level before overhaul operation. It is important to note that HPP3 policy is proposed in order to measure the effectiveness of the new production policy (two critical thresholds Z1 and Z2) compared to the classical HPP proposed for HPP1 and HPP2.

In this paper, three different control policies are proposed; for the first policy HPP1, the emission issue is not explicitly present but the fact of considering overhaul allows mitigating emissions. In another side, the second policy HPP2 offers more control in the overhaul policy compared to HPP1 in order to minimize the backlog cost by considering the condition of the safety stock. Finally, the third policy HPP3 directly introduces the emission control from inventory level and target emission level.

Our objective is to propose more way that allows managing these aspects and would like to study in detail the difference between them and find the best policy in specific contexts. An experimental resolution approach is applied to find optimal parameters of each control policy. The following section details the steps of this approach.

3.4 Resolution approach

In order to estimate the optimal cost value with respect to the each policy parameters, an approach combining simulation with experimental design and response surface methodology techniques is used (Gharbi et al. 2011). This approach is described in the following main steps:

- Step 1: Description of the control policies

  In section 3.3, the structures of three policies are presented and expressed by mathematical equations.

- Step 2: Simulation models

  Three simulation models are developed to reflect the system dynamics governed by each of the control policies considered. These policies are used as an input to conduct several experiments and thus evaluate the system performance. Section 3.5 provides more details on our simulation models.

- Step 3: Experimental design and response surface methodology

The experimental design approach defines the experiments number, the levels of the input factors (independent variables) considered and the variation extent of each factor. The analysis of variance is subsequently used to determine the main factors and their interactions which have a significant effect on the cost (dependent variable). Then, the response surface methodology allows obtaining the relationship between the dependent variable (cost) and significant main factors and their significant interactions. The resulting model is then optimized in order to determine the best combination of the control parameters which minimize the total cost.

3.5 Simulation model

Using the simulation language SIMAN under «ARENA» software, a combined discrete-continuous model is developed with C++ routines for each control policy. Lavoie et al. (2010) showed the advantage of using this combination in terms of simulation time and reproducibility of the system dynamics. Figure 3.3 presents the diagram of the simulation model.

After initializing the model parameters required for the simulation ($Z1$, $Z2$, U_{max},, time step ...) (bloc 1), the manufacturing system (bloc 3) allows producing parts according to production policy (bloc 7) described by equations (3.10) or (3.13) and (3.14) to meet the demand rate (bloc 2). The machine is subject to random failures and repair activities (bloc 4). Therefore, the age of the machine increases over time and equipment degradation increases too (bloc 5). The state equations (bloc 8) describe the variation of inventory level $x(t)$ and the emission level $e(t)$ which takes into account the degradation state of the machine ($q_{12}(a)$ and $\theta(a)$). At a certain level of degradation, the overhaul policy (bloc 6) determines the execution time of an overhaul operation when the conditions imposed by equations (3.11) or (3.12) or (3.15) are satisfied. The simulation advances (bloc 9) and the model updates the inventory level and the emission level (bloc 10). At the end of the control period T_i, the emission level $e(t)$ is set to zero (bloc 11). Finally, we calculate the cost according to the variables of inventory levels and backlog (x^+ and x^-), the emission penalty, and the maintenance costs (bloc 12).

The only difference between the three models is in the definition of the structure of the control policy (bloc 6 and 7).

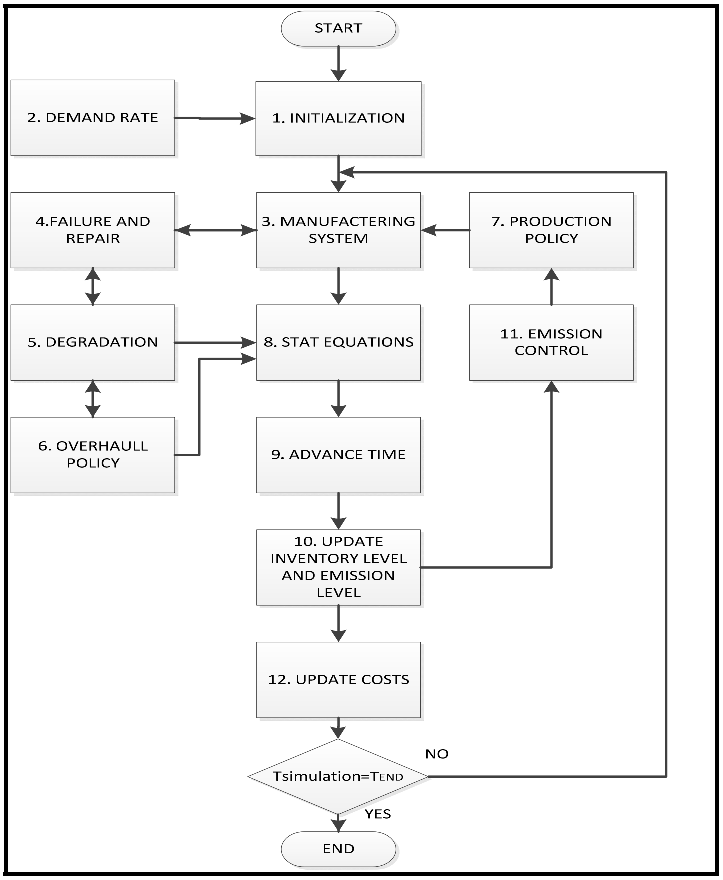


Figure 3.3 Diagram of the simulation model

In order to validate that the simulation model adequately represents the system under study, we present the evolution of the inventory level *x(t),* the emission level *e(t)* and the age level *a(t)* over time generated by the simulator when the HPP3 is applied. Figure 3.4 presents the results obtained when the parameters are set to $Z1=20$, $Z2=10$, $Ca_{over} = 70$, $Y=85$, $L= 60$ and $i = 140$ time unit (TU).

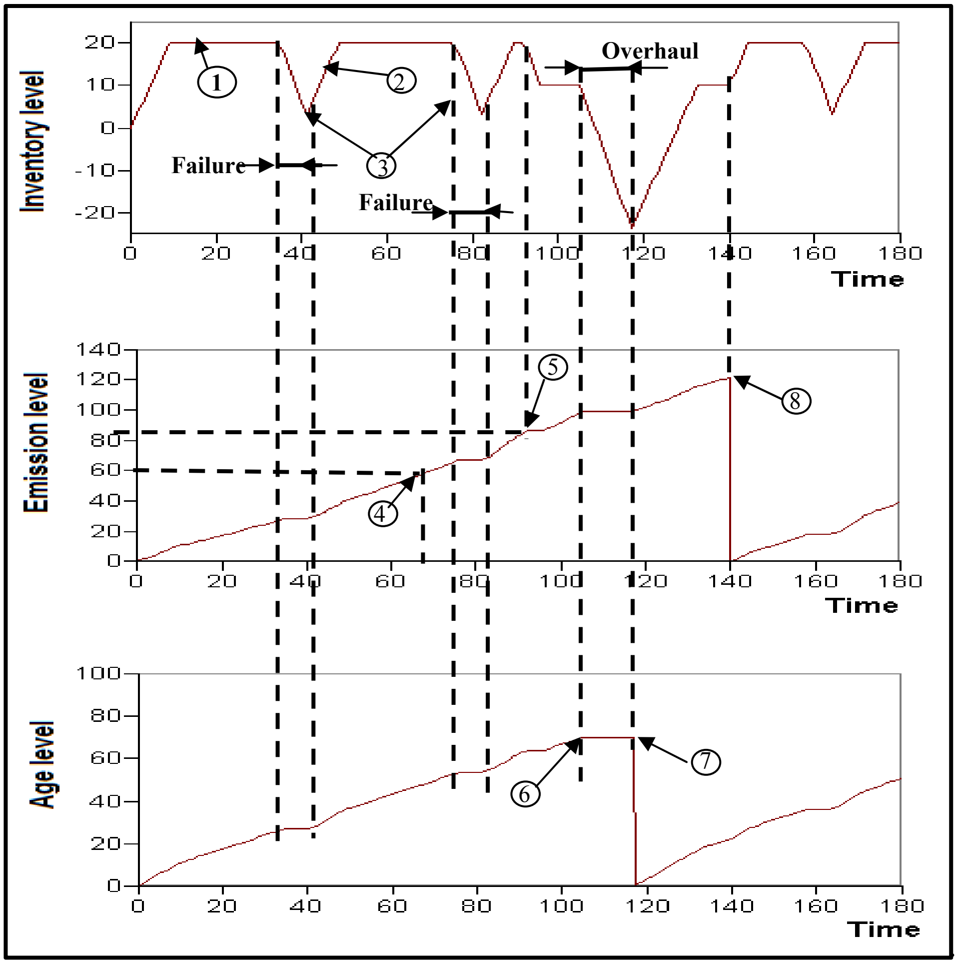


Figure 3.4 Trajectory of inventory, emission and the age levels over time

According to Figure 3.4, we note that, when:

- $0 \leq t < 68$ TU; the emission level and the age level increase as function of the production rhythm. The manufacturing system produces according to classical HPP with a critical inventory threshold $Z1 = 20$; production rate $u(t) = d$ ① if $x(t) = Z1$ and $u(t) = U_{max}$ ② if $x(t) \leq Z1$. When a random failure event occurs ③, the production is stopped, thus the emission and the age levels remain at the same values. Production is restarted after a random repair activity.

- $68 \leq t < 92$ TU, the simulation time advance and the emission level reaches the limit *L* at t=68 TU④, consequently an emission cost is added to other costs (inventory, backlog and maintenance).

- $92 \leq t < 104$ TU, the emission level *e(t)* reached the level *Y* at t= 92 TU ⑤ resulting to the production stop. From this moment, the critical inventory threshold decreases to *Z2=10* compared to *Z1=20* before this time. Then, production continues normally and the degradation state increases.

- $104 \leq t < 118$ TU, the machine degradation reaches an advanced stage and at t= 104 TU, *a(t)* is equal to Ca_{over} =70 ⑥. After checking that the condition of safety stock ($x(t) \geq Z2$) is satisfied, production is stopped and first overhaul operation is carried out in order to return the machine to (AGAN) condition. From the trajectory of inventory level *x(t)*, we note that the operation overhaul can cause a shortage of stock.

- t= 118 TU, overhaul operation is finished⑦, so the age of the machine; the failure rate and the emission rate are restored to the initial values.

- $118 < t \leq 140$ TU, the emission level continues to increase over time until the end of the emission control period at t= 140 TU ⑧. From this moment, the emission level is reset to zero and the production continue but with the critical inventory threshold Z1.

Based on several illustrations of this type, we can affirm that our simulation models adequately describe the dynamic of the manufacturing system under study.

3.6 Experimental design and response surface methodology

This section presents the third step of the resolution approach. Given the convexity of the cost function for this type of problem, we define three levels for each policy factor. The objective is to find the optimal parameters values of each policy.

3.6.1 Numerical example

The different parameters of operations and costs characterizing the system under study are as follows:

Table 3.1 Parameter values

Parameters	**d**	**U_{max}**	**L**	**θ_0**	**q_1**	**q_2**	**q_{12}**	**q_{31}**	**α**	
Value	2	3	80000	2	0.0042	0.0044	0.1	0.05	0.6	
Parameters	**C^+**	**C^-**	**C^e**	**C_{cor}**	**C_{over}**	**k1**	**k2**	**k3**	**k4**	**T_i**
Value	1	75	25	5000	100000	0.023	0.6	-2.10^4	0.02	1 year

We adopt the complete factorial design (3^2 for HPP1 and 3^3 for HPP2). This type of plan gives more precise results since each interaction is estimated separately. Regarding HPP3, the number of factors is greater than three, thus we choose the Box-Behnken factorial design which is usually very efficient in terms of the number of required runs (Montgomery, 2005). The duration of each simulation is 1.000.000 TU to insure that the steady-state is reached. For each combination of values, five replications are made.

3.6.2 Results analysis

In this section, we present the results of the application of the resolution approach to the numerical example. Throughout this paper, the statistical treatment of the data is carried out using the «STATGRAPHICS» software. The results of the control parameters optimization of three policies are summarized in Table 3.2.

From Table 3.2, we note that the correlation coefficients $R^2_{adjusted}$ found are higher enough to judge the good quality of the models. In the same direction, an analysis of the residual normality and of the homogeneity of variance was also carried out to check the conformity of the models.

The second order models for the three proposed control policies are given by:

$$\widehat{Cost}_{HPP1} = 427.074 - 3.19173 \times Z1 - 1.80408 \times Ca + 0.0175362 \times Z1^2 + 0.00267334 \times Z1 \times Ca + 0.0124261 \times Ca^2 \tag{3.16}$$

$$\widehat{Cost}_{HPP2} = 410{,}275 - 2{,}80064 \times Z1 - 12.4918 \times p - 2.02378 \times Ca + 0.0165707 \times Z1^2 - 0.106157 \times Z1 \times p + 0.00170812 \times Z1 \times Ca + 16.2192 \times p^2 + 0.0146577 \times Ca^2 \tag{3.17}$$

$$\widehat{Cost}_{HPP3} = 570.55 - 0.014968 \times Y - 3.4844 \times Z1 - 214.679 \times r - 1.48338 \times Ca + 6.51902 \times 10^{-7} \times Y^2 + 9.15854 \times 10^{-5} \times Y \times Z1 - 0.000100067 \times Y \times Ca + 0.0145241 \times Z1^2 + 162.703 \times r^2 + 0.0185879 \times Ca^2 \tag{3.18}$$

Figure 3.5 presents the cost response surfaces when HPP3 is applied:

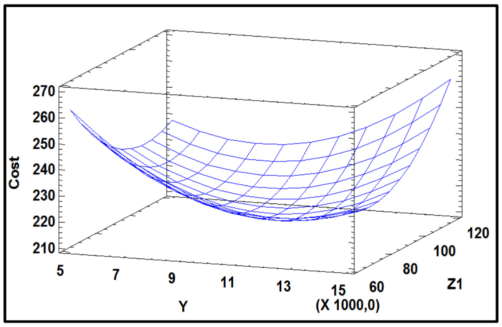


Figure 3.5 Cost response surfaces for HPP3

To cross-check the validity of our models, we confirm that the optimal cost for each control policy falls within the confidence interval at 95% ($\overline{\mathrm{C.T}} \pm \mathrm{t}_{1-(\alpha/2)}^{\mathrm{n}-1}\sqrt{\mathrm{S}^2/\mathrm{n}}$) equivalent (Table 3.2). This confidence interval obtained using n= 100 replications of the simulation model, where $\overline{\mathrm{C.T}}$ is the average optimal cost and S is the sample standard deviation.

Table 3.2 Optimum values of the variables

Control policy	**Factor**	**Optimum values**	**Cost***	**$R^2_{adjusted}$**	**Confidence interval (95 %)**
HPP1	*Z1*	86	232.43	99.03%	[230. 52 ; 233.79]
	Ca	63.32			
HPP2	*Z1*	83	224.58	97.74%	[223.41 ; 224.86]
	Xs	56			
	Ca	64.21			
HPP3	*Z1*	86	218.75	95,17%	[217.64; 219. 21]
	Z2	56			
	Ca	68.675			
	Y	10579			

From Table 3.2, for selected system parameters (Table 3.1), we conclude that the safety stock constraint introduced in the overhaul policy gives an advantage to HPP2 over HPP1 with an improvement of 3.37% in total cost. Indeed, HPP2 reduce the backlog cost through the safety stock condition before the overhaul activities. The results also show that HPP3 policy is the best in terms of total cost with an improvement of 5.88% and 2.6% compared respectively to HPP1 and HPP2. Indeed, HPP3 has two advantages; first, in the production policy, the emission level is taken into consideration which reduces the emission cost. Second, in the maintenance policy, a safety stock is required to carry out the overhaul operations which reduce backlog cost.

3.6.3 Sensitivity analysis

The objective of this analysis is to demonstrate the efficiency and robustness of our resolution approach and to study the impact of the variation of the cost parameters on the each control policy performance. Table 3.3 summarizes the results of this sensitivity analysis and compared to the basic case.

From Table 3.3, in all cases studied, the obtained results show that, first, HPP2 remains better than HPP1in term of total cost with an improvement around 3%. Second, the policy HPP3 remains the best in terms of total cost incurred. The gain of HPP3 can reaches 7.56% and 4.93% compared to HPP1 and HPP2, respectively.

The variation of each parameter is analysed:

- Variation of C^+ and C^-: the variation of C^+ and C^- has an opposite effect on the policies parameters. Indeed, when C^+ decreases (case 1) (respectively C^- increases (case 4)), the critical threshold (*Z1* for HPP1 and HPP2, *Z1* and *Z2* for HPP3) and the level of safety stock (*Xs* for HPP2 and *Z2* for HPP3) increase to benefit from the low holding cost (respectively to avoid additional backlog cost) leading to an increase of emissions. Therefore, the system reacts by reducing the critical age *Ca*, for the three policies, in order to carry out more overhauls which reduce the emission rate. The opposite occurs when C^+ increases (case 2) (respectively C^- decreases (case 3)).

- Variation of C^e: when C^e (case 5) decreases, the total emission cost decreases. In this case, less overhaul actions are conducted. This explains the increase in the critical age *Ca* (for the three policies). Therefore, the risk of shortages are reduced which requires less safety stock (*Xs* for HPP2 and *Z2* for HPP3 decrease). When C^e increases (case 6), the opposite occurs.

- Variation of C_{over} and C_{cor}: the variation of C_{over} and C_{cor} has an opposite effect on the policies parameters. Indeed, decreasing C_{over} (7 cases) (respectively C_{cor} increases (case 10)), more overhaul is conducted (respectively less CM is conducted), leading to a decrease in the critical age *Ca* (for the three policies). Consequently, the level of safety stock (*Xs* for HPP2 and *Z2* for HPP3) increase to protect system against shortage risks. The opposite occurs when C_{over} increases (case 8) (respectively C_{cor} decreases (case9)).

- Variation of the adjustment parameter α: from Table 3.3, the adjustment parameter α has an effect on the overhaul and production policy. When α decreases (case 11), the emissions rate decreases. Thus, *Ca* increases in order to execute less overhaul operations which need less safety stock (*Xs* for HPP2 and *Z2* for HPP3 decrease). The opposite occurs when α increases (case 12).

For HPP3, the variation of the cost parameters (C^+, C^-, C^e, C_{cor}, C_{over}) has an effect on the level *Y*. In all the cases, the parameter *Y* moves in the opposite direction of the critical threshold *Zi* (*i=1, 2*). Indeed, we note that if the values of *Z1* and *Z2* increase, the system produce more at the maximum rate (U_{max}) which implies an increase in the total cost in general, and the emission cost in particular. Consequently, *Y* decreases to reduce this cost.

Table 3.3 Results of the sensitivity analysis

Case	Parameters						HPP1			HPP2				HPP3					
	C^+	C^-	C^e	C_{over}	C_{cor}	α	Z1*	Ca*	Cost*	Z1*	Xs*	Ca*	Cost*	Z1*	Z2*	Y*	Ca*	Cost*	Remark
-	**1**	**75**	**25**	**100000**	**5000**	**0.6**	**86**	**63.32**	232.43	**83**	**56**	**64.21**	224.58	**86**	**56**	**10579**	**68.67**	218.75	**basic case**
1	**0.8**	75	25	100000	5000	0.6	92	62.68	215.83	89	62	63.8	208.47	95	62	10007.3	66.24	201.83	Z1*↑, (Z2*, Xs*)↑, Y*↓, Ca*↓
2	**1.2**	75	25	100000	5000	0.6	81	63.96	247.9	77	51	64.61	239.51	76	50	11481.7	71.83	233.94	Z1*↓, (Z2*, Xs*)↓, Y*↑, Ca*↑
3	1	**45**	25	100000	5000	0.6	67	66.48	213.67	63	38	64.51	207.37	62	41	12224.3	70.95	203.17	Z1*↓, (Z2*, Xs*)↓, Y*↑, Ca*↑
4	1	**105**	25	100000	5000	0.6	95	58.7	245.54	93	66	63.54	238.73	101	67	9136.91	66.88	226.97	Z1*↑, (Z2*, Xs*)↑, Y*↓, Ca*↓
5	1	75	**20**	100000	5000	0.6	86	71.61	229.33	83	55	71.61	221.4	86	54	11196.5	77.5	215.64	Z1*↔, (Z2*,Xs*)↓, Y*↑, Ca*↑
6	1	75	**30**	100000	5000	0.6	86	56.72	234.17	83	57	57.81	226.39	86	57	10351.7	63.46	220.31	Z1*↔, (Z2*, Xs*)↑, Y*↓, Ca*↓
7	1	75	25	**80000**	5000	0.6	86	51.12	216.21	83	57	55.25	209.19	86	57	10189.5	61.43	204.07	Z1*↔, (Z2*, Xs*)↑, Y*↓, Ca*↓
8	1	75	25	**120000**	5000	0.6	86	71.47	246.18	83	55	70.87	238.24	86	55	11033	75.14	232.15	Z1*↔, (Z2*, Xs*)↓, Y*↑, Ca*↑
9	1	75	25	100000	**3000**	0.6	86	65.6	220.55	83	55	66.19	212.7	86	55	10676.7	70.39	206.83	Z1*↔, (Z2*, Xs*)↓, Y*↑, Ca*↑
10	1	75	25	100000	**7000**	0.6	86	60.83	244.16	83	57	62.04	236.34	86	57	10485.6	66.91	230.59	Z1*↔, (Z2*, Xs*)↑, Y*↓, Ca*↓
11	1	75	25	100000	5000	**0.55**	86	71.99	227.2	83	55	71.67	219.58	86	54	11051.4	76.09	217.69	Z1*↔, (Z2*, Xs*)↓, Y*↑, Ca*↑
12	1	75	25	100000	5000	**0.65**	86	54.84	236.37	83	60	59.98	230.27	86	62	9143.01	60.15	222.62	Z1*↔, (Z2*, Xs*)↑, Y*↓, Ca*↓

From all numerical examples analyzed in this study, it seems that the results are logical and the structures of the policies are always maintained. In general, the parameters of the control policies are influenced by the variation in the cost and the adjustment α parameters. Thanks to the practical usefulness of our resolution approach, we develop, in the next section, a more thorough analysis of the influence of system parameter on the overhaul strategy for HPP3 policy.

3.7 Extension of HPP3: Preventive maintenance policy

Over time, the failure and the emission rates increase due to the machine degradation. The role of the overhaul operation is to eliminate the effect of this degradation and make the machine AGAN. Since this perfect maintenance is very expensive, in this section, we assume that less perfect preventive maintenance (PM) activities are possible in order to reduce the maintenance cost.

The PM defines a fourth state of the system ξ (t) = 4. We define ω_p (.) a decision variable which controls the transition to PM. We assume that the transition to PM can be done only if the machine is operational (ξ (t) = 1), thus ω_p (.) = q_{14}.

We consider that PM reduces proportionally the age of the machine compared to its value before maintenance activity. This method is called an arithmetic reduction of the age (Rivera-Gómez et al. 2013b). The effect of PM on the age of the machine is given by the following equation:

$$a(t)^{+} = a(t)^{-} - \sigma a(t)^{-} \tag{3.19}$$

Where $\sigma, (0 \leq \sigma \leq 1)$, is the parameter of the PM efficiency, a^{-} is the age of the machine before PM and a^{+} is the age after PM. The key idea is to modelize the case between the two extreme maintenance activities (overhaul and CM). Indeed, if $\sigma = 0$; PM is a minimal maintenance and equivalent to CM, if $\sigma = 1$; PM is a perfect maintenance similar to overhaul.

Figure 3.6 presents the trajectory of the emission index and failure rate as function of the age when PM efficiency is set to σ = 0.3:

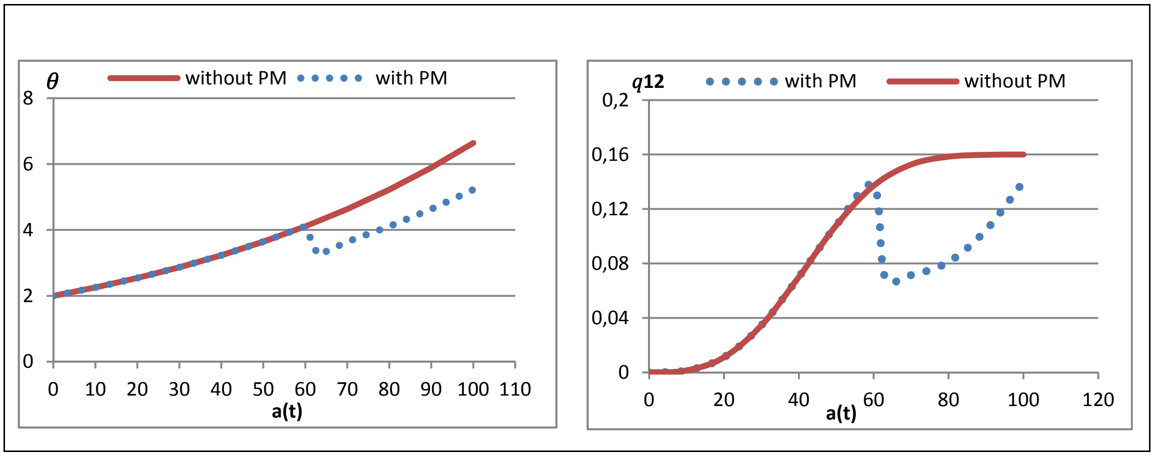


Figure 3.6 Effect of PM on emission index and failure rate

From Figure 3.6, it is clear that PM reduces partially the emission index because the age of the machine is reduced. The same results are observed for the failure rate.

3.7.1 Preventive maintenance policy

In this section, we propose the PM policy based on the overhaul policy given in the equation (3.15)). The PM policy is defined by the following equation:

$$\omega_0(.) = \begin{cases} 1 & if \quad a(t) > Ca_{pm} \quad and \quad x(t) \geq Z2 \\ 0 & else \end{cases} \tag{3.20}$$

Where Ca_{pm} denotes the critical age level at which a PM is required. Similar to overhaul, the policy consists in doing the PM when the age of the machine reaches a critical value Ca_{pm}. The threshold Z2, defined in the production policy, is also considered as the comfortable inventory level before PM activity.

3.7.2 Results analysis

We proceed in this section by the same resolution approach used in section 6 in order to optimize the HPP3 parameters. It should be noted that, at this state, the optimization problem is more difficult because of the high number of factors (*Z1, Z2, Ca, Ca_{pm}, Y*). Despite this difficulty, we succeeded in finding a good model with a correlation coefficients $R^2_{adjusted}$= 95.62%. The results of the control parameters optimization are summarized in Table 3.4 for q_{41}=0.083, σ =0.3 and a PM cost, noted C_{pm} = 25000.

The second order model for the control policy is given by:

$$\widehat{Cost}_{HPP3} = 546{,}693 - 0{,}00927035 \times Y - 3{,}4795 \times Z1 - 129{,}57 \times r - 1{,}68477 \times Ca - 186{,}262 \times Ca_{pm} + 3{,}27741\, 10^{-7} \times Y^2 + 0{,}0000311447 \times Y \times Z1 + 0{,}00732884 \times Y \times r - 0{,}0000820377 \times Y \times Ca + 0{,}0242229 \times Z1^2 - 0{,}00342752 \times Z1 \times Ca - 0{,}394327 \times Z1 \times Ca_{pm} + 70{,}9878 \times r^2 - 0{,}616441 \times r \times Ca + 0{,}0205111 \times Ca^2 + 0{,}818501 \times Ca \times Ca_{pm} + 144{,}155 \times Ca_{pm}^2 \tag{3.21}$$

Table 3.4 Optimum values of the variables

Factor	Optimum values	Cost*	Confidence interval (95 %)
Z1	72	212.157	[210.53 , 213.48]
Z2	35		
Ca_{over}	72		
Ca_{pm}	39		
Y	14304		

From Table 3.4, for selected system parameters, we conclude that considering the PM in the maintenance strategy, in addition to overhaul, allows reducing the total cost compared to the case where only overhaul activities are considered in the maintenance planning.

3.7.3 Sensitivity analysis

An extensive sensitivity analysis is performed in this section in order to confirm the structure of HPP3 when PM is considered. Thanks to the practical usefulness of our resolution approach, we study the influence of system parameter on the maintenance strategy of HPP3. Figure 3.7 presents the variation of *Z1* and *Z2* as a function of the machine age for the basic case.

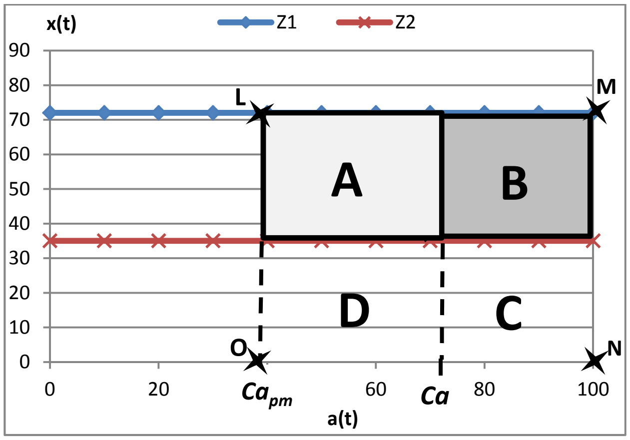


Figure 3.7 Overhaul and PM zones

From Figure 3.7, the contour (L, M, N, O) indicates the intersection between the critical ages (Ca, Ca_{pm}) and the inventory levels ($Z1$, $Z2$). This area is limited in the top by *Z1* because the inventory level cannot in any case exceed this threshold. We can devise the contour in four zones:

- Zone A: is defined by the area between the inventory thresholds *Z1* and *Z2* limited by Ca_{pm}. In this zone, PM is possible because the two conditions are satisfied ($a(t) \geq Ca_{pm}$) and ($x(t) \geq Z2$).

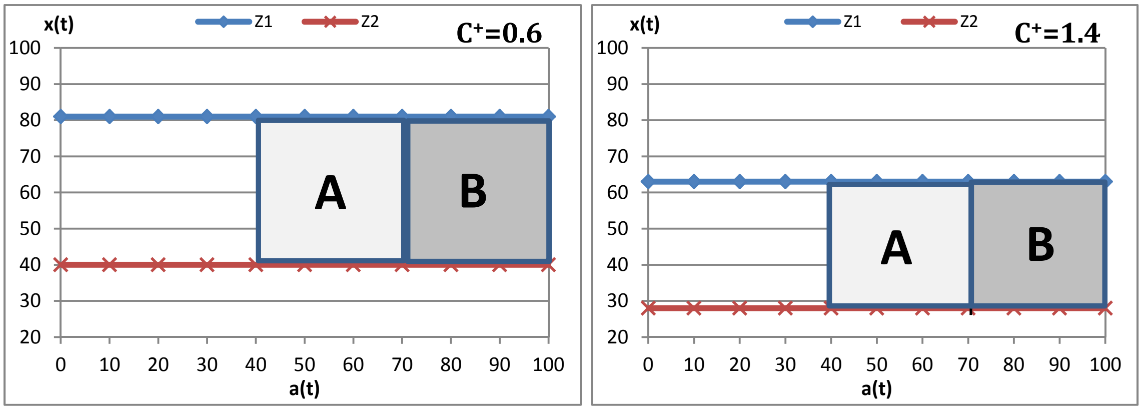
- Zone B: is defined by the area between the inventory thresholds *Z1* and *Z2* limited by *Ca*. In this zone, overhaul actions are possible because the two conditions are satisfied ($a(t) \geq Ca$) and ($x(t) \geq Z2$).

- Zone C and Zone D: in these zones, despite the fact that ($a(t)\geq Ca$) and ($a(t)\geq Ca_{pm}$), the overhaul and PM are not possible because the inventory level is less than *Z2*.

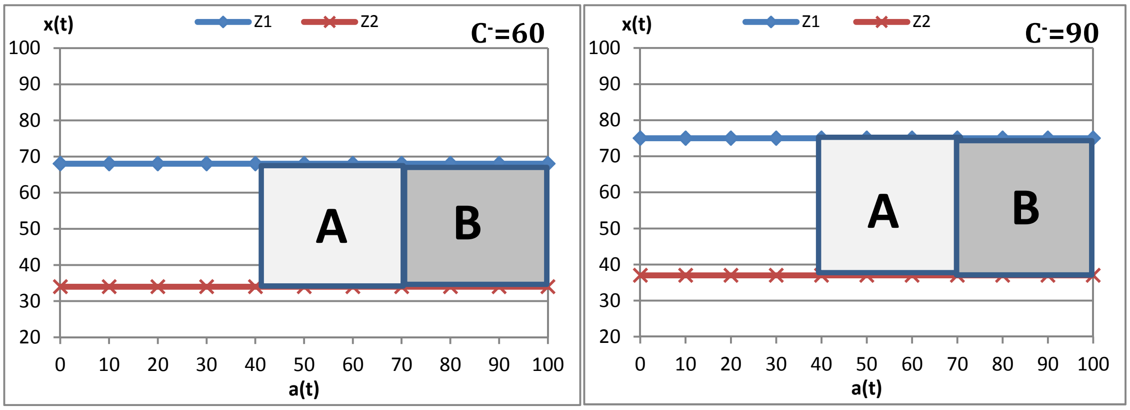
In the next subsection, we will show the effect of the system parameter's variation on the PM zone (zone A) and overhaul zone (zone B). The objective of this study is to provide an in-depth analysis of the influence of the system parameters on the maintenance policy when emission degradation is considered.

3.7.3.1 Variation of C^+ and C^-

From Figure 3.8, we remark that the variation of C^+ and C^-has an inverse effect on the size of the PM and overhaul zones. Results show that when $C^+ = 1.4$ (respectively $C^- = 60$), the zone A and B covers a limited space in the study domain. When C^+ decreases to 0.6 (respectively C^- increases to 90), there is a significant enlargement in the zone which means that overhaul and PM are more recommended. This enlargement is explained by the increases of the critical threshold *Z1* when C^+ decreases (respectively C^- increases). Regarding *Z2*, the increase is less significant compared to *Z1* and the difference $Z1\text{-}Z2= \Delta Z$ increases in order to reduce the emission which explain the enlargement.



a. (C^+)



b. (C^-)

Figure 3.8 Variation of C^+ and C^-

3.7.3.2 Variation of C^e

As presented in Figure 3.9, the variation of the emission penalty has a considerable effect on the zones A and B. We note that increasing the penalty from C^e =20 to 30 leads to an enlargement of the overhaul zone and a reduction in the PM zone. Indeed, overhaul activities are more recommended when C^e increases in order to completely restore the machine to (AGAN) condition. Recall that PM has less significant effect on the emission degradation of the machine. A general remark that both maintenance activities can be done earlier when C^e increases to reduces emission rate.

To finish with the emission penalty cost, we note that increasing C^e increases the safety stock Z2 (see section 3.6.3) because more maintenance activities are conducted.

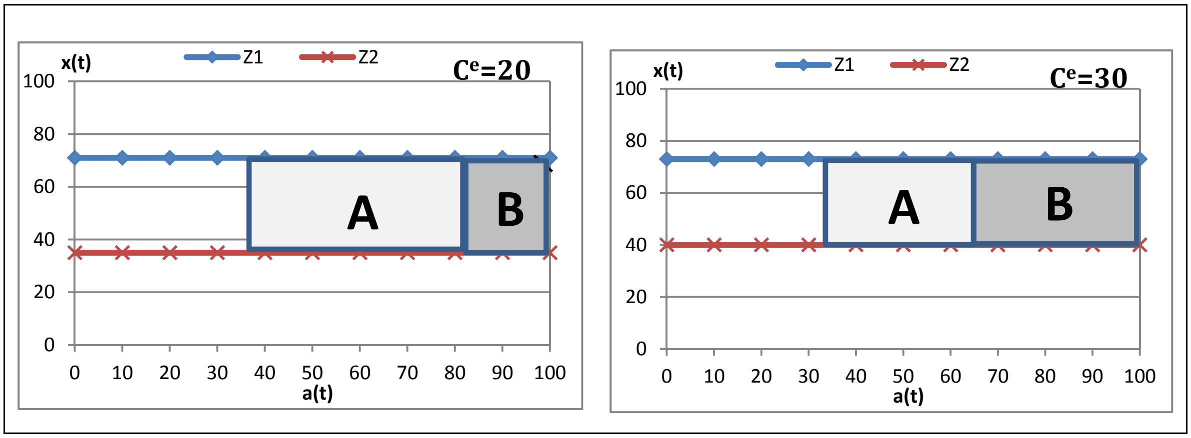


Figure 3.9 Variation of C^e

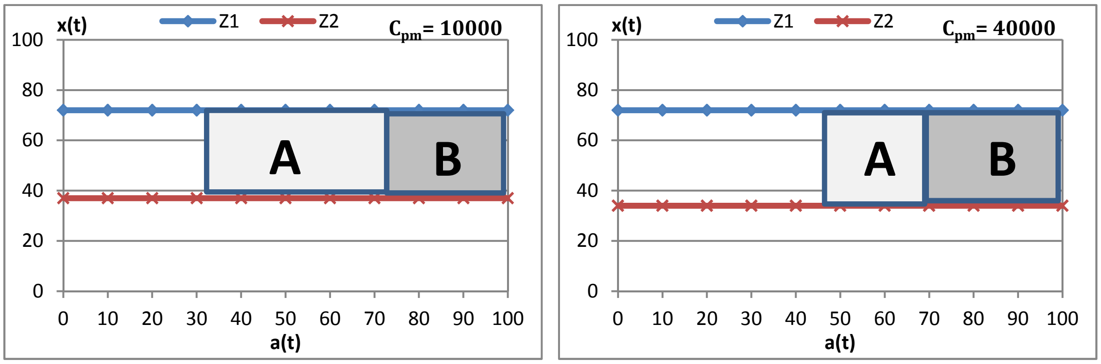
3.7.3.3 Variation of C_{pm} and C_{over}

In this section, we turn our attetntion to the effect of the mainenance costs on the overhaul and PM zones.

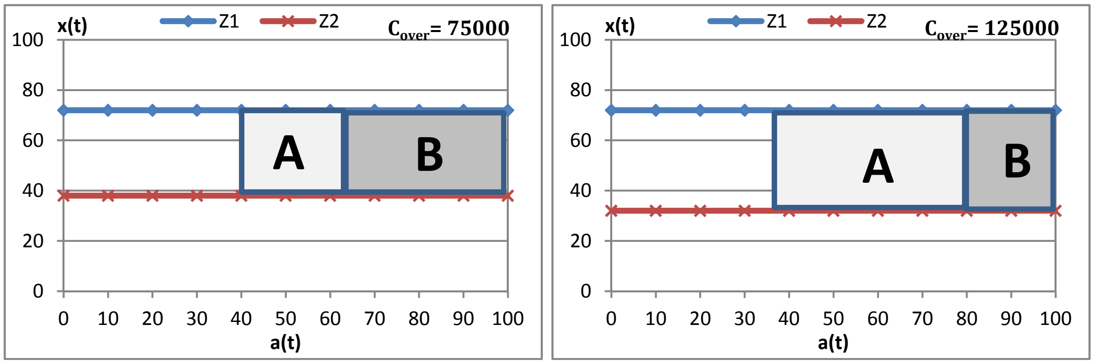
Figure 3.10.a presents the results of two cases of C_{pm}. From the graphics, when C_{pm} increases from 10000 to 40000, we remark that the space occupied by the zone A is reduced. Thus, PM is carried out only at a high level of degradation to justify its higher cost. In the other side, increasing C_{pm} has enlarged the zone B in order to recommend more overhaul activities to compensate the reduction of PM activities.

Regarding the overhaul cost, we study the effect of two cases (C_{over} = 125000 and C_{over} = 75000) on the zone A and B. From Figure 3.10.b, a significant reduction of the zone B is observed when C_{over} increases from 75000 to 125000. Indeed, the system has a tendency to reduce overhaul interventions in order to minimize overhaul cost. Therefore, more PM is carried out which explain the enlargement in the zone A to compensate the reduction of the overhaul activities.

Another observation is that when C_{over} or C_{pm} increases, the safety stock Z2 decreases because maintenance activities are less recommended.



a. (C_{pm})



b. . (C_{over})

Figure 3.10 Variation C_{pm} and C_{over}

3.7.3.4 Variation of the adjustment parameter α

In this section, we focus on the effect of the variation of the adjusted parameter of the emission index trajectory α (see Figure 3.2) on the zone A and B. Figure 3.11 shows the results for two cases of α = 0.55 and α = 0.65.

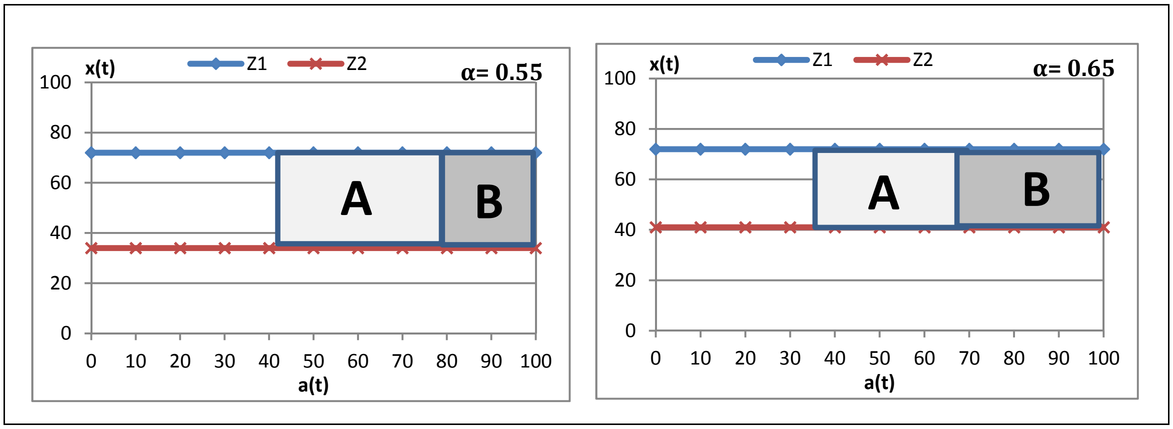


Figure 3.11 Variation of adjustment parameter α

From Figure 3.11, the adjustment parameter α has an effect on the overhaul and PM zones. Indeed, when α increases from α = 0.55 to 0.65, we observe a significant enlargement in the zone B. This result is explained by the fact that increasing α increases the emission generated which need more frequent overhaul activities. In addition, recall that overhaul has a more significant effect on the machine degradation than PM which explains the reduction in zone A.

Globally, it is important to note that both maintenance activities can be done earlier when α increases from 0.3 to 0.4 to reduce the effect of the degradation. Therefore, the safety stock Z2 increases to protect system from backlog.

3.7.3.5 Variation of the preventive maintenance efficiency

The integration of the PM policy in HPP3 aims to study more general case of maintenance. The performance of this imperfect maintenance is modelized by the PM efficiency parameter σ. Figure 3.12 illustrate the variation of PM efficiency for two cases σ = 0.3 to 0.4.

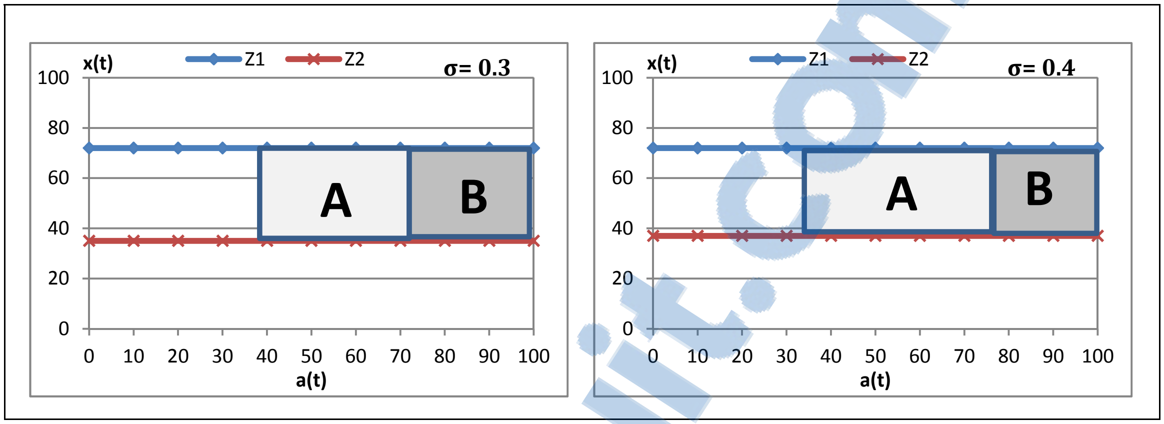


Figure 3.12 Variation of the preventive maintenance efficiency

For the cases studied, we observe a significant enlargement on the zone A when σ increases from 0.3 to 0.4. To explain, more performant PM is more recommended to benefit from it in order to reduce the effect of degradation. Hence, less overhaul activities are carried out which explain the reduction of the zone B.

From the above analysis, we note that all results obtained make sense, and confirm our expectations. Under this section, the relationship between the system parameters and the maintenance strategy has been studied. The diversity of cases treated allowed us to form new findings on the effect of the degradation of a pollutant system. Thanks to the practical usefulness of the resolution approach, we have quantified these aspects in a realistic presentation taking into account the stochastic and dynamic behaviour of the system.

3.8 Conclusion

This work addressed the problem of production planning in interaction with the environmental issue from a perspective of degradation. The integration of environmental issue in the production policy in the presence of equipment degradation is the major contribution of this paper. We considered a degradation model that directly affects the failure rate and the emission rate which increase over time. Therefore, maintenance operations are able to restore completely (overhaul) or reduce partially (PM) the effect of the deterioration of the machine.

Three production control policies have been proposed inspired from the well-known of hedging point policy (HPP). For maintenance activities, three overhaul policies have been proposed and studied in this work. Simulation models have been developed taking into account the dynamic and stochastic system characteristics. Then, a numerical example has been considered in order to analyze and compare the behavior of the manufacturing system by applying each of the three proposed policies HPP1, HPP2 and HPP3.

The results showed that the HPP3 policy is better than HPP1 and HPP2. Indeed, on the one hand, HPP3 allows better inventory management facing environmental constraints. On the other hand, the maintenance strategy for this policy minimizes the risk of shortage.

The multi-hedging point policy HPP3, which takes into account the emission level, has given interesting results. With an improvement in the inventory management and maintenance strategy, HPP3 policy has led an economic gain and allows reaching the environment objectives in terms of emission balance. In addition, sensitivity analysis provides further evidence of the usefulness of this policy through the study of the effect of system parameters on the maintenance strategy.

References

Akella, R. and Kumar, P.R., 1986. Optimal control of production rate in a failure-prone manufacturing system. IEEE Transactions on Automatic Control, AC-31 (2), 116–126.

Bai, S.X., & Elhafsi, M., 1997. Scheduling of an unreliable manufacturing system with non-resumable set-ups. Computers Ind. Eng., 32, 909-925.

Barlow, R. E. & Hunter, L., 1960, Optimal preventive maintenance policies. Operations Research, 8, 90-100.

Battini, D., Persona, A., & Sgarbossa, F., 2013. A sustainable EOQ model: Theoretical formulation and applications. International Journal of Production Economics, 149, 145–153.

Berthaut, F., Gharbi, A., Kenné, J. P., and Boulet, J. F., 2010. Improved joint preventive maintenance and hedging point policy. International Journal of Production Economics, 127(1), 60-72.

Berthaut, F., Gharbi, A., & Dhouib, K., 2011. Joint modified block replacement and production/inventory control policy for a failure-prone manufacturing cell. Omega, 39(6), 642-654.

Bloemhof-Ruwaard, J.M.1; van Beek, P.; Hordjik, L., Van Wassenhove, L.N, 1995. Interactions between operational research and environmental management. European Journal of Operational Research, 85, 229-243.

Bouchery, Y., Ghaffari, A., Jemai, Z., & Dallery, Y. , 2012. Including sustainability criteria into inventory models. European Journal of Operational Research, 222(2), 229-240.

Caramanis, M. and Sharifnia, A., 1991. Near optimal manufacturing flow controller design. International Journal of Flexible Manufacturing Systems, 3, 321-336.

Chelbi, A., Ait-kadi, D., 2004. Analysis of a production/ inventory system with randomly failing production unit submitted to regular preventive maintenance. European Journal of Operational Research, 156, 712–718.

Chen, X., Benjaafar, S. and Elomri, A, 2013. The carbon-constrained EOQ. Operations Research Letters, 41, 172–179.

Chouikhi, H., Dellagi, S., & Rezg, N. (2012). Development and optimisation of a maintenance policy under environmental constraints. International Journal of Production Research, 50(13), 3612-3620.

Dehayem, N.F.I., Kenne, J.P. and Gharbi, A., 2009. Hierarchical Decision Making in Production and Repair/Replacement Planning With Imperfect Repairs Under Uncertainties" European Journal of Operational Research, (198), 173-189.

Dehayem, N.F.I, Kenné J.P., Gharbi A., 2011. Production planning and repair/replacement switching policy for deteriorating manufacturing systems. Int. J. Adv. Manuf. Technol., 57, 827–840.

Dhouib, K., Gharbi, A. and Ayed, S., 2008. Availability and Throughput of Unreliable, Unbuffered Production Lines with Non-Homogeneous Deterministic Processing Time. International Journal of Production Research Vol.46, No.20, October 2008, pp.5651-5677.

Dhouib, K., Gharbi, A. and M.N. Ben Aziza., 2012. Joint Optimal Production Control/Preventive Maintenance Policy for Imperfect Process Manufacturing Cell. International Journal of Production Economics, 137, (1), 126-136.

Dobos, I., 1998. Production- inventory control under environmental constraints, International Journal of Production Economics, 56, 123- 131.

Dobos, I., 1999. Production strategies under environmental constraints in an Arrow-Karlin model. International Journal of Production Economics, 59, 337-340.

Dobos, I., 2001. Production strategies under environmental constraints: Continuous-time model with concave costs. International Journal of Production Economics, 71, 323-330.

Fernandes, F.C.F., Azeka, F.1., Barreto, M.C.M., Filho, M.G., 2009. Identifying production planning and control top authors: analysis of a survey. International Journal of Business Innovation and Research, 3 (5), 461- 478.

Gharbi, A., Kenne, J.-P., and Hajji, A., 2006. Operational Level-Based Policies in Production Rate Control of Unreliable Manufacturing Systems With Setups. International Journal of Production Research , 44 (3), 545-567.

Gharbi, A., Hajji, A., and Dhouib, K., 2011, Production rate control of an unreliable manufacturing cell with adjustable capacity. International Journal of Production Research, 49 (21), 6539-6557.

Hajji, A., Gharbi, A., and Kenne, J.P., 2009. Joint replenishment and manufacturing activities control in two stages unreliable supply chain. International Journal of Production Research, 47 (12), 3231–3251.

Hajji, A., Gharbi, A., Kenne, J. P., & Pellerin, R. , 2011. Production control and replenishment strategy with multiple suppliers. European Journal of Operational Research, 208(1), 67-74.

Kimemia, J.G. and Gershwin, S.B., 1983. An algorithm for the computer control production in flexible manufacturing systems. IIE Transactions, 15 (4), 353–362.

Lam, Y., Zhu, L.X., Chan, J.S.K., Liu, Q., 2004, Analysis of data from a series of events by a geometric process model. Acta Mathematicae Applicatae, 20, 263-282.

Lavoie, P., Gharbi, A. and Kenne, J.-P., 2010. A comparative study of pull control mechanisms for unreliable homogenous transfer lines" International Journal of Production Economics, 124, (1), 241-251.

Li, S., and Gu, M., 2012. The effect of emission permit trading with banking on firm's production–inventory strategies. Int. J. Production Economics, 137, 304–308.

Li, S., 2013: Optimal control of the production–inventory system with deteriorating items and tradable emission permits. International Journal of Systems Science, DOI:10.1080/00207721.2013.770103.

Li, S., 2014. Optimal control of production-maintenance system with deteriorating items emission tax and pollution R&D investment. International Journal of Production Research, 52 (60), 1787-1807.

Love, C.E., Zhang, Z.G., Zitron, M.A., Guo, R., 2000. Discrete semi- Markov decision model to determine the optimal repair/replacement policy under general repairs. European Journal of Operational Research, 125(2), 398–409.

Mckay, K. N., 2003. Historical survey of manufacturing control practices from a production research perspective. International Journal of Production Research, 41(3), 411-426.

Montgomery, D.C., 2005. Design and analysis of experiments. New York: John Wiley & Sons.

Przepiórski J., 2006. Activated Carbon Surfaces in Environmental Remediation. Interface Science and Technology, (7), 421–474.

Parlar, M., Perry, D., 1995. Analysis of a (Q, r, T) inventory policy with deterministic and random yields when future supply is uncertain. European Journal of Operational Research, 84, 431–443.

Radhoui, M., Rezg, N., and Chelbi, A., 2009. Integrated Model of Preventive Maintenance, Quality Control and Buffer Sizing for Unreliable and Imperfect Production Systems. International Journal of Production Research, 47 (2), 389–402.

Rivera-Gómez, H., Gharbi, A., & Kenné, J. P. , 2013a. Joint production and major maintenance planning policy of a manufacturing system with deteriorating quality. International Journal of Production Economics, 146(2), 575-587.

Rivera-Gomez, H., Gharbi, A., & Kenné, J. P., 2013b. Joint control of production, overhaul, and preventive maintenance for a production system subject to quality and reliability deteriorations. The International Journal of Advanced Manufacturing Technology, 69(9-12), 2111-2130.

Sethi, S. P., and Zhang, Q., 1999. Average-Cost Optimal Policies for an Unreliable Flexible Multiproduct Machine. The International Journal of Flexible Manufacturing Systems, 11, 147–157.

Yan, H. and Zhang, Q., 1997. A numerical method in optimal production and set-up scheduling of stochastic manufacturing systems. IEEE Trans. Automat. Contr., 42, 1452–1455.

Zhang, J. J., Nie, T. F., & Du, S. F., 2011. Optimal emission-dependent production policy with stochastic demand. International Journal of Society Systems Science, 3(1), 21-39.

CHAPITRE 4

ARTICLE 3: PRODUCTION PLANNING AND EMISSION CONTROL FOR AN UNRELIABLE MANUFACTURING SYSTEM WITH SUBCONTRACTING STRATEGY TO ACHIEVE ENVIRONMENTAL OBJECTIVES.

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Abstract: In this paper, we address the problem of production planning control of a manufacturing system which generates harmful emissions in the environment. The manufacturing system is composed of a single production facility subject to random failures and repairs activities, producing one product family type. In addition to the manufacturing system, we assume that a subcontractor characterized by a cost and a delivery delay can provide finished product to meet demand. Under the emission cap approach, subcontracting allows the company to avoid the emission cost when a good compromise through subcontracting costs and delivery delay exist. A production control policy of the manufacturing system with subcontracting taking into account emission aspect is proposed. The objective is to optimize the total cost (inventory, backlog, production, emission and subcontracting cost) over an infinite horizon. Using an experimental resolution approach combining the experimental design, simulation and response surface methodology (RSM), the optimal policies parameters are obtained and their behaviours regarding variation of cost parameters are analyzed. The results show that effective coordination between in-house production and subcontracting strategy can allow the company to reduce its emission balance. Moreover, we benefit from the usefulness of the resolution approach to study practical and realistic situations in the context of subcontractor selection.

Keywords: unreliable manufacturing system, production, emission, subcontracting, experimental approach, delivery delay.

4.1 Introduction

The current environmental situation is one of the most important actuality topics and everyone (citizens, countries, companies…) is affected by this issue. It is clear that pollution is among the main factors responsible for such situations. Although the transport is the most concerned by these problems, the manufacturing industry is involved and can contribute significantly to better control its activities to reduce its emission. For a long time, the managers are interested in resources optimization in order to minimise the cost where the environmental issue is often omitted. However, nowadays, the authorities have begun to put pressure on companies to limit the pollution and encourage the integration of sustainable development in their managerial practices. Faced with the norms and regulations imposed by the authorities, decision makers are required to revise their strategy in the short and medium-long terms. In this context, we study in this paper, a pollutant and unreliable manufacturing system, under an emission cap approach, in the presence of a subcontractor who can provide finished products.

In the literature, many studies have noted the important role of subcontracting for a company to deal with demand fluctuations or equipment unavailability or lack of capacity problems (Ayed *et al.* 2012). According to Van Mieghem (1999), subcontracting occurs because the company can find less profitable or impossible to have all required capabilities within exclusively in-house production. Thus, the objective behind opting for subcontracting is to keep a high level of customer satisfaction and avoid backlogs of finished products.

In this paper, we address the advantage of using subcontracting from a different perspective of what already exists in the literature. Indeed, we want to study this advantage in a context where the company wants to improve its environmental strategy and limit the emissions generated by the production system without losing customers.

In the recent years, public awareness about environmental protection has greatly increased giving rise to many sustainable concepts. On a global scale, the Kyoto Protocol (1997), signed by 37 industrialized countries and the members of the European Union (EU) have encouraged those countries to reduce their emissions of greenhouse gas (GHG) (Toptal, 2014). The companies are also affected by this change in the consideration of the environment aspect given that they are among the major emission sources. Therefore, decision makers have to use effective methods in order to improve their environmental management. In this context, changes in the production- inventory management (xepapadeas (1992)), in the supply chain management (Sheu *et al.* 2005) and in the transportation strategy (Bae *et al.* 2011) has been proposed to deal with environmental regulations policies.

In the literature, many authors addressed the problem of integrating the environmental aspect in the industrial activities. Bouchery *et al.* (2012) studied a multi-objective EOQ model that minimizes the cost and environmental damages. An EOQ model taking into account sustainability issues was proposed by Battini *et al.* (2013). Wirl (1991) focused on the effect of the environmental strategies on the production policy. The author analysed the influence of taxes or emission limits on the production- inventory decisions of the company. The concept of sustainable supply chain design is developed and studied in the work of Chaabane *et al.* (2012). In the context of aluminum industry, the authors considered that the production and transportation process generates emission, solid and liquid waste. The results showed that efficient emission management can help the company to achieve its environmental objectives. These works, among others (Hua *et al.* (2011); Dobos (2005); Jaber *et al.* (2013)) have examined the effect of integrating the environmental aspect in the manufacturing industry with one or more control and protection approach (taxes, permit trading and cap approach). Despite the variety of research papers, their main objective remain the same; developing practical methods to help decision makers to improve their environmental strategy.

In the same direction, our study aims to propose a new way in order to help manufacturing companies to achieve their emission objectives. According to Chen and Monahan (2010), the company is obliged to comply with emission standards that form, in most cases, a capacity constraint. Thus, in this paper, we focus on the possibility to benefit from outsourcing to reduce the emission balance of the firm.

The problem of production control of unreliable manufacturing systems has attracted a considerable attention. In the literature, several modeling and resolution approaches have been proposed to study this problem. The optimal control theory is one of the approaches that have been widely applied for this type of problem (Salama (2000)). In this context, Kenné and Gharbi (2000) studied a manufacturing system composed of a single machine- single product with holding and backlog cost. The optimal control policy considered has a special structure called Hedging Point Policy (HPP). Since, many extensions have been developed based on HPP by integrating several aspects in the manufacturing domain such as maintenance (Gharbi *et al.* 2007), setup (Assid *et al.* 2014), quality (Hajji *et al.* 2012), and subcontracting (Hajej *et al.* 2014).

In the literature, several studies have considered the subcontracting in various areas such as aerospace, supply chain, manufacturing domain (Dahane *et al.* 2011). The problem of production control with subcontracting has already been addressed by various researchers (Tan and Gershwin (2004); Dellagi *et al.* (2007). In the context of networked manufacturing systems, Chan *et al.* (2007) studied the problem of production control with demand uncertainty. Faced to the limit of the production capacity, they assumed that an additional capacity with additional costs can be used to meet demand. The authors proposed a multiple hedging point policy for the manufacturing system with delay. Based on a probability distribution of system states, optimal policy parameters are found. Hajej *et al.* (2014) addressed the problem of production/maintenance control for a single machine with random demand. A subcontracting machine, characterized by a transportation delay and availability, is also considered in order to support the principal machine to meet all the demand. The effect of the subcontracting transportation delays on the production plan and maintenance policy was analysed. Gharbi *et al.* (2011) focused on a manufacturing system composed of a central machine producing a single product type in a stochastic context. To meet demand, another machine (stand by) is used in the case of capacity lack of the central machine. The authors have considered two different production rates for the central and the stand by machine. Results showed that the optimal production policy is under the class of multiple HPP.

The main contribution of this paper lies in the consideration of the problem from an operational point of view. Under the optimal control theory, we consider a stochastic manufacturing system subject to random failures and repair activities with a reliable subcontractor.

Moreover, in our study, an integrated production, environmental and subcontracting control problem is investigated in order to better approach the real context of the manufacturing industry. Indeed, we address the problem of a company that can benefit from a subcontractor to deal with these economic and environmental problems in order to ensure the continuity and the stability of the relationship with its traditional customers. While in-house production parameters (inventory, backlog and production costs, capacity, availability and pollutant emission) are considered, a subcontractor delivery time and cost are integrated. To the best of our knowledge, the production planning problem has never been addressed with the consideration of the subcontracting and the emission control simultaneously. The originality of this study is in the consideration of subcontracting as an alternative to provide the environmental strategy of the company and better control its emissions.

The remainder of this paper is organized as follows. System description, the mathematical formulation of the problem and the control policy are presented in the section 4.2. In section 4.3 and section 4.4, we present the experimental resolution approach and the simulation model, respectively. In section 4.5, based on an illustrative numerical example, the results of the experimental design and the respond surface methodology are presented. In the same section, an extensive sensitivity analysis is conducted in order to confirm the robustness of the resolution approach and analyze the behaviour of the control policy when the system parameters change. We develop, in section 4.6, an extension of the control policy with the consideration of a non-negligible delivery delay of the subcontractor. A general discussion is presented in section 4.7. Section 4.8 is the conclusion part.

4.2 Problem statement

4.2.1 System description

In this paper, the manufacturing system under study is composed of single production facility subject to random failures and repair activities, producing a single product type to satisfy a constant demand rate. Failure events and repair durations are assumed to evolve according to a continuous time discrete state stochastic process characterized by the variable $\alpha\ \{\alpha\ (t), t > 0\} \in$ Î $\{0, 1\}$; with $\alpha(t)=1$ when the system is available and $\alpha(t)=0$ if the system is down. Figure 1 presents the manufacturing system under study.

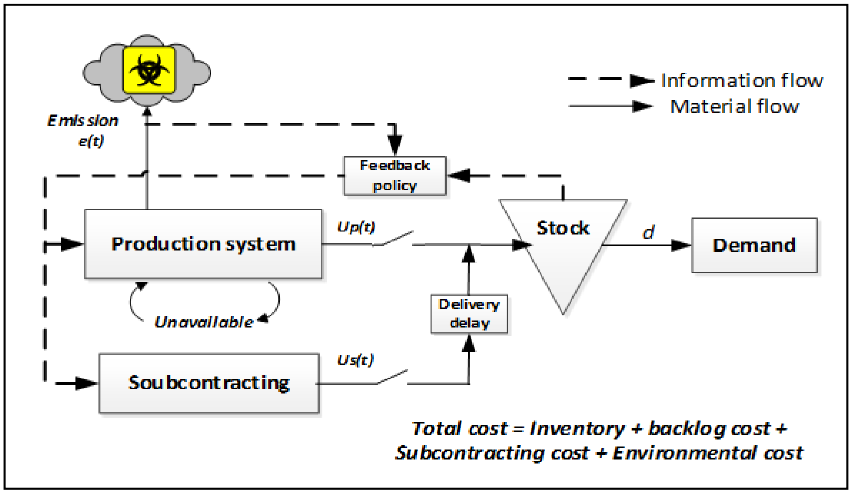


Figure 4.1 Manufacturing system under study

From Figure 4.1, the production facility produces with a rate $u_p(t)$ to build a stock $x(t)$ from which the demand rate d is directly satisfied. In addition to the inventory cost, given the unavailability (failure events and repair activities) of the machine during certain periods, the demand may be backlogged and delivery is delayed, with a backlog penalty. The manufacturing facility's operations generate harmful emissions to the environment and may incur sanctions in the form of an environmental cost imposed by the relevant authorities. To explain, the emission cost is due to a penalty paid by the firm when its emission level $e(t)$, in a control period, exceeds a standard limit L fixed by the authorities (Chen and Monahan, 2010). It is important to note that this environmental control policy, called «Cap policy» is considered by the « Congressional Budget Office (CBO) » and « Congress of the United States » as an option to reduce emissions (Konor, 2014).

Faced with the increase in the environmental cost, we assume that finished product demand can be satisfied also from a subcontractor to reduce emissions generated. The subcontractor, characterized by a delivery delay τ and a subcontracting cost, ensure a regular rate of finished production $u_s(t)$.

Given the significant compromise that must take place between economic gain and environmental objectives, this paper aims to propose a feedback adaptive policy which provides a better control of the production and subcontracting rates considering the emissions generated.

For any specific time t, the state of the system can be described by the pair of state variables $(x(t), \alpha(t))$ with $x(t) \in R$, $\alpha(t) \in M = \{0,1\}$; $x(t)$ is a continuous component describing the cumulative surplus level and $\alpha(t)$ is a discrete component describing the manufacturing system state. The differential equation (4.1) presents the dynamic behaviour of the finished products surplus:

$$\dot{x}(t) = u_p(t) + u_s(t+\tau) - d \, , \; x(0) = x_0 \tag{4.1}$$

Where x_0 denotes the initial surplus level.

The production rates $u_p(t)$, at any instant t, must satisfy the capacity constraint of the production unit given by the equation (4.2):

$$0 \leq u_p(t) \leq U_{max}^p \tag{4.2}$$

Where U_{max}^p denotes the maximum production rate for the production unit.

The capacity of the production system and subcontractor must satisfy at minimum the demand rate taking into account the random availability of the production system. Hence, capacity constraint of the production system and the subcontractor can be presented as in equation (4.3) and (4.4), respectively:

$$\mathrm{d} \leq U_{max}^p \times \frac{MTTF}{MTTF + MTTR} \tag{4.3}$$

$$\mathrm{d} \leq u_s(t+\tau) \tag{4.4}$$

Where MTTF and MTTR present, for the production system, the mean time to failure and the mean time to repair, respectively.

When processing parts at a fixed rate $u_p(t)$, the system is constrained to generate a quantity of emission for each part produced. Let θ be the emission index expressed as the quantity of pollutants per unit produced (Chen and Monahan (2010)). The dynamic behaviour of the emission rate is given by equation (4.5):

$$\dot{e}(t) = u_p(t) \times \theta, \quad t \in [t_i, t_{i+1}[, e(t_i) = 0, i = 1,..,\infty, \tag{4.5}$$

Under the cap approach, in each reference period i, if the quantity of emissions exceeds a standard level L fixed by the relevant authorities, the excess quantity is penalized with an environmental cost (Jaber *et al.* 2013). At the end of the reference period, the emission counter is reset to zero.

The decision variables of the control policy are the production rate $u_p(t)$ and the subcontracting rate $u_s(t)$. The state variables are the inventory level $x(t)$, the emission level $e(t)$ and the production system state $\alpha(t)$. The manager decision is strongly conditioned by the involved costs; inventory, backlog, production, subcontracting and emission cost. The total cost $J(.)$ is given by the following equation:

$$J(x,\alpha,e) = \int_0^{\infty} e^{-\rho t}\left[C^+x^+ + C^-x^- + C_{\mathrm{p}}\ u_{\mathrm{p}}(\mathrm{t}) + C_{\mathrm{s}}\ u_{\mathrm{s}}(\mathrm{t}+\tau)\right]dt + \frac{\sum_{i=1}^{N} EC(t_i)}{N \times P_{er}} \tag{4.6}$$

Where $x^+ = max\ (0,\ x)$, $x^- = max\ (-x,\ 0)$, C^+ and C^- are the inventory and backlog cost, respectively; C_p and C_s represent the production and the subcontracting cost, respectively. The penalty emission cost ($EC(t_i)$), at the end of reference periods i, is given by the equation (4.7):

$$EC(t_i) = C^e \times \max\left(0, e(t_i) - L\right), i = 1,..,\infty \tag{4.7}$$

4.2.2 Control policy «HPPS», with negligible delivery delay

In the literature, HPP is largely used because of its ease of implementation and its ability to adapt decisions when the system is facing random events (failures, repairs activities, delivery delay...). Thanks to these characterizes, we propose a feedback control policy that takes into account the emissions generated in the production and subcontracting decision. In this context, the manager should have an adapted emission control level beyond which he can decide to act if the emission cost rises. However, this decision cannot be taken independently of the inventory level, and thus a coupled feedback control should be considered.

The proposed policy, called HPPS, summarizes a voluntary commitment of the firm which aims to improve its environmental strategy. Indeed, we consider that the firm can set its own emissions cap (Y), different from the standard limit L imposed by the government, from which the emission reduction became a priority. For the reasons of simplification, we consider, firstly, that the delivery time of the subcontractor is negligible (τ = 0).

Equations (4.8) and (4.9) present HPPS for a given emission control period i:

$$\begin{cases} \quad\quad\quad\quad\quad\quad if\ e(t) \le Y: \\ u_s(t) = 0 \quad and \quad u_p(x,\alpha) = \begin{cases} U_{\max} & if \quad x(t) < Z\ and\ \alpha(t) = 1 \\ d & if \quad x(t) = Z\ and\ \alpha(t) = 1 \\ 0 & if \quad x(t) > Z \quad or\ \alpha(t) = 0 \end{cases} \end{cases} \tag{4.8}$$

$$\begin{cases} \quad\quad\quad\quad\quad\quad if\ e(t) > Y: \\ u_p(x,\alpha) = \begin{cases} U_{\max} & if \quad x(t) < 0\ and\ \alpha(t) = 1 \\ 0 & if \quad x(t) = 0\ \ or\ \alpha(t) = 0 \\ 0 & if \quad x(t) > 0\ \ or\ \alpha(t) = 0 \end{cases} \quad and \quad u_s(t) = \begin{cases} 0 & if \quad x(t) < 0 \\ d & if \quad x(t) = 0 \\ 0 & if \quad x(t) > 0 \end{cases} \end{cases} \tag{4.9}$$

According to the emission level *e(t)*, we distinguish two cases:

- Equation (4.8): when the emission level is lower than *Y*, the control policy consists on producing in-house without subcontracting. The production is governed by the classical HPP which requires producing at the maximum rate to reach the hedging level Z, than producing just at the demand rate. At this stage, the total cost is composed only of production, inventory and backlog costs. In the case where the emission level *e(t)* exceed the standard limit *L*, an emission penalty is added to the other costs.

- Equation (4.9): when the emission level *e(t)* exceeds *Y*, the weight of total emission penalty becomes very significant compared to others costs . Therefore, a production stop decision is logical in order to minimize the total cost. At this stage, the subcontracting process can begin in order to meet demand and avoid additional emission and backlog costs. Given that we have already assumed that the delivery time τ = 0, the subcontracting rate allows just to meet demand ($u_s(t)= d$). However, before switching to subcontracting, it is logical that the system gives priority to the inventory of finished products manufactured in-house to satisfy the demand when the inventory level is positive ($x(t)> 0$) in order to avoid additional inventory cost. In either case, if the inventory level is negative ($x(t)<0$), to meet the backlogged demand, the system must provide products at the maximum rate from in-house production (case 1) or subcontracting (case 2). In this context, we tested both cases using an illustrative numerical example. Results showed that producing in-house at $u_p(t) = U^p_{max}$ before switching to subcontracting is more interesting.

Compared to classical HPP, HPPS gives to the company the possibility to use the subcontracting products to meet the demand and avoid emission cost.

In the following sections, the resolution approach is presented, proposed policy is implemented and several experiments are developed to optimize the policy parameters and show HPPS effectiveness compared to classical HPP.

4.3 Resolution approach

The objective of the following sections is to find the optimal values of control policies parameters. The effect of each system variable on the parameters of both control policies and on the total cost difference is studied and analyzed thoroughly. Thus, an experimental approach combining simulation, design of experiment and RSM is used as in Gharbi *et al.* (2011). The main steps of the experimental resolution approach are:

- Step 1: Description of the control policies:

  In section 4.2.2, the structures of control policy is presented and expressed by mathematical equations (4.8) and (4.9). Regarding the classical HPP, we refer the reader to Kenné and Gharbi (2000). These policies will govern our simulation models.

- Step 2: Simulation models:

Two simulation models are developed to reflect the system dynamics governed by each of the control policies considered. These policies are used as an input to conduct several experiments and thus evaluate the system performance.

- Step 3: Experimental design and response surface methodology:

  The experimental design approach defines the experiments number, the experimental domain of the independent variables and the variation of each factor. The ANOVA is subsequently used to determine the factors and their interactions which have a significant effect on the cost (dependent variable). After that, the RSM allows obtaining the relationship between the cost and significant main factors. The resulting model is then optimized in order to determine the optimal policy parameters and the optimal total cost.

4.4 Simulation model

Using the simulation language SIMAN under «ARENA» software, a combined discrete-continuous model is developed with C++ routines. Lavoie et al. (2010) justified the advantage of this type of model in terms of simulation run time. Figure 4.2 presents the diagram of the simulation model:

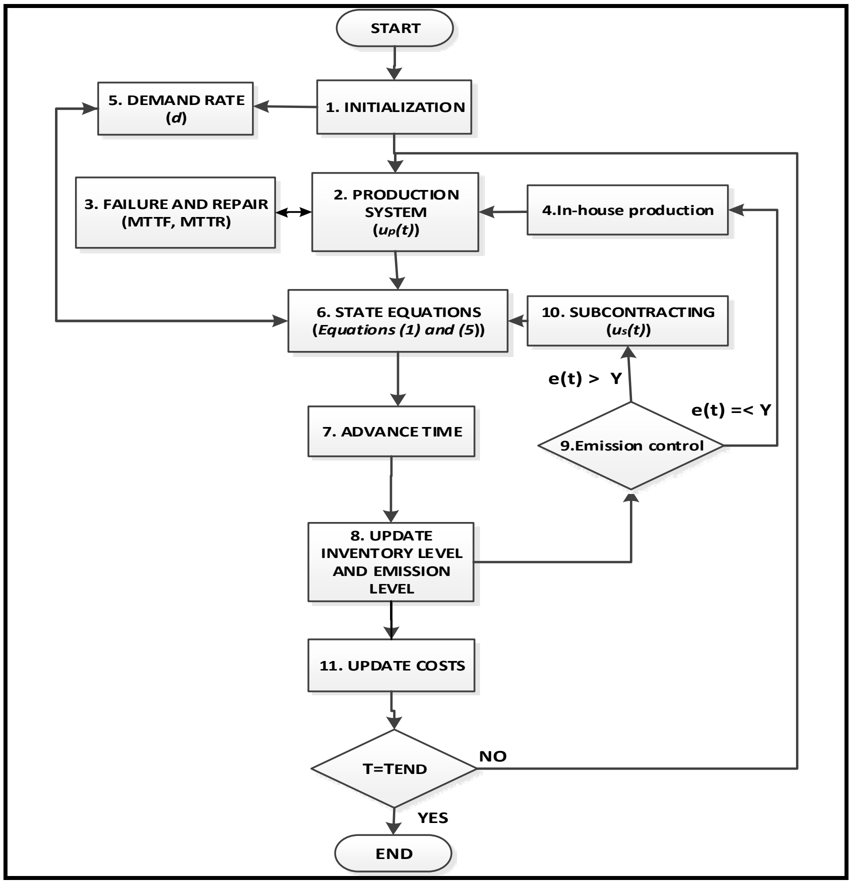


Figure 4.2 Diagram of the simulation model

After initializing the model with the necessary simulation parameters and inputs (Z, U_{max}, d, simulation duration ...) (block 1), the production system (block 2), subject to random failures and repairs activities (block 3), allows to produce in-house according to the control policy (block 4) described by equations (4.8) in order to meet the demand (block 5). The state equations (block 6), which are defined using C ++ routines, describe the variation of inventory levels $x(t)$ and the emission levels $e(t)$ according to the equations (4.1) and (4.4). The simulation time advance (block 7) and the model updated the level of surplus inventory (when the machine product or demand arrives) and the emission level generated (block 8). The control of the emission level, in a reference period i (block 9), allows to check the condition ($e(t)> Y$). When $e(t)$ exceeds the level Y, production is stopped and subcontracting (block 10) can begin (equation (4.9)). Finally, a calculation operation of each cost (inventory, backlog, emission, production and subcontracting cost) is executed (block 11).

To verify that the simulation model adequately reproduces the considered system, we present the variation of the inventory level, the emission level, the production rate and the subcontracting rate over time. For the parameters Z = 20, U_{max}^{p}=3, d= 2, Y=280, L= 200 and the length of a reference period = 150 units of time (UT), the graphics are given in Figure 4.3:

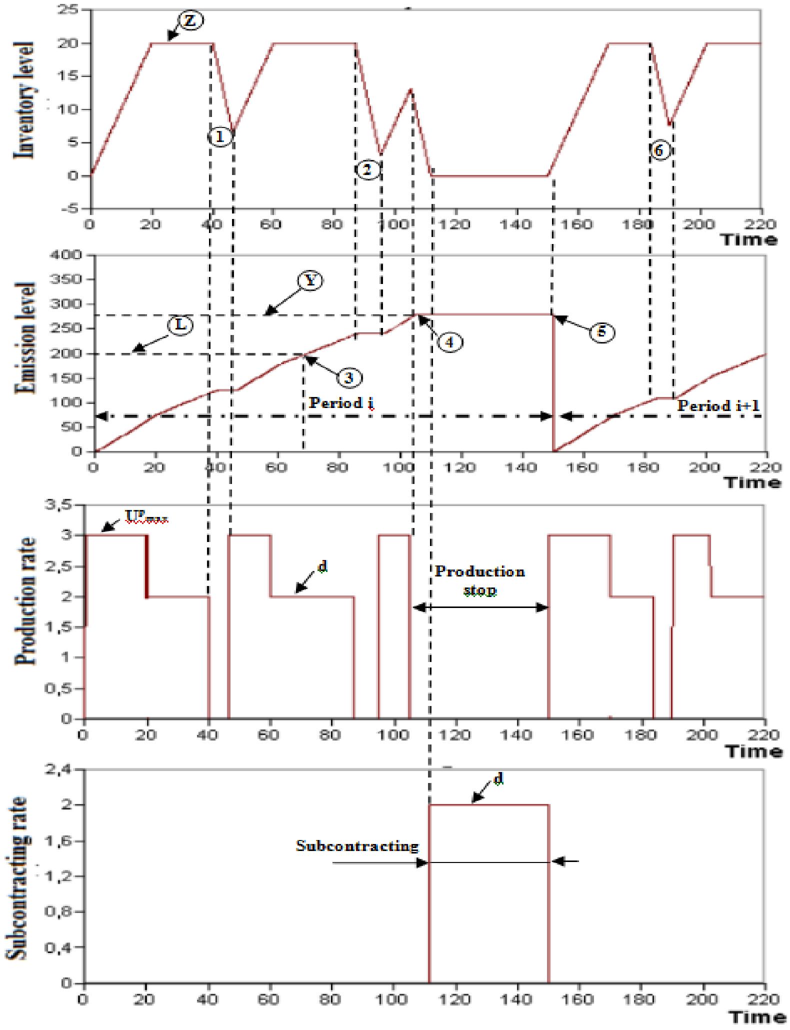


Figure 4.3 Variation of $x(t)$, $e(t)$, $u_p(t)$ and $u_s(t)$ over time

Initially t = 0 UT, the emission level increases in synchronization with the production rhythm. The manufacturing system produces according to control policy with a critical threshold Z = 20; production rate $u_p(t) = d$ if $x(t)= Z$ and $u_p(t) = U_{max}^{p}$ if $x(t) < Z$ as presented in the graph of the production rate. When a random failure (like ① or ②or⑥) occurs, the production is stopped, therefore the emission level remains at the same values and the production rate is set to zero. Production is restarted after a random repair activity. The simulation time advances and the emission level reaches the standard limit L_s at t=68 TU③, thus from this moment, an emission cost is added to others costs (inventory, backlog and production).

When the simulation time t = 104 UT ④ , the emission levels $e(t)$ reaches the value Y. From this moment, the production is stopped immediately after checking the inventory condition ($x(t) > 0$). Then, when the inventory level reached zero ($x(t) = 0$) at t=112 UT, the subcontracting begins with a rate $u_s(t)=d$. Therefore, the emission level $e(t)$ and the inventory level remain constants until the end of the reference period i at t = 150 UT⑤. At this moment, the emission level is reset, subcontracting is stopped and production begins again with a critical threshold Z for the next period i+1.

Based on several analyzes of this type, we confirm that the simulation model adequately reproduces the dynamics of the system under study.

4.5 Experimental design and response surface methodology

This section presents the third step of the resolution approach. The objective is to find the optimal parameters values for the control policy (Z^*, Y^*) which give the optimal total cost $T.C^*$. Therefore, an illustrative numerical example is considered. Table 1 summarizes the different parameters of operations and costs characterizing the system. In order to take into account the stochastic aspects of emission, we consider θ varying uniformly in a given interval [a, b] as in Chen and Monahan (2010).

Table 4.1 Values of the system parameters

Parameters	**d**	**U^{p}_{max}**	**MTTF**	**MTTR**	**L**	**C^{+}**	
Values	100	125	Exp (7 UT)	Exp (0,4 UT)	550000	1	
Parameters	**C^{-}**	**C^{e}**	**C_{p}**	**C_{s}**	**a**	**b**	**Per**
Values	20	3.5	3	7	0.5	2	5760 UT

A complete (3^2) experimental design is used with five replications for each factors combinations (Y, Z) which means (3^3) × 5= 135 simulations. This type of plan gives more precise results since each interaction is estimated separately. The duration of each simulation is set to 500.000 UT to ensure that the steady-state is reached. Note that one simulation run time is around 5.5 seconds.

Throughout this paper, the statistical treatment of the data is carried out using «STATGRAPHICS» software to develop the second order regression model and optimize the independents variables.

4.5.1 Proposed control policy HPPS

In this section, we present the results of the application of the resolution approach to the numerical example in the case of HPPS.

We note that, for the selected parameters (Table 4.1), the correlation coefficients $R^2_{adjusted}$ found is greater than 97%. Hence, we conclude that more than 97% of the total variability is explained by the model. ANOVA analysis of the model showed that all the factors and their interactions, except the interaction (Z×Y), are significant at 95%. An analysis of the residual normality and of the homogeneity of variance was also carried out to check the conformity of the model.

Figure 4.4 shows the projection of the cost response surface for HPPS policy.

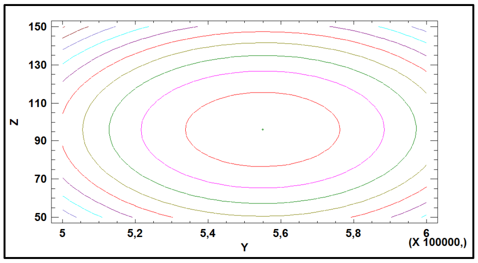


Figure 4.4 Response surface contour plot for the total cost

The second order equation of total cost function is given by:

$$\widehat{T.C}_{HPPS} = 2413.47 - 6.69058\,10^{-3} \times \mathrm{Y} - 1.36724 \times \mathrm{Z} + 6{,}02699\,10^{-9} \times \mathrm{Y}^2 + 7.11878\,10^{-3} \times \mathrm{Z}^2 \qquad (4.10)$$

Optimal control policy is defined by the optimal cost function located at Z* = 96 and Y*= 554979 leading to an optimal total cost $\widehat{T.C}_{HPPS}{}^{*}$ = 491,274.

The proposed control policy seems have interesting results. However, a comparative study with the classical HPP allows us to better judge the effectiveness of HPPS.

4.5.2 Classical control policy HPP

In this section, the classical HPP is adopted for the manufacturing system under study. Compared with HPPS, this policy does not take into account the emission level in the production decision. Therefore, customer demand cannot be satisfied from subcontracting and the production system produces always according to the control policy given by the equation (4.8) whatever the emission level.

Using the regression analysis approach as in Kenne and Gharbi (2000), the objective is to optimize the only independent variable Z. For the system parameters (Table 4.1), the estimated model found has $R^2_{ajusted}$=96.15% judged higher enough to show the good quality of the model. The model obtained is quadratic as presented in the following equation:

$$\widehat{T.C}_{HPP} = 615.547 - 1.78564 \times Z + 9.29263\ 10^{-3} \times Z^2 \tag{4.11}$$

The optimal value of the critical threshold is Z^*= 96 leading to a total cost $\widehat{T.C}_{HPP}{}^*$=529,766. To cross-check the validity of our models, we confirm that the optimal cost for each control policy (HPPS and HPP) falls within the confidence interval at 95%. The confidence intervals found are [490.696, 495.786] and [528.512, 533.012] for HPPS and HPP, respectively.

It is interesting to conclude that, for the same selected system parameter (Table 4.1), HPPS policy gives a lower optimal cost than that given by the HPP. The gain in terms of total cost is more than 7.2%. Regarding the environmental issue, it is important to note that the proposed policy (HPPS) reduces the average emission quantity to 554979 emission units/period, compared to 720059 emission units/period, in the case of HPP, which means a gain of 22.93%. These results show the advantage of taking into account the emission levels in the structure of the control policy. In addition, the consideration of the subcontracting in the production planning allows the company to improve its environmental strategy by reducing emissions.

4.5.3 Sensitivity analysis

In this section, a sensitivity analysis is carried out to evaluate the effect of the variation in the different costs on the control policies parameters. This analysis aims to show the robustness of the resolution approach. The obtained results are compared to the basic case and summarized in Table 4.2:

Table 4.2 Sensitivity analysis results for HPP and HPPS policy

Case	***Cost parameters***						***HPP***		***HPPS***			***Gain (%) of HPPS/HPP***	***Remarks***
	C^+	C^-	C^e	C_p	C_s		***Z****	***T.C****	***Z****	***Y****	***T.C****		
1	**1**	**20**	**3.5**	**3**	**7**		**96**	**529.766**	**96**	**554979**	**491.274**	**7.26**	**Basic case**
2	**0.6**	**20**	**3.5**	**3**	**7**		117	492.07	117	559920	462.023	**6.1**	**Z*↑; Y*↑**
3	**1.4**	**20**	**3.5**	**3**	**7**		76	559.651	76	551852	514.255	**8.11**	**Z*↓; Y*↓**
4	1	**15**	**3.5**	**3**	**7**		79	516.994	79	556946	481.315	**6.9**	**Z*↓; Y*↑**
5	1	**25**	**3.5**	**3**	**7**		106	539.316	106	553772	498.684	**7.53**	**Z*↑; Y*↓**
6	1	**20**	**3**	**3**	**7**		96	515.142	96	559975	490.903	**4.7**	**Z*↔; Y*↑**
7	1	**20**	**4**	**3**	**7**		96	544.389	96	551213	491.419	**9.73**	**Z*↔; Y*↓**
8	1	**20**	**3.5**	**2**	**7**		96	429.766	96	566476	413.236	**3.84**	**Z*↔; Y*↑**
9	1	**20**	**3.5**	**4**	**7**		96	629.766	96	543464	567.716	**9.85**	**Z*↔; Y*↓**
10	1	**20**	**3.5**	**3**	**6**		**96**	**529.766**	96	543464	467.716	**11.71**	**Z*↔; Y*↓**
11	1	**20**	**3.5**	**3**	**8**		**96**	**529.766**	96	566476	513.236	**3.12**	**Z*↔; Y*↑**

From Table 4.2, we note that the critical threshold Z* is the same for HPP and HPPS.

- Variation of C^+ : when C^+ increases (case 3), the system avoids storing more finished product by reducing Z*. In this case, more orders are given to the subcontractor by reducing *Y** to avoid surplus inventory (x^+). When C^+ decreases (case 2), the opposite occurs.

- Variation of C^- : the variation in the backlog cost has an inverse effect on the threshold Z* compared to C^+. Indeed, from Table 4.2, the increase in C^- (case 5) increases the critical threshold Z* level to avoid additional backlog costs. In this case, the level Y* decreases to give more priority to subcontractor who does not present any backlog risk (no x^-). The opposite occurs when C^- decreases (case 4).

- Variation of C_e: the variation of the emission penalty has no effect on the value of Z. This result can be explained by the fact that the critical threshold is related only to the variation of the stock. Indeed, the variation of Z* is related only with C^+ and C^-. However, the emission penalty cost C_e has an influence on the parameter Y* of HPPS policy. We note that if C_e increases (case 7), the total emission cost increases, consequently, Y* decreases to advance the moment of switch to subcontracting and avoid paying additional emission cost. If C_e decreases (case 6), the opposite occurs.

- Variation of C_p and C_s: this variation does not affect the optimal value of Z*. However, C_p and C_s has an effect on the decision to switch from in-house production to subcontracting. Indeed, when C_p increases (case 9) (respectively, C_s decreases (case 10), the system encourages more subcontracting by decreasing Y*. Decreasing C_p (case 8) (respectively increasing Cs (case 11) gives the opposite behaviour of Y*.

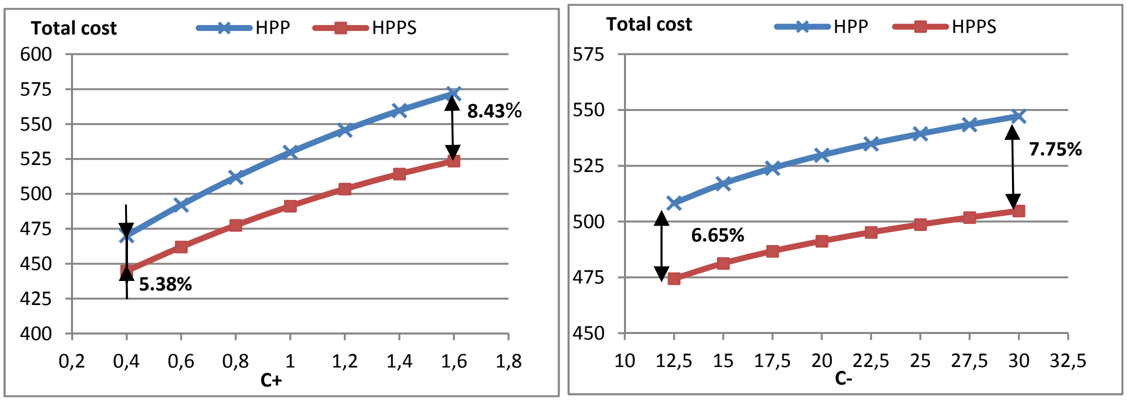
From all numerical examples, the results found seem logical and the structures of the policies are always maintained. From Table 4.2, in all cases studied, the obtained results show that HPPS remains better than HPP and gives a gain in term of total cost which varies from 3.12% to 11.71%. However, the gain is linked to the variation of each cost parameter. Therefore, in the next section, we develop a more in-depth analysis of the economic improvement of HPPS compared to HPP.

4.5.4 Influence of cost parameters

In this section, a comparative study of the effect of the cost parameter variation on the total cost for the policies is carried out.

4.5.4.1 Effect of C^+ and C^-

Figure 4.5 shows, for the basic case, the variation of the optimal total cost of HPP and HPPS when the cost parameters C^+ (Figure 4.5.a) and C^- (Figure 4.5.b) varies from 0.4 to 1.6 and from 12.5 to 30 respectively.



(a). C^+ (b). C^-

Figure 4.5 Variation of optimal total cost for HPP and HPPS

From Figure 4.5, if C^+ and/or C^- increase, the gain of HPPS compared to HPP increases. This result is explained by the fact that subcontracting (HPPS) is more recommended when stock costs increase. Indeed, in our case, the use of subcontracting avoids inventory surplus (x^+) and backlog (x^-). Thus, increasing C^+ and/or C^- gives more advantage to subcontracting because in-house production is more penalized. If C^+ and/ or C^- decrease, the opposite occurs.

4.5.4.2 Effect of C_p

Figure 4.6 shows, for the basic case, the variation of the optimal total cost of HPP and HPPS when the production cost varies from 2 to 4:

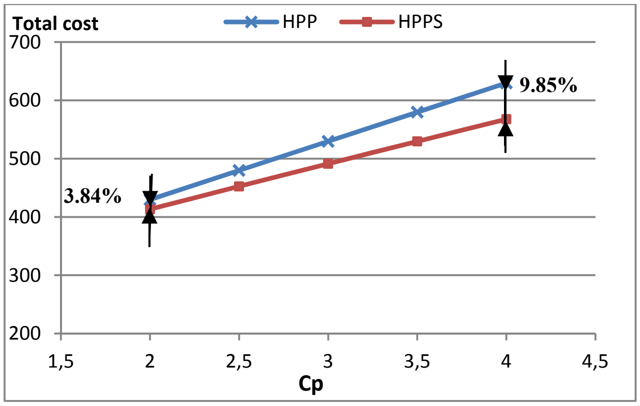
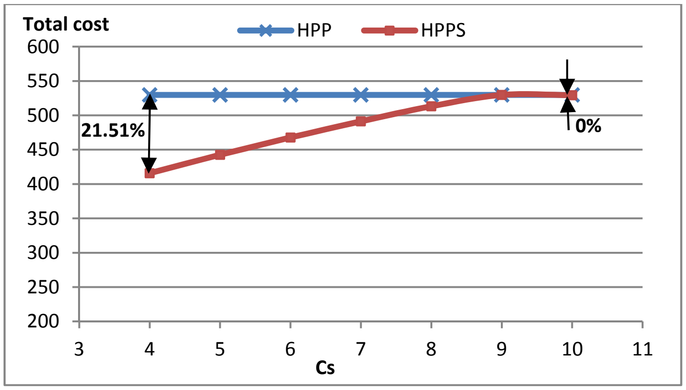


Figure 4.6 Variation of total cost for HPP and HPPS

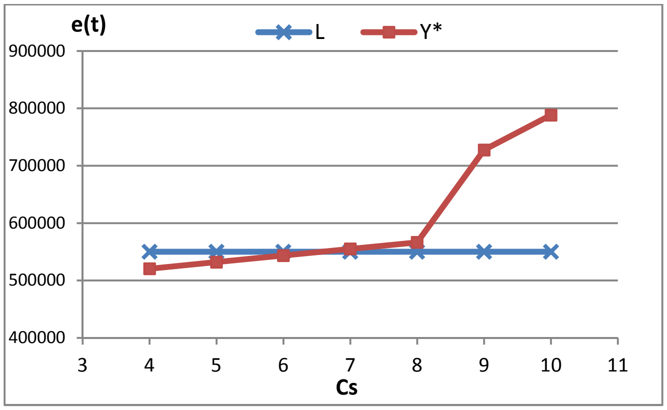
The increase in the gain between the total cost of HPP and HPPS is observed when the production cost increases (Figure 4.6). This result is due to the fact that HPPS gives the possibility to meet demand from subcontracted finished products. Consequently, if the in-house production cost increases, the disadvantage of the subcontracting is reduced which increases the benefit of HPPS.

4.5.4.3 Effect of C_s

Figure 4.7.a shows the variation of the optimal total cost of HPP and HPPS when C_s varies from 4 to 10. Since subcontracting is not permitted in the case of classical HPP, the optimal total cost of this policy remains at the same value of the basic case, $\widehat{T.C}_{HPP}^{\ *}$=529,766. In the same context, Figure 4.7.b shows the variation of Y* (HPPS) as function of C_s.



(a). Total cost (HPP and HPPS)



(b). L and Y* (HPPS)

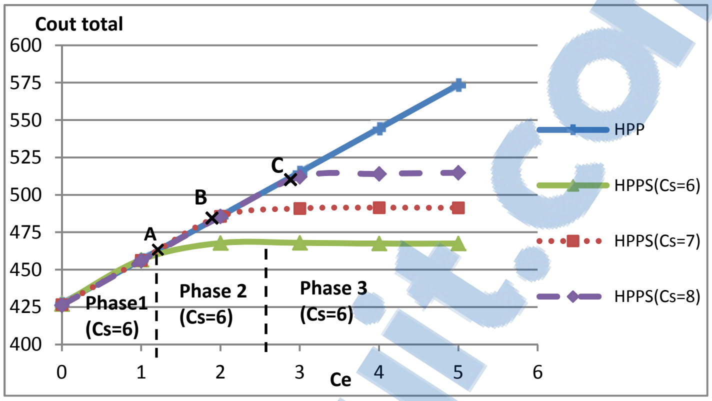
Figure 4.7 Variation of the total cost (HPP and HPPS), L and Y* (HPPS).

From Figure 4.7.a, we remark that the difference between the total cost of the two policies decreases when C_s increases and the economic gain changes from 21.51% to 0%. Indeed, the subcontracting (HPPS) is less beneficial when the cost proposed by the subcontractor increases. In the same direction, the level Y* (Figure 4.7.b) increases to delay the switching from in-house production to subcontracting whenever C_s increases. Ultimately, when C_s is very expensive, Y* becomes very high and the emission level can never reach this value (Y*). At this stage, HPPS and HPP are equivalent and gives the same optimal total cost ($\widehat{T.C}_{HPP}{}^{*} = \widehat{T.C}_{HPPS}{}^{*}$=529,766). When C_s decreases, the opposite occurs.

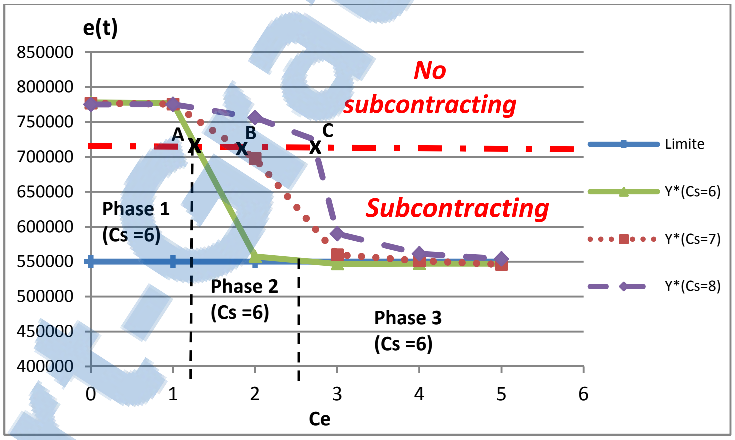
It is important to note that, according to Figure 4.7.b, the levels of Y* can be lower than the standard limit *L (*for $C_s < 6.5$*)*. In this case, HPPS avoids to the system to pay the emission penalty.

4.5.4.4 Effect of C_e

To better understand the reaction of the manufacturing system facing environmental regulations, we conduct a more detailed study of the behaviour of the policies parameters when C_e and C_s vary simultaneously. Figure 4.8.a and 4.8.b show, for the basic case, the variation of the total cost for each policy and the variation of Y*, respectively, as function of C_e and for different values of C_s.



a. Total cost for HPP and HPPS



b. The standard limit L and the level of Y* (HPPS)

Figure 4.8 Variation of total cost and Y* (HPPS) for different values of C_s

Let's start with a general observation, we note that the graph of the variation of Y* (Figure 4.8.b) can be devised in two main zones; in the first zone, subcontracting is not permitted since the values of Y* are higher than 720059. In the second zone, subcontracting is permitted because the values of Y* are less than or equal to 720059. This special value of the emission level *e(t)*= 720059 represents the maximum emission level at the end of a control period when only in- house production is considered (HPP is applied as described in section 4.5.2).

From the Figure 4.8, we remark that the evolution of the total cost and Y* can be analyzed on the basis of three phases. To better understand, these phases are presented in the graphs for C_s= 6:

- Phase 1: the optimal costs of HPPS and HPP are very close for low values of C_e. Indeed, subcontracting does not give much benefit when emission cost is negligible. Therefore, Y* (Figure 4.8.b) remains higher than 720059 in order to delay the switching to subcontracting. For example, for $C_s = 6$, when the emission cost is lower than C_e=1.3 (see point A), the system meets the demand from only its in-house production. When C_s increases to $C_s = 7$, the system accepts to pay an emission cost that can reach $C_e = 1.9$ (see point B), without switching to a more expensive subcontractor. Increasing more C_s to $C_s = 8$, the system accepts to pay an emission cost $C_e = 2.9$ (see point C) without switching to the subcontracting.

- Phase 2: HPPS policy starts giving a significant gain compared to HPP when C_e increases because subcontracting help the system to avoid the emission cost. In the same direction, the level of Y*, in Figure 4.8.b, decreases to allow the production stopping and switching to the subcontracted products. Compared to $C_s = 6$, it is clear that the reduction of Y* is delayed by increasing $C_s = 7$. To explain, the system has no benefit to switch quickly from in-house production to subcontracting which is expensive even if a high emission cost is imposed. When C_s increases to $C_s = 8$, the HPPS policy begins to have an economic gain compared to HPP only when $C_e \geq 2.9$.

- Phase 3: for high values of C_e, the Figure 4.8.a shows that the total cost given by HPPS remains constant. Indeed, the level Y* has reached the limit *L* (Figure 8.b). Thus, subcontracting begins, at each control period i when the emission level e(t) reaches the limit L= 550000 and the emission cost is no longer paid.

4.6 Extension of HPPS, to no-negligible delivery delay case

In an industrial context, subcontractor cannot often provide the order immediately. Indeed, a delay or a delivery time is possible in most cases due to important transport, administrative or set up times. Therefore, in this section, delivery time of subcontracted products is considered non-negligible. Thus, we proceed to update the proposed control policy HPPS described by equations (4.8) and (4.9) to take into account this aspect. Equations (4.12) and (4.13) present the new control policy, called HPPSD, for a given reference period i:

$$\begin{cases} \qquad\qquad\qquad\qquad \mathit{if}\ e(t) \le Y: \\ u_s(t)=0 \quad \mathit{and} \quad u_p(x,\alpha)=\begin{cases} U_{\max} & \mathit{if} \quad x(t)<Z\ \mathit{and}\ \alpha(t)=1 \\ d & \mathit{if} \quad x(t)=Z\ \mathit{and}\ \alpha(t)=1 \\ 0 & \mathit{if} \quad x(t)>Z\ \mathit{or}\ \alpha(t)=0 \end{cases} \end{cases} \tag{4.12}$$

$$\begin{cases} \qquad\qquad\qquad\qquad \mathit{if}\ e(t) > Y: \\ u_p(x,\alpha)=\begin{cases} U_{\max} & \mathit{if} \quad x(t)<S^*\ \mathit{and}\ \alpha(t)=1 \\ 0 & \mathit{if} \quad x(t)=S^*\ \ \mathit{or}\ \alpha(t)=0 \\ 0 & \mathit{if} \quad x(t)>S^*\ \ \mathit{or}\ \alpha(t)=0 \end{cases} \quad \mathit{and} \quad u_s(t+\tau)=\begin{cases} 0 & \mathit{if} \quad x(t)<S^* \\ d & \mathit{if} \quad x(t)=S^* \\ 0 & \mathit{if} \quad x(t)>S^* \end{cases} \end{cases} \tag{4.13}$$

The difference between the HPPSD and HPPS is at the level of the equation (4.13). Indeed, before switching form in-house production to subcontracting and given a random delivery delay, a safety stock S* (order point) is required in the case of HPPSD to avoid backlogs. In other words, the system has to continue meeting its customer demand from the safety stock until the arriving of the subcontracted finished products after a random delay (τ).

In the same context of outsourcing, the concept of safety stock has been used in several research papers (Gharbi *et al*. (2011); Saharidis *et al*. (2009)). Berhtaut *et al*. (2010) used an order point policy (s, Q) in the context of remanufacturing. Gharbi *et al.* (2007) focused on the joint implementation of preventive maintenance and safety stocks for unreliable manufacturing system.

4.6.1 RSM model and optimization

Compared to the numerical example and the optimization parameters used considering the HPPS, in this section, we define another independent variable (safety stock S) and the delivery time τ as a system parameter. To respect the condition ($S \leq Z$), we consider a continuous variable $K = S / Z$, with $0 \leq K \leq 1$.

Regarding the delivery time, we consider that τ follows a Normal distribution with a mean μ and a standard deviation; $\tau \sim N(\mu,\sigma)$. For the basic case, we consider $\mu = 1$ UT and $\sigma = 0.1$ UT. The correlation coefficient of the model found is $R^2_{\text{adjusted}} = 96.23\%$ judged higher enough to demonstrate good quality of the model given by:

$$\begin{aligned}\widehat{T.C}_{HPPSD} = {} & 5378{,}6 - 0{,}00988467 \times Y - 2790{,}7 \times S - 11{,}7157 \times Z \\ & + 6{,}0686\ 10^{-9} \times Y^{2} + 2.03643\ 10^{-3} \times Y \times S \\ & + 8.62588\ 10^{-6} \times Y \times Z + 634{,}572 \times S^{2} + 3{,}35665 \times S \\ & \times Z + 14.1762\ 10^{-3} \times Z^{2}\end{aligned} \tag{4.14}$$

Optimal control policy is defined by the optimal cost function located at $Z^* = 129$, $S^*=123$ ($K^*=0.955$) and $Y^*=562465$ leading to an optimal total cost $\widehat{T.C}^{*}_{\text{HPPSD}}=510.237$ which falls in the confidence interval (at 95%) [507.03; 510.7].

4.6.2 Sensitivity analysis

In this section, a sensitivity analysis is carried out to evaluate the effect of the variation in different system parameters on the optimal HPPSD parameters. The obtained results are compared to the basic case and summarized in Table 4.3.

Table 4.3 Sensitivity analysis results for HPPSD policy

Case	***system parameters***							***HPPSD parameters***				***Remark***
	Cost parameters					τ		***Z****	***S****	***Y****	***T.C****	
	C^+	C^-	C^e	C_p	C_s	**μ**	σ					
1	**1**	**20**	**3.5**	**3**	**7**	**1**	**0.1**	**129**	**123**	**562465**	**510.237**	**Basic case**
2	**0.6**	20	3.5	3	7	1	0.1	146	138	556032	466.498	**Z*↑, S*↑, Y*↓**
3	**1.4**	20	3.5	3	7	1	0.1	112	108	569518	548.015	**Z*↓, S*↓, Y*↑**
4	1	**15**	3.5	3	7	1	0.1	114	111	569172	504.366	**Z*↓, S*↓, Y*↑**
5	1	**25**	3.5	3	7	1	0.1	138	132	554263	513.326	**Z*↑, S*↑, Y*↓**
6	1	20	**3**	3	7	1	0.1	127	120	572183	509.242	**Z*↓, S*↓, Y*↑**
7	1	20	**4**	3	7	1	0.1	130	125	556026	510.712	**Z*↑, S*↑, Y*↓**
8	1	20	3.5	**2**	7	1	0.1	126	118	579088	430.767	**Z*↓, S*↓, Y*↑**
9	1	20	3.5	**4**	7	1	0.1	132	128	54773	587.39	**Z*↑, S*↑, Y*↓**
10	1	20	3.5	3	**6.5**	1	0.1	130	126	554128	499.107	**Z*↑, S*↑, Y*↓**
11	1	20	3.5	3	**7.5**	1	0.1	127	121	570753	520.79	**Z*↓, S*↓, Y*↑**
12	1	20	3.5	3	7	0.8	0.1	117	102	572963	498.345	**Z*↓, S*↓, Y*↑**
13	1	20	3.5	3	7	1.2	0.1	148	142	558420	523,551	**Z*↑, S*↑, Y*↓**
14	1	20	3.5	3	7	1	0.05	128	121	565158	509.8	**Z*↓, S↓*, Y*↑**
15	1	20	3.5	3	7	1	0.15	130	124	561865	512.98	**Z*↑, S*↑, Y*↓**

From Table 4.3, it is important to note that, for the same selected system parameter (Table 1), HPPSD presents an economic gain of 3.69% compared to HPP. This gain remains less then that find in the case of HPPS due to the delivery delay which can cause backlogs. In addition, there is a difference between the effects of the variation of the cost parameters on the HPPSD compared to their effects on HPPS (Table 2). Indeed, in the case where a delivery delay is considered (HPPSD), the decision of switching from in-house production to subcontracting is not only due to the emission level (case of HPPS), but also related to the inventory level. To explain, from Table 4.3, it is clear that the system increases Z* and S* to avoid backlog due to the delivery delay when subcontracting is more recommended (C_p increases or C_s decreases or C^e increases.).

In another hand, results show that increasing the inventory threshold Z* and the safety stock S* when the storage costs vary (C^+ decreases and/or C^- increases), leads to a decrease in the level of Y* in order to advance the switching from in-house production to subcontracting.

In the following paragraph, we will turn our attention to the effect of the variation of probability distribution parameters for delivery delay τ on the HPPSD parameters. From Table 4.3, the variation of τ has an influence in the critical threshold Z* and the safety stock S* which affect the decision to switch from in-house production to subcontracting.

- Variation of μ: increasing μ (case 13) indicates that the delivery time increases leading to a more backlog risks. Therefore, Z* and S* increase to avoid backlog. Consequently, the level Y* decreases to advance the switching from in-house production to subcontracting. The opposite occurs when μ decreases (case 12).

- Variation of σ: the variation of the standard deviation (case 14 and 15) has the same effects of the probability distribution average μ on HPPSD parameters. In fact, when σ increases (case 15), the backlog risks increases which obliges the system to put more inventory levels (Z* and S*). Decreasing σ (case 14) gives the opposite results.

In the light of the previous analysis, it is important to note that the structure of the control policy HPPSD is significantly affected by the subcontractor cost and delivery time. Thus, in order to find a good compromise through economic and environmental aspect, company should consider subcontractor characteristics (τ and C_s) in its decision-making process. Therefore, in the following section, we focus on developing a decision support tool that allows the manager to choose the subcontractor based on its characteristics.

4.6.3 Decision support to subcontractor selection

In the literature, several studies have addressed the problem of production control with subcontracting possibility. Compared to these works, in this study, the proposed resolution approach allows us to examine practical and realistic situations. In this context, we focus on the selection decision of the subcontractor based on its cost and delivery time. In the previous section (section 4.6.1), the results showed that, for a certain subcontractor characteristics (τ ~ Normal (1, 0.1) and C_s=7), HPPSD policy provides an optimal cost $\widehat{T.C}^*_{HPPSD}$= 510.237.

We consider now that the manager may face the decision to change the subcontractor without increasing the optimal cost $\widehat{\mathrm{T.C}}^{*}_{\mathrm{HPPSD}}$= 510.237. The selection decision of the new subcontractor is based on its characteristics (delivery delay / cost). Figure 4.9 presents the variation of the total cost as a function of C_s for different delivery time; τ ~ Normal (0.8, 0.1), Normal (1, 0.1) and Normal (1.2, 0.1). These results have been found after considering C_s as an independent variable in the RSM model and maintaining the cost at the value 510.237 for different values of delivery delay.

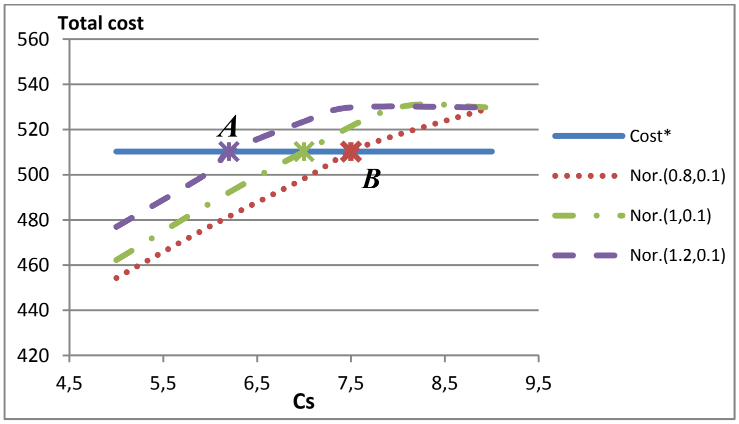


Figure 4.9 Decision support curve

From the Figure 4.9, we note that if the new subcontractor proposes a lower delivery time, the manager can accept to pay a higher subcontracting cost. The intersection points A and B indicate the maximum subcontracting cost that the manager can pay without increasing the optimal total cost when delivery time changes.

In order to generalize, Figure 4.10 shows the indifference curve that may help the manager to decide to change or not the subcontractor depending on its characteristics (cost/delivery time). From Figure 10, the indifference curve devises the graph in two zones according to the decision to keep the subcontractor or to change to a new one. Indeed, when the subcontractor provides a low delivery delay, the manager can accept to pay a more expensive cost and vice versa. The curve between the two areas indicates that the changing of the subcontractor has no effect on the optimal total cost $\widehat{\mathrm{T.C}}^{*}_{\mathrm{HPPSD}}$= 510.237.

Another important aspect, according to the Figure 4.10, is the fact that backlog cost affects the decision of subcontractor changing. Indeed, we notice that when C^- increases from 20 to 35, the system avoids changing to a subcontractor characterised by a high delivery delay which explain the enlargement of the zone «Keep the subcontractor». Thus, increasing C^-, the system becomes more severe in the subcontractor selection. When C^- decreases from 20 to 10, the opposite occurs.

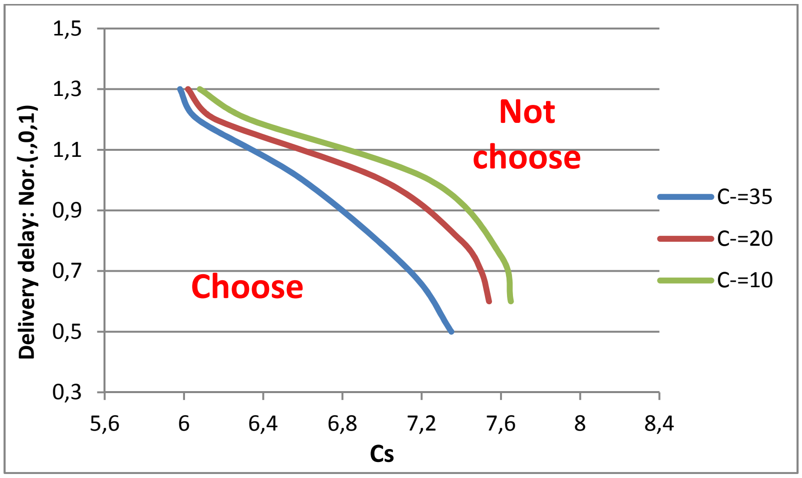


Figure 4.10 Indifference curve for different values of C^-

To finish with the Figure 4.10, we note that the curves, for different values of C^-, become very close when the subcontracting cost decreases. This result can be explained by the fact that subcontracting is more recommended and the inventory levels (Z* and S*) increase when C_s decreases. Consequently, the effect of C^- is less significant because subcontracting does not present any backlog risk (no x^-) after the delivery delay.

4.7 Discussions

From all what has been explained in the previous sections, results showed that the proposed HPPS and HPPSD have an economic advantageous compared to the classical HPP where subcontracting is not permitted. Furthermore, proposed policies, which consider the subcontracting possibility, allow the company to significantly reduce the total cost and in addition to the emissions generated. However, the advantages of such policies are strongly related to the subcontractor characteristics (delivery delay, cost). To better understand, Table 4.4 summarizes the control policies costs obtained for the basic case of the numerical example:

Table 4.4 Results of policies comparison

Control policy	$\overline{\mathbf{T.C}}$	**Inventory cost**	**Backlog cost**	**Emission cost**	**Production cost**	**Subcontracting cost**
HPP	530.76	84.17	44.21	102.37	300	-
HPPS	493.24	65.03	34.21	3.04	231.78	159.18
HPPSD	508.87	95.9	18.63	7.6	234.95	152.77

Where $\overline{\mathrm{T.C}}$ is the optimal total cost given by the simulation model when each control policy is considered. $\overline{\mathrm{T.C}}$ is the is the center of the confidence interval (at 95%).

From Table 4.4, it is important to note that HPPS reduces inventory cost and backlog cost compared to HPP. This result is due to the reliability of the subcontractor which allows the manager to just meet the demand from subcontracted products ($u_s(t)=d$). In addition, emission and production cost has been highly reduced in the case of HPPS thanks to subcontracting.

Regarding HPPSD, there is a significant change in the inventory cost and the backlog cost compared to HPPS. Indeed, when a delivery delay is considered, the critical threshold has increased from Z=96 (in the case of HPPS) to Z=129 (in the case of HPPSD) to avoid backlog which explain the decrease in the backlog cost and the increase in the inventory cost. Thus, the system produces more in-house when HPPSD is considered compared to HPPS leading to an increase of emission cost and production cost and reduction of subcontracting cost.

This comparative study shows that the two proposed control policies reduce the total cost and the emission balance. The gain these policies compared to HPP is related to subcontracting cost and delivery time.

4.8 Conclusion

In this study, we addressed the production control problem of a pollutant and unreliable manufacturing system with subcontracting. The main contribution of this paper is to consider the production, emission and subcontracting issue simultaneously from an operational level.

Control policies which take into account the emission level are proposed when the subcontractor delivery delay is negligible or not. We adopted an experimental resolution approach in order to solve the problem and find the optimal values of the policies parameters. An illustrative numerical example and an extensive sensitivity analysis are conducted in order to illustrate the robustness of the resolution approach and confirm the structure of the control policies. The results show that subcontracting can be an effective solution to the company in order to achieve its environmental and economic objectives. Indeed, it was clear that a better coordination between production and subcontracting strategies, which need a good inventory management and a good choice of subcontractor, can reduce the emission balance and provide a gain in term of total cost for the company.

Finally, we conclude that, under an emission cap approach, the use of subcontracting can help the company to improve its environmental strategy. However, the efficiency of this solution is strongly related to the subcontractor characteristics (cost, delivery delay).

References

Assid, M., Gharbi, A., & Hajji, A. (2014). Joint production and setup control policies: an extensive study addressing implementation issues via quantitative and qualitative criteria. International Journal of Advanced Manufacturing Technology, 1-18.

Ayed, S., Dellagi, S., & Rezg, N. (2012). Joint optimisation of maintenance and production policies considering random demand and variable production rate. International Journal of Production Research, 50(23), 6870-6885.

Battini, D., Persona, A., & Sgarbossa, F. (2013). A sustainable EOQ model: Theoretical formulation and applications. International Journal of Production Economics, 149, 145–153.

Bae, S. H., Sarkis, J., & Yoo, C. S. (2011). Greening transportation fleets: Insights from a two-stage game theoretic model. Transportation Research Part E: Logistics and Transportation Review, 47(6), 793-807.

Berthaut, F., Gharbi, A., & Pellerin, R. (2010). Joint hybrid repair and remanufacturing systems and supply control. International Journal of Production Research, 48(14), 4101-4121.

Bonney, M. (2009). Inventory planning to help the environment. Inventory Management: Non-Classical Views. Taylor & Francis Ltd, 43.

Bouchery, Y., Ghaffari, A., Jemai, Z., & Dallery, Y. (2012). Including sustainability criteria into inventory models. European Journal of Operational Research, 222(2), 229-240.

Chaabane, A., Ramudhin, A., & Paquet, M. (2012). Design of sustainable supply chains under the emission trading scheme. International Journal of Production Economics, 135(1), 37-49.

Chan, F. T., Wang, Z., & Zhang, J. (2007). A two-level hedging point policy for controlling a manufacturing system with time-delay, demand uncertainty and extra capacity. European journal of operational research, 176(3), 1528-1558.

Chen, C., and Monahan, G. E. (2010). Environmental safety stock: The impacts of regulatory and voluntary control policies on production planning, inventory control, and environmental performance. European Journal of Operational Research, 207(3), 1280-1292.

Chen, X., Benjaafar, S., & Elomri, A. (2013). The carbon- constrained EOQ. Operations Research Letters, 41(2), 172-179.

Choi, S.B., and Hwang, H. (1986). Optimizing of Production Planning Problem with Continuously Distributed Time-lags. International Journal of Systems Science, 17, 1499–1508.

Dahane, M., Clementz, C., & Rezg, N. (2007). Impact of the delay of subcontracting in a context of integrated maintenance: Analytical approach. In Emerging Technologies and Factory Automation, 2007. ETFA. IEEE Conference on, 273-279. IEEE.

Dahane, M., Rezg, N., & Clementz, C. (2011). Subcontracting integration in a joint maintenance/production policy: study on profitability conditions. European Journal of Industrial Engineering, 5(4), 412-423.

Dellagi, S., Rezg, N., & Xie, X. (2007). Preventive maintenance of manufacturing systems under environmental constraints. International Journal of Production Research, 45(5), 1233-1254.

Dobos, I., 2005. The effects of emission trading on production and inventories in the Arrow–Karlin model. International Journal of Production Economics, 93–94, 301–308.

Gharbi, A., Kenné, J. P., & Beit, M. (2007). Optimal safety stocks and preventive maintenance periods in unreliable manufacturing systems. International Journal of Production Economics, 107(2), 422-434.

Gharbi, A., Hajji, A., & Dhouib, K. (2011). Production rate control of an unreliable manufacturing cell with adjustable capacity. International Journal of Production Research, 49(21), 6539-6557.

Hajej, Z., Rezg, N., & Gharbi, A. (2014). Forecasting and maintenance problem under subcontracting constraint with transportation delay. International Journal of Production Research, (ahead-of-print), 1-22.

Hajji, A., Gharbi, A., & Pellerin, R. (2012). Joint production control and product quality decision making in a failure prone multiple-product manufacturing system. International Journal of Production Research, 50(13), 3661-3672.

Jaber, M.Y., Glock C.H., El Saadany A.M.A., (2013). Supply chain coordination with emissions reduction incentives. International Journal of Production Research, 51 (1), 69–82.

Kenne, J. P., & Gharbi, A. (2000). Production planning problem in manufacturing systems with general failure and repair time distributions. Production Planning & Control, 11(6), 581-588.

Konur, D. (2014). Carbon Constrained Integrated Inventory Control and Truckload Transportation with Heterogeneous Freight Trucks. International Journal of Production Economics, http://dx.doi.org/10.1016/j.ijpe.2014.03.009i.

Lavoie, P., Gharbi, A. and Kenne, J.-P., 2010. A comparative study of pull control mechanisms for unreliable homogenous transfer lines. International Journal of Production Economics, 124 (1), 241-251.

Saharidis, G. K., Kouikoglou, V. S., & Dallery, Y. (2009). Centralized and decentralized control polices for a two-stage stochastic supply chain with subcontracting. International Journal of Production Economics, 117(1), 117-126.

Sheu, J. B., Chou, Y. H., & Hu, C. C. (2005). An integrated logistics operational model for green-supply chain management. Transportation Research Part E: Logistics and Transportation Review, 41(4), 287-313.

Tan, B., & Gershwin, S. B. (2004). Production and subcontracting strategies for manufacturers with limited capacity and volatile demand. Annals of Operations Research, 125(1-4), 205-232.

Tan, B., 2004. Subcontracting with availability guarantees: production control and capacity decisions. IIE Transactions, 36 (8), 711–724.

Toptal, A., Özlü, H., & Konur, D. (2014). Joint decisions on inventory replenishment and emission reduction investment under different emission regulations. International Journal of Production Research, 52(1), 243-269.

Van Mieghem, J. A. (1999). Coordinating investment, production, and subcontracting. Management Science, 45(7), 954-971.

Wirl, F. (1991). Evaluation of management strategies under environmental constraints. European Journal of Operational Research, 55(2), 191-200.

Xepapadeas, A. P. (1992). Environmental policy, adjustment costs, and behavior of the firm. Journal of Environmental Economics and Management, 23(3), 258-275.

CHAPITRE 5

ARTICLE 4: PRODUCTION AND EMISSION CONTROL FOR UNRELIABLE MANUFACTURING SYSTEM WITH SUBCONTRACTOR UNCETAIN

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Abstract: Faced with environmental legislation imposed by the authorities, manufacturers have to review their strategies at short and mid-long term in order to integrate the environmental dimension in the decision making process. In this context, we address in this paper the problem of an unreliable manufacturing system producing one product family type to meet a constant demand rate. We consider that the manufacturing system's operations generate harmful emissions to the environment. Hence, in addition to the inventory, production and backlog costs, an environmental penalty is imposed when the emission level reaches a specific limit (cap approach). To improve its environmental strategy and reduce emission cost, we consider that demand can be satisfied from an unreliable subcontractor characterized by a cost and a random availability. This work deals with this decision making problem in order to propose a new production and subcontracting control policy which takes into account the emission level. The objective is to optimize the total cost: inventory, backlog, production, emission and subcontracting cost, over an infinite horizon. An experimental approach combining simulation, experimental design and response surface methodology is used to solve the problem. Through numerical examples and further sensitivity analysis, the structure of the control policy is confirmed and analyzed. Thanks to the practical usefulness of the resolution approach, we provide a decision support system to

help managers to choose between using subcontracting or not based on subcontractor characteristics (availability and cost).

Keywords: unreliable manufacturing system, unreliable subcontractor, production, emission, experimental resolution approach, decision support.

5.1 Introduction

In the literature, several approaches have been developed to provide better control and management of unreliable manufacturing systems. Feedback control policies are among the topics that have attracted the attention of many researchers. Through several research studies, this type of policy has been proved to be efficient in managing random events in a stochastic and dynamic manufacturing environment. In this context, the hedging point policy (HPP) has been developed for a manufacturing system composed of a single machine subject to failures and repairs (Kenné and Gharbi, 2000). This policy considers the production rate as a control variable and the state of the system, the inventory level as state variables. The idea consists of maintaining the stock level at a specific threshold when the production system is available to avoid backlog during failures periods. The concept of HPP has evolved to study more complex problems based essentially on the HPP extensions in a specific area such as maintenance (Berthaud et al. 2011), supply chain (Hajji et al., 2009), quality (Bouslah et al. (2014)) and subcontracting (Assid et al. 2014)).

Recently, the integration of environmental aspects in the manufacturing systems control has begun to attract the attention of researchers. In the context of the optimal control theory, Ben-Salem et al. (2014) studied a pollutant manufacturing system composed of a single machine subject to random failures and repairs activities producing a single type of product. Under the emission cap approach, the authors developed a control policy with multiple thresholds, called EHPP, which integrates the emission level in the production decision. The results showed that EHPP has an economic advantage and reduces the emission balance compared to the classical HPP. Li (2014) focused on the problem of production and maintenance control for a manufacturing system subject to quality deterioration under the emission tax approach. In addition to production and maintenance rates, the author considers the rate of investment in pollution R & D as a decision variable. Under the emission cap and trade system, Zhang et al. (2011) developed an optimal production policy for a manufacturing system with stochastic demand. Three sources of emission permits (emission quota allocated by the government, emission trading and emission savings thanks to purification) were considered. The authors proposed an optimal policy taking into account production and emission simultaneously. Drake et al. (2012) investigated the importance of technology choice and capacity decision in the context of emission control. Among the important results, the authors showed that the choice of technology could reduce emissions.

All the aforementioned works, in addition to many others, have introduced environmental dimension in the manufacturing systems control. It should be noted here that the main objective is to provide methods that may help companies to improve their environmental strategies such as the effective production / inventory manage, the choice of the technology, the investment in pollution R & D...etc. In this work, inspired by industrial practices, we investigate the possibility to take advantage from subcontracting as an external source (outsourcing) of the company in order to reduce the environmental costs. Note that several research studies have shown that outsourcing can help the company to achieve its objectives such as reducing inventory and backlog costs (Abernathy et al. 2000).

With regard to the subcontracting, the problem of in-house production and outsourcing has been the subject of several research papers. Among them, Dahane et al. (2011) addressed the joint production maintenance control problem in a subcontracting environment. In addition to the production system composed of a machine M1, the authors consider an unreliable subcontracting machine M2 characterized by a constant failure rate. The machine M2 is used because of the capacity lack of the machine M1 in order to meet a constant demand. Analytical and simulation models are developed to study the performance of the production system when governed with integrated maintenance-subcontracting strategy. Bradly (2004) considered the problem of production / inventory for a manufacturing system that can take advantage of two subcontractors to meet a stationary demand. Based on the approximations of Brownian, the author has developed a model that approximates the optimal threshold of the basic stock for an M/M/1 system. Results showed that, for this system, the threshold policy (HPP) is optimal when the second subcontractor is used in preventive mode to build up the stock (make-to-stock) or to solve the problem of expected orders (make-to-order). Bradly considered that subcontractor is always available. In another study, Tan and Gershwin (2004) addressed the problem of optimal production and subcontracting control with random demand. Yang et al. (2005) studied an inventory/ production system with Markovian capacity and the possibility of subcontracting when production cannot meet demand. The authors considered a reliable subcontractor. This assumption may not be very realistic in practice. In the context of the subcontractor unavailability, Tan (2004) presented and studied a model composed of a manufacturer and an unreliable subcontractor with random demand. The author considered that the subcontractor provides services to several manufacturers and, as a result, he may not be available to satisfy the demand immediately. The problem was modeled analytically based on the stochastic control theory (continuous flow, discrete state) and a multiple HPP is proposed. The author showed that the immediate unavailability of subcontractor allows him to benefit from demand pooling to reduce his optimal capacity and propose a lower cost. As in Tan (2004), unreliable subcontractor is considered in this paper.

However, we will investigate the problem at the producer level which is different from Tan who has focused on the behaviour of the subcontractor face of demand fluctuation. In addition, in our study, we consider that subcontractor unreliability is due to his manufacturing system failures.

In the light of the high needs and new reality, the main contribution of this paper is to provide decision makers with manufacturing strategies that incorporate both economic and environmental dimension. Hence, in this paper, we address the problem of an unreliable manufacturing system that generates emissions in the context of environmental legislation with the possibility of satisfying demand from subcontracted products. In this work, we combine the environmental aspects in manufacturing system control with the concept of outsourcing in a stochastic dynamic context. Therefore, a joint production, emission and subcontracting feedback control policy is developed. The objective is to measure the effectiveness of using outsourcing to improve the environmental strategy of the company and minimize the total cost. In this paper, we propose an experimental resolution approach combining simulation, experimental design and response surface methodology. This approach has proved its effectiveness in treating control problems for unreliable manufacturing systems when the analytical or numerical resolution is very difficult (Assid et al. (2014), Berthaud et al. (2011), Bouslah et al. (2013)).

The rest of the paper is organized as follows. The notations used in this work and the description of the studied system are presented in Section 5.2. The proposed control policy is described in detail in Section 5.3. In sections 5.4 and 5.5, the resolution approach and the simulation model are presented respectively. A numerical example and the sensitivity analysis are developed in Section 5.6. Section 5.7 presents a decision support tool for using or not subcontractor based on his characteristics (cost and availability). Finally, Section 5.8 concludes the paper and summarizes the most important results.

5.2 Problem statement

5.2.1 Notation

The following notations are used in this paper:

$x(t)$	Inventory level
x_0	Initial inventory level
$u_1(t)$	Production rate
$u_2(t)$	Subcontracting rate
$e(t)$	Emission level
U_{max}	Maximum production rate of the manufacturing system
d	Demand rate

L_s	Standard permitted limit of emission
L_v	Voluntary limit of emission
θ	Emission index
T_i	Length of emission control period
N	Number of periods in the planning horizon
ρ	Discount rate
Ds	Subcontractor availability
Dp	Production system availability
C^+	Holding cost/Unit/Time unit
C^-	Backlog cost/Unit/Time unit
C^e	Penalty cost for emissions/Unit
C_p	Production cost/Unit
C_s	Subcontracting cost/Unit
Z	Hedging level
MTTF	Mean Time To Failure of the production system
MTTR	Mean Time To Repair of the production system
MTTFS	Mean Time To Failure of the subcontractor manufacturing system
MTTRS	Mean Time To Repair of the subcontractor manufacturing system

5.2.2 Problem description

We study a manufacturing system composed of production facility subject to random failures and repairs activities producing one product family type to meet a constant demand rate. Because of the harmful emission to the environment caused by the manufacturing facility's operations, production may incur sanctions imposed by the relevant authorities. Thus, the company can meet demand from subcontracted finished product to deal with the increase in its in-house total cost: inventory, backlog, production and emission cost. Figure 1 presents the system under study.

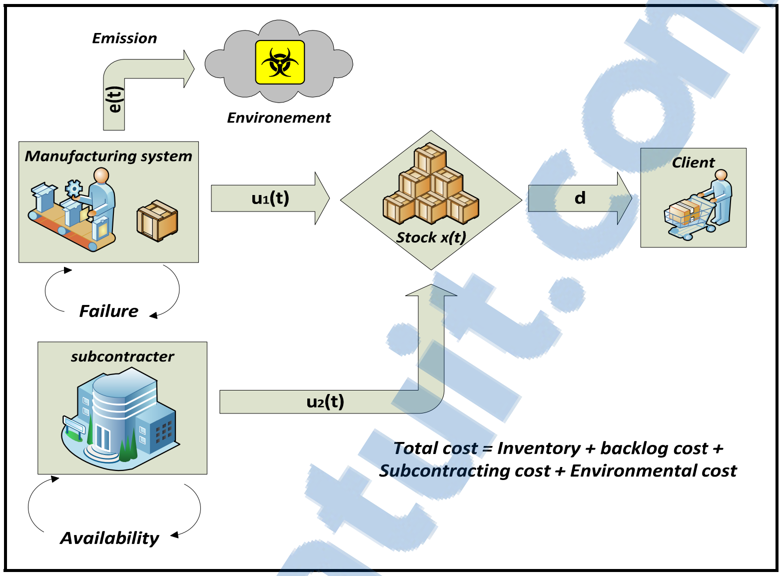


Figure 5.1 System under study

As shown in Figure 5.1, the manufacturing system makes products at a rate $u_1(t)$ to build a stock $x(t)$. In addition to the inventory, backlog and production cost, emission generated with a rate $\dot{e}(t)$ can cause an environmental cost under the emission cap approach. This cost is due to the emission penalty paid by the company when its emission level in a control period (e.g. one year) exceeds a standard limit (*Ls*) fixed by the authorities (Chen et al. (2013)). Faced with the increase in the company in-house cost, subcontracting, with a rate $u_2(t)$, is one of the effective solutions that can help meeting the customer demand. We assume that subcontractor will not provide additional capacity to the company all the time.

Given the significant compromise that must take place between in-house production and emissions, the main objective of this paper is to propose a feedback adaptive policy which provides a better control of the production and the subcontracting rate taking into account the environmental aspect.

For any specific time t, the manufacturing system and the subcontracting states can be described by a continuous- time discrete space stochastic process $\{\alpha(t), t > 0\} \in I\{0,1\}$ and $\{\beta(t), t > 0\} \in I\{0,1\}$, respectively, with $\alpha(t) = 1$ when the system is operational and $\alpha(t) = 0$ if the system is under repair and $\beta(t)$= 1 when the subcontractor is available and $\beta(t)$= 0 if the subcontractor is unavailable. Note that in Tan (2004), the subcontractor can be unavailable only at the beginning of the subcontracting process. However in our study, we assume that the subcontractor unavailability is due to the random failures and repair activities of his manufacturing system. Let $D_s = \frac{MTTFS}{MTTFS+MTTRS}$ be the subcontractor availability. In the same context, we define the production system availability as $D_p = \frac{MTTF}{MTTF+MTTR}$. Hence, the state of the production system and subcontractor can be described by the state variables $(x(t), \alpha(t), \beta(t))$ with $x(t) \in$ R, $\alpha(t)$ and $\beta(t) \in$ I= {0,1}.

The differential equation (5.1) presents the inventory dynamic:

$$\frac{dx(t)}{dt} = u_1(t, \alpha) + u_2(t, \beta) - d, \; x(0)=x0 \tag{5.1}$$

The production rate, at any time t, must satisfy the capacity constraint of the production system given by equation (5.2):

$$0 \leq u_1(t) \leq U_{max} \tag{5.2}$$

Given the random unavailability of the production system, its capacity must satisfy at minimum the demand rate presented as follow:

$$\text{d} \leq U_{max} \times D_p \tag{5.3}$$

When processing at the rate $u_1(t)$, the system generates a quantity of harmful pollutants θ, called emission index, for each part produced. The dynamic behaviour of the quantity of emissions is given by equation (5.4):

$$\frac{de(t)}{dt} = u_1(t, \alpha) \times \theta \tag{5.4}$$

To take account of the stochastic aspect of emissions, we adopt θ as a random variable that follows a uniform distribution [a, b] as in Chen and Monahan (2010).

5.2.3 Cost function

The instantaneous inventory, backlog, production and subcontracting cost function $g_1(.)$ is given by the following equation:

$$g_1\left(x(t),u_1\,(\mathrm{t}),u_2\,(\mathrm{t})\right)=C^+x^+ + C^-x^- + C_{\mathrm{p}}\,u_1\,(\mathrm{t}) + C_{\mathrm{s}}\,u_2\,(\mathrm{t}) \tag{5.5}$$

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

The emission cost at the end of reference periods *i* is given by the following equation:

$$g_2(t_i)=C^e\times\max\left(0,e(t_i)-Ls\right), i=0,..,N \tag{5.6}$$

Hence, the total cost *J(.)* can be defined by the equation (5.7) using $g_1(.)$ and $g_2(.)$:

$$J(x,e,\alpha,\beta)=\int_0^\infty e^{-\rho t}g_1\left(x(t),u_{\mathrm{p}}(\mathrm{t}),u_{\mathrm{s}}\,(\mathrm{t})\right)dt+\frac{\sum_{i=1}^{N}g_2(t_i)}{N\times T_i}, with \quad N\to\infty \tag{5.7}$$

The production and subcontracting planning problem considered here is to find an admissible decision or control policy that minimizes *J(.)*, given by (5.7) subject to equations (5.1) to (5.4). Hence, the objective is to determine the production and the subcontracting rates as a function of the inventory level, the emission level, the production system and the subcontractor states in order to minimize the total cost.

5.3 Control policy

An extended version of HPP taking into account the subcontracting possibility and the environmental aspects is developed in this section. As presented in the introduction, for continuous flow manufacturing systems, HPP is optimal for the same class of system (Kenné and Gharbi, 2000), but without considering emission nor subcontracting. From an operational level, to control the manufacturing system under study, manager has to choose between reducing the production and accepts backlog costs or increase production and accepts inventory and emission cost. In an unreliable manufacturing environment, the manager, in order to remain competitive in the market, cannot accept to permanently limit production at the standard limit L_s or ignore the possibility of an occasional emissions overflow. Hence, subcontracting can be an effective way for the company to avoid backlogs and reduce its emissions at the same time.

In the light of this discussion, we start from the HPP to develop a modified one which introduces the emission level in the production planning decision and take advantage from the subcontracting to reduce emission costs. In this context, the decision maker should consider a specific emission level beyond which the in-house production is reduced and subcontracting is started. In this context, we propose a new control policy which consists in setting a voluntarily emission limit L_v that control the production and the subcontracting rates based on the emission level. When called, the subcontractor provides products with a rate u_2 during his up time until the end of the control period.

Equations (5.8) and (5.9) present the proposed control policy for a given emission control period i:

$$\begin{cases} \text{if } e(t) < Lv: \\ u_1(t,\alpha) = \begin{cases} U_{\max} & \text{if} \quad x(t) < Z^* \,\text{and}\, \alpha(t) = 1 \\ d & \text{if} \quad x(t) = Z^* \,\text{and}\, \alpha(t) = 1 \\ 0 & \text{if} \quad x(t) > Z^* \,\text{or}\, \alpha(t) = 0 \end{cases} \\ \\ u_2(t,\beta) = 0 \end{cases} \tag{5.8}$$

$$\begin{cases} \text{if } e(t) \geq Lv: \\ u_1(t,\alpha) = \begin{cases} U_{\max} & \text{if} \quad x(t) < Z^* \,\text{and} \quad \alpha(t) = 1 \quad \text{and} \quad \beta(t) = 0 \\ Max((U_{\max} - u_2^{*}),0) & \text{if} \quad x(t) < Z^* \,\text{and} \quad \alpha(t) = 1 \quad \text{and} \quad \beta(t) = 1 \\ d & \text{if} \quad x(t) = Z^* \,\text{and} \quad \alpha(t) = 1 \quad \text{and} \quad \beta(t) = 0 \\ Max((d - u_2^{*}),0) & \text{if} \quad x(t) = Z^* \,\text{and} \quad \alpha(t) = 1 \quad \text{and} \quad \beta(t) = 1 \\ 0 & \text{if} \quad x(t) \leq Z^* \,\text{and} \quad \alpha(t) = 0 \quad \text{and} \quad \forall \beta(t) \\ 0 & \text{if} \quad x(t) > Z^* \end{cases} \\ \\ u_2(t,\beta) = \begin{cases} u_2^{*} & \text{if} \quad x(t) \leq Z^* \quad \text{and} \quad \beta(t) = 1 \quad \text{and} \quad \forall \alpha(t) \\ 0 & \text{if} \quad x(t) \leq Z^* \quad \text{and} \quad \beta(t) = 0 \quad \text{and} \quad \forall \alpha(t) \\ & 0 \quad \text{if} \quad x > Z^* \end{cases} \end{cases} \tag{5.9}$$

The proposed policy consists of monitoring the emission level *e(t)* over an emission control period *i*. When the emission level is below the level L_v, the policy involves producing in-house according to the classical HPP without subcontracting (see equation 5.8). When the emission level reaches L_v, the system can use subcontracted products to meet a proportion of the demand and reduce emissions (see equation 5.9).

This policy is a voluntary commitment which consists in setting a specific limit that controls the production and the subcontracting rates, based on the inventory and emission levels.

5.4 Resolution approach

An approach combining simulation and statistical optimization methods is used as in Gharbi et al. (2011), Assid et al. (2014), Bouslah et al. (2013) in order to solve the problem. This approach is described in the following main steps:

- Control policy:

The structures of the control policy was established in section 5.3 and presented by equations (5.8) and (5.9). This policy is used to control inventory-production and emission in the simulation model.

- Simulation model:

  The objective of this step is to develop a simulation model (see section 4) to describe the system dynamics. Then, the control policy is used as an input to conduct several experiments and thus evaluate the system performance.

- Experimental design:

  The experimental design approach defines the experimental domain of the independent variables and the number of experiments.

- ANOVA and response surface methodology

  The main factors and their interactions which have a significant effect on the dependent variable (cost) using the ANOVA are obtained. The response surface methodology is used to obtain the relationship between the dependent variable (total cost) and the significant factors. The obtained model is then optimized in order to minimize the total cost.

5.5 Simulation model

In this paper, we use «ARENA» simulator with C++ routines to develop a combined discrete-continuous simulation model. This type of model showed the advantage of using this combination in terms of simulation time and reproducibility of the system dynamics (Bouslah et al. 2013). Figure 5.2 presents the diagram of the simulation model.

The model is initialized by defining the parameters required for the simulation (*d, MTTR,* simulation run time...) (bloc 1). Then, the manufacturing system (bloc 2) allows producing parts according to production policy (bloc 3) presented by equations (8) to meet the demand rate (bloc 4). The machine is subject to random failures and repair activities (bloc 5). The state equations (bloc 6) describe the variation of inventory level $x(t)$ and the emission level $e(t)$. The simulation time advances (bloc 7) and the model updates the inventory and the emission levels (bloc 8). Emission level is controlled (bloc 9) in order to check the condition $e(t) \geq L_v$. When e(t) reaches the level of L_v, the production strategy changes according to the equation (9) (bloc 10); in-house production is reduced and subcontracting starts (bloc 11). Note that the subcontractor system is also subject to random failures and repair activities (bloc 12). Finally, we calculate the cost according to the variables of inventory and backlog (x^+ and x^-), emission, production and subcontracting levels (bloc 13).

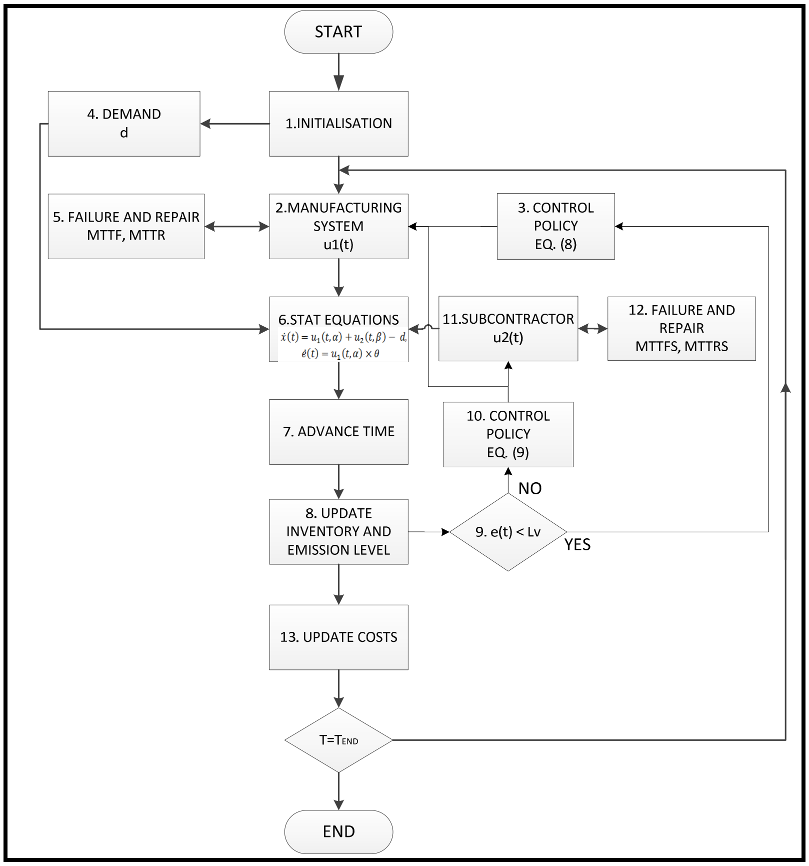


Figure 5.2 Diagram of the simulation model

In order to validate the simulation model, the variation of $x(t)$, $e(t)$, $u_1(t)$ and $u_2(t)$ over the time is generated by the simulator. Figure 5.3 presents the results obtained when the system parameters are set to $U_{max}= 3$, $d= 2$, $u_2 =1$, $Z=10$, $L_v=150$, $L_s=100$ and $T_i= 100$ units of time (UT).

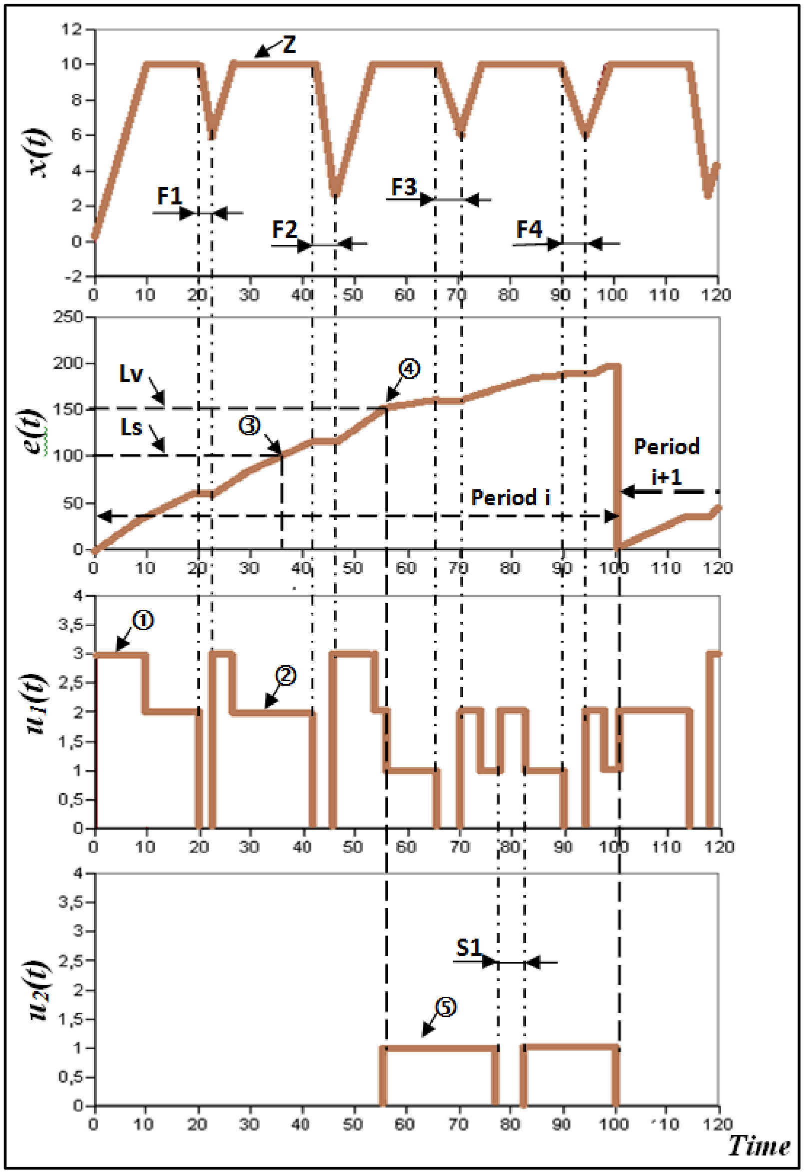


Figure 5.3 Variation of $x(t)$, $e(t)$, $u_1(t)$ and $u_2(t)$ over time.

According to Figure 5.3, when:

- $0 \leq t < 56$ UT; the manufacturing system produces according to classical HPP with $Z = 10$; production rate $u_1(t) = U_{max} = 3$ if $x(t) \leq Z$ ① and $u_1(t) = d = 2$ if $x(t) = Z$ ②. The emission level increases as function of the production rhythm. When a random failure (like F1 or F2) occurs, the production is stopped, therefore the cumulative emission level remains at the same value. Production is restarted after a random repair activity. The simulation time advances and the emission level reaches the standard limit L_s at t=36 UT ③, thus from this moment, an emission cost is added to others costs (inventory, backlog and production).

- 56≤ t <78 UT, the emission level $e(t)$ reached the voluntary limit L_v at t= 56 UT ④, hence, production rate is reduced and subcontracting is started⑤; $u_1(t)+ u_2(t) =2 +1 = U_{max}$ if $x(t) \leq Z$ and $u_1(t)+ u_2(t)=1 + 1= d$ if $x(t)=Z$. Therefore, the emission rate decreases which explain the change of the slope in the emission level graph. At t= 65 UT, a new failure (F3) occurs.

- 78≤ t <90 UT: at t= 78, subcontractor failure (S1) occurs as presented in the subcontracting rate graph ($u_2(t)=0$)) and the demand is satisfied from only in-house production ($u_1(t)= 2=d$). Then, at t= 82 UT, the subcontracting is restarted ($u_1(t)+ u_2(t) =1 +1 = d$) after the subcontractor repair activity.

- 90 ≤ t <100 UT: after that, the simulation time advances and another failure (F4) which occurs at t= 90 UT, before the end of the control period at t= 100 UT. From this moment, the cumulative emission level is reset to zero and the subcontracting is stopped for the beginning of the next control period.

Based on several verifications and validation simulation runs, we can affirm that our simulation model adequately describes the dynamic of the system under study.

5.6 Numerical exemple

Through this section, we use the resolution approach adopted in order to find the optimal total cost and optimal values of parameters (Z, u_2, L_v) defining the control policy. Therefore, an illustrative numerical example is defined, followed by a sensitivity analysis.

Table 5.1 summarizes the different parameters of operations and costs characterizing the system for a basic case.

Table 5.1 Parameter values

Parameter	**d**	**U_{max}**	**MTTF**	**MTTR**	**L**	**C^+**	**C^-**	
Value	100	125	Exp (8UT)	Exp (0,5UT)	550000	1	20	
Parameter	**C^e**	**C_s**	**C_p**	**a**	**b**	**MTTRS**	**MTTFS**	**T_i**
Value	3	6	3	0.5	2	Exp (1UT)	Exp (20UT)	5760 UT

We adopt a full factorial design 3^3 with five replications for each combination of the factors (Z, u_2, L_v) which means 135 simulation experiments. The levels of each factor are presented in Table 5.2. The duration of each simulation is set to 500.000 UT to insure that the steady-state is reached.

Table 5.2 Factor levels

Factor	**Low**	**Medium**	**High**
L_v	530000	565000	600000
Z	50	90	130
u_2	0	62.5	125

5.6.1 RSM model and optimization

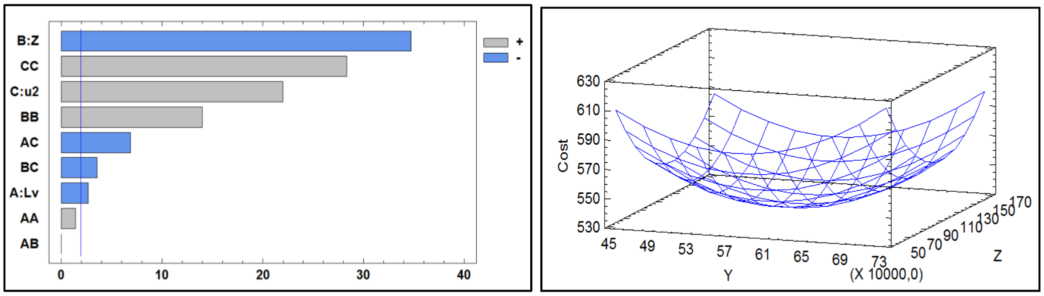
The statistical treatment of the data is carried out using «STATGRAPHICS» software in order to perform the ANOVA. Thus, we obtain the effects of independent variables (policy parameters), their interactions, and their quadratic effect on the dependant variable (total cost).

For the selected system parameters (Table 5.1), the correlation coefficients $R^2_{adjusted}$ found is equal to 95.35%, which is higher enough to judge the good quality of the model. In the same direction, an analysis of the residual normality and of the homogeneity of variance was also carried out to check the conformity of the model.

The second order model for the proposed control policy is given by:

$$\widehat{\mathrm{Cost}} = 641.758 + 1.27201\ 10^{-4} \times \mathrm{L}_{v} - 2.71879 \times \mathrm{Z} + 0.866834 \times \mathrm{u}_2 - 3.00375\ 10^{-6} \times \mathrm{L}_{v} \times \mathrm{u}_2 + 1.18145\ 10^{-2} \times \mathrm{Z}^2 - 1.3659\ 10^{-3} \times \mathrm{Z} \times \mathrm{u}_2 + 9.81962\ 10^{-3} \times \mathrm{u}_2^2 \tag{5.10}$$

Figure 5.4.a and 5.4.b presents the Pareto diagram and the estimated response surface of the model, respectively.



(a). Pareto Diagram.

(b). Estimated response surface

Figure 5.4 Optimisation results

The optimal policy to apply for this manufacturing system case study is defined by optimal parameters summarized in Table 5.3.For comparison purposes, we present also, in the same Table, the results of the optimization when the classic HPP is adopted for the manufacturing system. Note that the classical HPP does not take into account the emission level in the production decision and does not allow the system to call up on subcontracting ($u_2(t) = 0, \forall\, e(t)$). Therefore, we use a polynomial regression model in order to optimize its unique HPP parameter (Z) as in Kenné and Gharbi (2000). The model obtained is presented by the following equation:

$$\widehat{\text{Cost}} = 725.973 - 2.8853 \times \text{Z} + 0.0122047 \times \text{Z}^2 \tag{5.11}$$

Table 5.3 Optimization results

Control Policy	**Factor**	**Optimum**	**Cost***	$R^2_{adjusted}$	**Confidence interval (95 %)**
Proposed policy	***Z****	118	530.898	95.35%	[529.64; 532.07]
	u_2*	51.893			
	L_v *	574235			
Classical HPP	***Z****	118	555.44	97.29%	[554.05; 558.82]

To cross-check the validity of our models, we confirm that the optimal cost for each control policy falls within the confidence interval at 95% confidence level (see Table 5.3). This confidence interval is obtained using n= 25 replications of the simulation models.

From Table 5.3, for the selected system parameters (Table 5.1), we note that the proposed control policy has an economic advantage compared to the classical HPP, with a 4.42% reduction in term of total cost. In the other side, the results show that the proposed policy reduces the average quantity of emission to 640.407x10^3emission unit/control period, compared to 713.360 x 10^3emission unit/ control period, for classical HPP, a reduction of 10.23% in terms of emissions generated. These improvements are mainly due to the ability of proposed control policy to better control the production rate and the use of subcontracting effectively such as to obtain a good compromise between costs and emissions.

5.6.2 Sensitivity analysis

In this section, a sensitivity analysis is conducted to illustrate the effect of the variation of the cost parameters on the proposed control policy. This analysis is a further evidence of the usefulness and robustness of our resolution approach. Table 5.4 shows results of the sensitivity analysis. From this Table, we note that the economic gain of the proposed control policy compared to classical HPP can reach 5.55 %.

Table 5.4 Results of sensitivity analysis

Case	***Cost parameters***						***Control policy parameters***				***Remark***
	C^+	C^-	C^e	C_p	C_s		Z^*	u_2^*	L_v *	*Cost**	
1	**1**	**20**	**3**	**3**	**6**		**118**	**51.893**	**574235**	**530.898**	**Basic case**
2	**0.8**	20	3	3	6		126	52.57	574754	509.545	**Z^*↑, u_2^*↑, L_v *↑**
3	**1.2**	20	3	3	6		110	51.22	573658	550.708	**Z^*↓, u_2^*↓, L_v *↓**
4	1	**15**	3	3	6		105	51.61	571537	517.567	**Z^*↓, u_2^*↓, L_v *↓**
5	1	**25**	3	3	6		126	52.234	577211	541.654	**Z^*↑, u_2^*↑, L_v *↑**
6	1	20	**2.5**	3	6		118	48.138	584589	522.611	**Z^*↔, u_2^*↓, L_v *↑**
7	1	20	**3.5**	3	6		118	56.12	566279	538.395	**Z^*↔, u_2^*↑, L_v *↓**
8	1	20	3	**2**	6		118	45.008	584896	440.243	**Z^*↔, u_2^*↓, L_v *↑**
9	1	20	3	**4**	6		118	58.796	558501	619.553	**Z^*↔, u_2^*↑, L_v *↓**
10	1	20	3	3	**5.5**		118	55.488	566545	525.228	**Z^*↔, u_2^*↑, L_v *↓**
11	1	20	3	3	**6.5**		118	48.329	580561	536.016	**Z^*↔, u_2^*↓, L_v *↑**

- Variation of C^+ and C^-: from Table 5.4, the variation of C^+ and C^- has an opposite effect on the control policy parameters. Let's start with the critical threshold, when C^+ increases (case 3) (respectively C^- decreases (case 4)), the critical threshold Z decreases to avoid additional inventory cost. The opposite occurs when C^+ decreases (case 2) (respectively C^- increases (case 5)).

In another side, results show that the variation of the parameter L_v and u_2 is related to the variation of the critical threshold Z. Indeed, we remark that when Z increases (case 2 and case 5), the system takes advantage from its high stock to meet demand before starting subcontracting by increasing L_v.

Regarding u_2, if the system increases the critical threshold due to the variation of the inventory or backlog cost (C^+ decreases (case 2) or C^-increases (case 5)), the subcontracting rate increases. In fact, it is more advantageous to increase the stock from subcontracted products than from in-house production to avoid additional emission cost. When Z* decreases (case 3 and 4), the opposite effects on L_v and u_2 occur.

- Variation of C^e: results show that the variation of C^e has no effect on Z. This makes sense since the critical threshold Z is mostly sensitive to C^+ and C^-. However, the variation of C^e mainly affects the voluntary limit L_v and the subcontracting rate u_2. Indeed, when C^e increases (case 7), the emission cost increases resulting in the decrease of L_v in order to start the subcontracting earlier. In the same direction, the subcontracting rate u_2 increases to avoid additional emission cost. When C^e decreases (case 6), the opposite occurs.

- Variation of C_p and C_s: when varying C_s or C_p, no effect is observed on Z. However, the variation of C_p or C_s has an effect in the decision relative to the subcontracting process. In fact, faced with the increase in C_p (case 9) (respectively decrease in C_s(case 10)), the system recommends more subcontracted products by reducing L_v and increasing u_2 to avoid additional in-house production cost. The opposite occurs when C_p decreases (case 8) (respectively C_s increases (case 11)).

To finish this sensitivity analysis, results show that, for higher values of C_s ($C_s \geq 6.8$), the system chooses to production only in-house ($u_2(t)$ =0) to avoid subcontracted products.

5.6.3 Effect of subcontracting and production system availability

As mentioned in the problem description, we defined the production system availability D_p as the fraction of time where the production system is available. In addition, in this paper, we assumed that subcontractor is unreliable in order to be more close to the industrial reality. In this section, the effects of the subcontracting and the manufacturing system availability on the control policy parameters are analyzed. Table 5.5 summarizes the results obtained.

Table 5.5 Results of the variation of subcontracting and manufacturing system availability

Case	*Availability*		*Control policy parameters*				*Remark*
	D_s%	*D_p%*	*Z^**	*u_2^**	*L_v **	*Cost**	
1	**95.23%**	**94.11%**	**118**	**51.893**	**574235**	**530.898**	***Basic case***
2	97.22%	94.11%	113	61.372	568270	520.914	**$Z^*\downarrow$, $u_2^*\uparrow$, $L_v^*\downarrow$**
3	95.23%	96.15%	69	40.272	594559	480.297	**$Z^*\downarrow$, $u_2^*\downarrow$, $L_v^*\uparrow$**

It is important to note that the results found are logical and confirm our expectations. Indeed, we remark that more priority is given to the in-house production when the production system availability increases (case 2) which explains the increase of L_v and the decrease of the subcontracting rate u_2. In the other side, results show that when the subcontractor availability increases (case 3), in-house production is reduced to allow more subcontracting by reducing L_v and increasing u_2. In other words, the system has more benefit to use a subcontractor which guarantees greater availability. Moreover, for both production system and subcontractor, we note that increasing the availability leads to a decrease in the critical threshold Z because backlog risk is reduced. For this reason, total cost decreases when the availability increases compared to the basic case (case 1).

Another observation is that for a low subcontractor availability ($D_s \leq 90$ %), the system produces only in-house ($u_2(t)$=0) because the subcontracting doesn't give any economic benefit. In fact, in this case, the optimal cost is equal to that obtained when classical HPP is applied $\text{Cost}^* = \text{Cost}^*_{\text{HPP}}$= 555.44, (see Table 5.3).

5.7 Decision support for the subcontractor selection

From the previous sections, subcontracting can be used to improve the environmental strategy of the company and minimize the total cost. The key idea consist in reducing the in-house production ($u_1(t)$) and making orders from an unreliable subcontractor ($u_2(t)$) when the emission costs increase. However, results show that the effectiveness of this solution (subcontracting) depends on the subcontractor characteristics (cost C_s and availability D_s).

Indeed, from section 5.6.2, we conclude that, compared to classical HPP, subcontracting does not present any economic advantage when $C_s \geq 6.8$. In the same direction, the availability is an important issue to take into account when choosing to subcontract or not as explained in section 5.6.3. In fact, for low subcontractor availability ($D_s \leq 90\%$), the manager meets the demand by only his in-house products. For both cases (high C_s and/or low D_s), the proposed control policy is equivalent to classical HPP with $u_2(t) = 0$ and $Z = Z_{HPP} = 118$, leading to the same optimal cost value 555.44.

Hence, in this section, the experimental resolution approach used in this paper provides the advantage to develop a further analysis in order to address the aspects related to the subcontracting process. This study aims to propose a tool to support decisions that allows the manager to choose the subcontractor based on its characteristics (C_s and D_s) to achieve the economic objectives of the company. At the extreme case, company can accept to produce only in-house when the subcontracting process has no economic benefit.

The approach consists in considering the subcontracting cost C_s as independent variable to optimize in addition to other independent variables (Z, u_2, L_v). Then, the total cost (dependant variable) is maintained at the value $\mathrm{Cost}^*_{\mathrm{HPP}} = 555.44$ for different subcontractor availability cases.

Figure 5.5 presents the indifference curve.

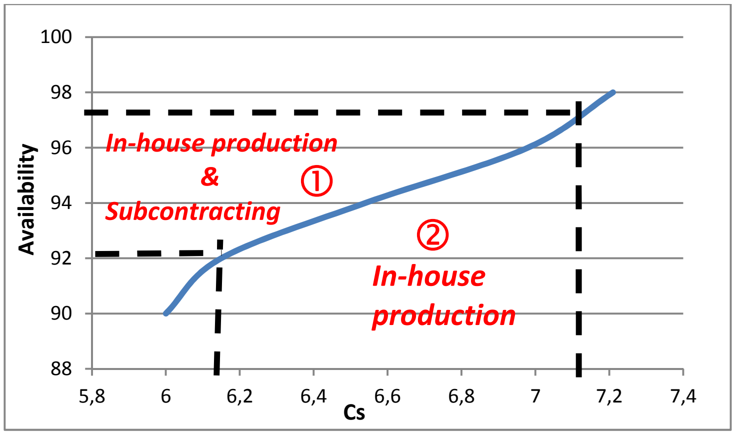


Figure 5.5 Indifference curve

Form Figure 5.5, we distinguish two main zones; a first zone ① where the system recommends subcontracting, in addition to in-house production, to reduce emissions generated and the total cost. The second zone ② mentions that in-house production is more profitable. The curve between the two zones indicates that the subcontracting has no effect on the total cost.

A general observation is that when the subcontractor provides high availability, the company accepts paying a more expensive subcontracting cost. As an example, for a subcontractor availability of only D_s= 92%, the manager could pay up to C_s= 6.15, otherwise he has no economic advantage to deal with this subcontractor. However, the manager can accept to pay more, up to C_s = 7.1 for a subcontractor that guarantees higher availability (D_s = 97%).

5.8 Conclusion

This paper addresses the integration of the environmental aspect in the manufacturing system control. Under the optimal control approach, we studied an unreliable manufacturing system that generates harmful emissions to the environment and may incur sanctions in the form of an environmental cost imposed by the relevant authorities. In addition, we assumed that the company can meet a proportion of the demand from an unreliable subcontractor characterized by a cost and availability. The main contribution of this paper is that these aspects (production, subcontracting and emission) are considered simultaneously in a dynamic and stochastic context (failure, repair activities, availability) which, to the best of our knowledge, has never been considered in the literature. A control policy inspired from the HPP that integrates the emission control in production and subcontracting decisions is developed. We used an experimental approach that combines simulation, experimental design and respond surface methodology in order to solve the problem and minimise the total cost: inventory, backlog, production, emission and subcontracting cost. Through numerical examples, results showed that the proposed control policy has an economic advantageous compared to the classical HPP where subcontracting is not permitted. This economic gain reached 5.55% and can increases if C_s decreases or D_s increases. Furthermore, the proposed policy, which considers the subcontracting possibility, allows the company to considerably reduce its emission generated. However, the advantages of such policy are strongly related to the subcontractor characteristics (availability, cost).

In addition, we presented a decision support system to help the manager to choose subcontracting or not based on the subcontractor characteristics (availability / cost) thanks to the particle usefulness of our resolution approach.

Given that in the industrial domain some companies have to use an environmental strategy based on trading emission permits, the consideration of this environmental policy in the manufacturing system management can be an interesting subject for future researches.

References

Abernathy, F.H., Dunlop, J.T., Hammond, J.H. and Weil, D. (2000) Control your inventory in a word of lean retaling. Harvard Business Review, November–December, 169–176.

Assid, M., Gharbi, A., & Dhouib, A. (2014). Joint production and subcontracting planning of unreliable multi-facility multi-product production systems. OMEGA: The International Journal of Management Science. In press. DOI: 10. 1016/j. OMEGA. 2014. 07. 007.

Ben-Salem, A., Gharbi, A. & Hajji, A. (2014). An Environmental Hedging Point Policy to control production rate and emissions in unreliable manufacturing systems.

International Journal of Production Research. In press DOI: 10.1080/00207543.2014.946161.

Berthaut, F., Gharbi, A., & Dhouib, K. (2011). Joint modified block replacement and production/inventory control policy for a failure-prone manufacturing cell. Omega, 39(6), 642-654.

Bouslah, B., Gharbi, A., & Pellerin, R. (2013). Joint optimal lot sizing and production control policy in an unreliable and imperfect manufacturing system. International Journal of Production Economics, 144(1), 143-156.

Bradley, J. R. (2004). A Brownian approximation of a production-inventory system with a manufacturer that subcontracts. Operations Research, 52(5), 765-784.

Chen, C. and Monahan, G.E., 2010. Environmental safety stock: The impacts of regulatory and voluntary control policies on production planning, inventory control, and environmental performance. European Journal of Operational Research, 207, 1280–1292.

Chen, X., Benjaafar, S., & Elomri, A. (2013). The carbon-constrained EOQ. Operations Research Letters, 41(2), 172-179.

Dahane, M., Dellagi, S., Clémentz, C., & Rezg, N. (2011). Development of joint maintenance and production strategies in a subcontracting environment. International Journal of Production Research, 49(23), 6937-6961.

Drake, D., Kleindorfer, P. R., & Van Wassenhove, L. N. (2012). Technology choice and capacity portfolios under emissions regulation. Harvard Business School Working Paper, Harvard University.

Gharbi, A., Hajji, A., & Dhouib, K. (2011). Production rate control of an unreliable manufacturing cell with adjustable capacity. International Journal of Production Research, 49(21), 6539-6557.

Hajji, A., Gharbi, A. and Kenne, J.-P. (2009). Joint replenishment and manufacturing activities control in a two stage unreliable supply chain. International Journal of Production Research, 47(12), 3231–3251.

Kenne, J. P., & Gharbi, A. (2000). Production planning problem in manufacturing systems with general failure and repair time distributions. Production Planning & Control, 11(6), 581-588.

Li. S., 2014. Optimal control of production-maintenance system with deteriorating items emission tax and pollution R&D investment. International Journal of Production Research, 52 (60), 1787-1807. DOI: 10.1080/00207543.2013.848486.

Tan, B., 2004. Subcontracting with availability guarantees: production control and capacity decisions. IIE Transactions, 36 (8), 711–724.

Tan, B. and Gershwin, S.B., 2004. Production and subcontracting strategies for manufacturers with limited capacity and volatile demand. Annals of Operations Research, 125, 205–232.

Yang, J., Qi, X., and Xia, Y., 2005. A production-inventory system with Markovian capacity and outsourcing option. Operations Research, 53 (2), 328–349.

Zhang, J. J., Nie, T. F., & Du, S. F. (2011). Optimal emission-dependent production policy with stochastic demand. International Journal of Society Systems Science, 3(1), 21-39.

CONCLUSION GÉNÉRALE

Dans le cadre de ce projet de recherche, nous nous somme intéressé à l'étude de l'intégration de l'aspect de protection de l'environnement dans le contrôle et la gestion des systèmes manufacturiers non- fiables. Dans le cadre de la théorie de commande optimal stochastique, l'objectif était de développer des politiques de commande qui tiennent compte des émissions générés par le système de production dans la décision de production, de maintenance et même de sous-traitance. La motivation essentielle du choix de ce sujet est venue du manque constaté au niveau des anciens travaux de recherche. En effet, une revue détaillée de la littérature a montré que la plupart des approches de résolution utilisées pour traiter ce genre de problème étaient essentiellement des approches mathématiques.

Alors, à l'aide d'une approche expérimentale de résolution, dans ce mémoire, nous avons choisi d'aborder le sujet d'un point de vue opérationnel et dans un contexte stochastique et dynamique (pannes, réparations, délai de livraison,..) afin de développer des politiques de commande et de proposer des outils d'aide à la décision aux industriels face aux réglementations en terme d'environnement.

Vu la complexité du problème posé et la limite au niveau des anciens travaux de recherche, nous avons commencé par un problème de base dans le Chapitre 2. Ainsi, nous avons étudié un système manufacturier polluant composé d'une seule machine qui fabrique un seul type de produit. Dans le cadre des politiques de commande rétroactives, nous avons proposé une nouvelle structure de la politique à seuil critique (EHPP) qui a montré un avantage par rapport la politique classique (HPP) dans un contexte de contrôle des émissions. Les résultats trouvés ont montré que la bonne gestion du planning de production peut aider l'entreprise non pas seulement à réduire les coûts, mais aussi à atteindre ses objectifs en terme d'émission.

Dans le Chapitre 3, nous avons augmenté le degré de complexité du problème en intégrant le contrôle de la maintenance (overhaul et maintenance préventive) pour le même modèle développé dans le Chapitre 2. Aussi, le phénomène de la dégradation d'équipement a été ajouté afin d'analyser l'effet d'un tel phénomène issu de la réalité industrielle sur les émissions générés. Les résultats ont montré que la considération des rejets dans le planning de production et de maintenance permet de réduire le bilan d'émission. Ainsi, dans ce cas, une bonne coordination entre les deux services (production et maintenance) est indispensable pour l'entreprise afin d'atteindre ces objectifs stratégiques (économiques et environnementaux).

Ensuite, dans le Chapitre 4, nous avons utilisé le modèle initiale (chapitre 2) en ajoutant la notion d'externalisation (out- sourcing). En effet, nous avons considéré la présence d'un sous-traitant caractérisé par un délai de livraison aléatoire et un coût. Une politique de commande de la production et de la sous-traitance qui tienne compte des émissions générées a été développée. Similaire aux deux autres Chapitres 2 et 3, l'objectif est de proposer des solutions au décideur pour réduire leurs émissions sans perdre de vue l'aspect économique. Éventuellement, les résultats ont montré que la sous-traitance peut être une solution efficace pour atteindre les objectifs environnementaux de l'entreprise. En effet, sous une approche de contrôle environnemental, une meilleur gestion des stocks et un bon choix du sous-traitant permet de réduire le bilan des émissions et par suit réduire le coût associé.

Le chapitre 5 est une extension du chapitre 4. Nous avons considéré, dans ce dernier travail, le même modèle du chapitre précédent mais avec un sous-traitant non- fiable. Une politique de commande de la production et de la sous-traitance a été développée. La considération simultanée des émissions et de la sous-traitance a pour but de rejoindre les préoccupations des décideurs en présence des contraintes environnementales. Nous avons proposé à la fin du chapitre, une analyse poussée de l'effet des caractéristiques (disponibilité et coût) du sous-traitant sur les paramètres de la politique de commande afin de supporter la décision de l'entreprise au niveau du choix du sous-traitant.

Pour toutes les problématiques étudiées, une approche expérimentale de résolution a été adoptée. Cette approche combine la simulation avec des techniques statistiques d’optimisation (plan d’expérience, régression polynomiale, ANOVA et méthodologie de surface de réponse (RSM)). En ce qui concerne la simulation, les modèles sont développés en langage SIMAN sous le logiciel ARENA de Rockwell Automation avec des routines C++. Cet outil a permis de présenter adéquatement la dynamique des systèmes manufacturiers étudiés dans un contexte stochastique et dépasser les limites des méthodes de résolution analytique. Pour l’analyse statistique, nous avons utilisé le logiciel STATGRAPHICS pour développer les modèles de régression polynomiale et les modèles RSM, étudier la qualité de ces modèles et optimiser les paramètres des politiques de commande.

Dans le cadre de ce projet de recherche, nous avons abouti à des résultats solides en ce qui concerne la problématique de l’intégration de la dimension environnementale dans le domaine d’industrie manufacturière. Malgré la complexité de l’implantation des politiques de commande et la difficulté de la démarche d’optimisation (nombre et durée de simulation, choix des plages expérimentales, nombre de facteurs, coefficient de corrélation,…), les analyses de sensibilités menées ont montré la robustesse des résultats trouvés dans chacun des travaux.

Finalement, dans le cadre de ce mémoire, nous avons pu rédiger quatre articles de journal tel qu’il est présenté dans le Chapitre 2, Chapitre 3, Chapitre 4 et Chapitre 5. Le premier article (Chapitre 2) a été publié dans «International Journal of Production Research». Le deuxième article (Chapitre 3) est déjà soumis à «International Journal of Advanced Manufacturing and Technology ». Les deux autres articles (chapitre 4 et 5) ont été soumis respectivement à «International Journal of Production Economics» et «International Journal of Production Research».

ANNEXE I

MODÈLE DE SIMULATION D'UN SYSTÈME MANUFACTURIER NON-FIABLE M1P1 QUI GÉNÈRE DES ÉMISSIONS

Cadre expérimentale (Experiment frame):

```
PROJECT,"M1P1_HPP_CLASS_avec_emission","Ali_BEN_SALEM",,Yes,No,Yes,No,No,
No,No,No,No,No,No;"
CONTINUOUS,   5,,.00001,0.1,,Euler,Warning;
FILES:        File 1,"C:\Documents and
Settings\absalem\Bureau\HPPclass.xlsx",MSExcel2007,,Dispose,,Hold,RECORDSET(Recor
dset 1,"A",2), RECORDSET(Recordset 2,"B",2);
VARIABLES:  PERIODE,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
            Beginning,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
            Ending,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
            Emission total,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
            Depass,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
            DepassTot,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
             Duration,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
              X0,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
```

```
CSTATS: SN1,Negative Stock,,DATABASE(,"Continuous","User Specified","Negative
Stock"):
        SP1,Positive Stock,,DATABASE(,"Continuous","User Specified","Positive stock"):
        ST1,Total Stock,,DATABASE(,"Continuous","User Specified","Total stock");

DSTATS:     X0,X0 Value,,DATABASE(,"Variable","User Specified","X0");

REPLICATE,   26,,HoursToBaseTime(200000),Yes,Yes,,,,24,Hours,No,No,,,No,No;

LEVELS:     1,ST1:
        2,SP1:
        3,SN1:
        4,E:
        5,BLOC:
        6,Dem1,100:
        7,TauxP1,:
        8,Um1,120:
        9,Z1:
        10,TETA,1:
        11,LIMITE,:
        12,aa,0.5:
        13,bb,2:
        14,Pr;

RATES:      1,DSTOCK1:
        2,DSP1:
        3,DSN1:
        4,DE:
        14,DPr;
```

Modèle de simulation :

```
24$         CREATE,       1,HoursToBaseTime(PERIODE),Entity 1:
HoursToBaseTime(PERIODE):NEXT(25$);
25$         ASSIGN:       Create 44.NumberOut=Create 44.NumberOut + 1:NEXT(16$);
16$         BRANCH,        1:
                   If,LIMITE >= E,28$,Yes:
                   Else,29$,Yes;
28$             ASSIGN:          Decide 11.NumberOut True=Decide 11.NumberOut True +
1:NEXT(18$);
29$             ASSIGN:          Decide 11.NumberOut False=Decide 11.NumberOut False +
1:NEXT(17$);
18$         ASSIGN:       Depass=0:
                   DepassTot=DepassTot+Depass:
                   Emission total=Emission total + E:NEXT(19$);
19$         ASSIGN:       E=0:NEXT(15$);
15$         ASSIGN:       Dispose 194.NumberOut=Dispose 194.NumberOut + 1;
30$         DISPOSE:       Yes;
17$         ASSIGN:       Depass=E-Limite:
                   DepassTot=DepassTot+Depass:
                   Emission total=Emission total + E:NEXT(19$);
31$       CREATE, 1,HoursToBaseTime(0.0),Entity 1:HoursToBaseTime(1),1:NEXT(32$);
32$         ASSIGN:       Create 1.NumberOut=Create 1.NumberOut + 1:NEXT(2$);
2$         READ,         File 1,RECORDSET(Recordset 1):
                   PERIODE,
                   LIMITE,
                   X0,
                   Z1:NEXT(12$);
12$         VBA:          1,vba:NEXT(0$);
0$         ASSIGN:       Time of simulation.NumberIn=Time of simulation.NumberIn + 1:
```

```
64$        STACK,        1:Save:NEXT(36$);

36$        DELAY:        TFIN,,NVA:NEXT(45$);

45$        TALLY:        Time of simulation.TotalTimePerEntity,Diff.StartTime,1;
46$        TALLY:        Time of simulation.TotalCostPerEntity,
                  Diff.WaitCost  +  Diff.VACost  +  Diff.NVACost  +  Diff.TranCost  +
Diff.OtherCost,1;
69$          ASSIGN:         Time of simulation.NVATime=Time of simulation.NVATime +
Diff.NVATime;
70$        TALLY:        Time of simulation.NVATimePerEntity,Diff.NVATime,1;
74$           ASSIGN:          Time of simulation.NVACost=Time of simulation.NVACost +
Diff.NVACost;
71$        TALLY:        Time of simulation.NVACostPerEntity,Diff.NVACost,1;
84$        STACK,        1:Destroy:NEXT(83$);
83$         ASSIGN:        Time of simulation.NumberOut=Time of simulation.NumberOut +
1:
13$        VBA:          2,vba:NEXT(14$);
14$        WRITE,        File 1,RECORDSET(Recordset 2):
                  Z1,
                  CAVG(Total Stock),
                  CAVG(Positive Stock),
                  CAVG(Negative Stock),
                  Duration,
                  E,
                  Emission total,
                  Depass,
                  DepassTot:NEXT(1$);
1$         ASSIGN:       Dispose 1.NumberOut=Dispose 1.NumberOut + 1;
86$        DISPOSE:      Yes;
```

```
87$          CREATE,          1,HoursToBaseTime(0.0),Entity
2:HoursToBaseTime(1),1:NEXT(88$);
88$       ASSIGN:     Create 2.NumberOut=Create 2.NumberOut + 1:NEXT(7$);
7$        ASSIGN:     ST1=0:NEXT(3$);
3$        ASSIGN:     BLOC=1:NEXT(4$);
4$        ASSIGN:     MTTF.NumberIn=MTTF.NumberIn + 1:
                MTTF.WIP=MTTF.WIP+1;
120$      STACK,      1:Save:NEXT(92$);
92$       DELAY:      EXPO(7, X0),,VA:NEXT(101$);
101$      TALLY:      MTTF.TotalTimePerEntity,Diff.StartTime,1;
102$        TALLY:        MTTF.TotalCostPerEntity,Diff.WaitCost + Diff.VACost +
Diff.NVACost + Diff.TranCost + Diff.OtherCost,
                1;
125$      ASSIGN:     MTTF.VATime=MTTF.VATime + Diff.VATime;
126$      TALLY:      MTTF.VATimePerEntity,Diff.VATime,1;
130$      ASSIGN:     MTTF.VACost=MTTF.VACost + Diff.VACost;
127$      TALLY:      MTTF.VACostPerEntity,Diff.VACost,1;
140$      STACK,      1:Destroy:NEXT(139$);
139$      ASSIGN:     MTTF.NumberOut=MTTF.NumberOut + 1:
                MTTF.WIP=MTTF.WIP-1:NEXT(5$);
5$        ASSIGN:     BLOC=0:NEXT(6$);
6$        ASSIGN:     MTTR.NumberIn=MTTR.NumberIn + 1:
                MTTR.WIP=MTTR.WIP+1;
171$      STACK,      1:Save:NEXT(143$);
143$      DELAY:      EXPO(0.4, X0+1),,VA:NEXT(152$);
152$      TALLY:      MTTR.TotalTimePerEntity,Diff.StartTime,1;
153$        TALLY:        MTTR.TotalCostPerEntity,Diff.WaitCost + Diff.VACost +
Diff.NVACost + Diff.TranCost + Diff.OtherCost,
                1;
176$      ASSIGN:     MTTR.VATime=MTTR.VATime + Diff.VATime;
```

```
177$      TALLY:      MTTR.VATimePerEntity,Diff.VATime,1;
181$      ASSIGN:     MTTR.VACost=MTTR.VACost + Diff.VACost;
178$      TALLY:      MTTR.VACostPerEntity,Diff.VACost,1;
191$      STACK,      1:Destroy:NEXT(190$);
190$      ASSIGN:     MTTR.NumberOut=MTTR.NumberOut + 1:
                MTTR.WIP=MTTR.WIP-1:NEXT(3$);
8$       DETECT:      ST1,Positive,Z1,0.001:NEXT(9$);
9$       ASSIGN:     Dispose 2.NumberOut=Dispose 2.NumberOut + 1;
193$      DISPOSE:     Yes;
10$       DETECT:     ST1,Either,0,0.001:NEXT(11$);
11$       ASSIGN:     Dispose 3.NumberOut=Dispose 3.NumberOut + 1;
194$      DISPOSE:     Yes;
20$       DETECT:     E,Positive,LIMITE,0.001:NEXT(21$);
21$       ASSIGN:     Dispose 22.NumberOut=Dispose 22.NumberOut + 1;
195$      DISPOSE:     Yes;
22$       DETECT:     E,Negative,LIMITE,0.001:NEXT(23$);
23$       ASSIGN:     Dispose 27.NumberOut=Dispose 27.NumberOut + 1;
196$      DISPOSE:     Yes;
```

Routine C++:

```
extern "C" void cdecl cstate  ()
{

   SMREAL        DSTOCK1;
   SMREAL        DE;
   SMREAL        dST1;
   SMREAL        value;
   SMREAL        dBLOC;
   SMREAL        dDem1;
   SMREAL        dTauxP1;
   SMREAL        dUm1;
   SMREAL        dZ1;
   SMREAL        dE;
   SMREAL        dTETA;
```

```
   SMREAL        dLIMITE;
   SMREAL        daa;
   SMREAL        dbb;
   SMREAL        x;


   static SMINT  ST1    =1;
   static SMINT  SP1     =2;
   static SMINT  SN1     =3;
   static SMINT  E       =4;
   static SMINT  BLOC    =5;
   static SMINT  Dem1    =6;
   static SMINT  TauxP1  =7;
   static SMINT  Um1     =8;
   static SMINT  Z1      =9;
   static SMINT  TETA    =10;
   static SMINT  LIMITE  =11;
   static SMINT  aa      =12;
   static SMINT  bb      =13;


// METRE AJOUR LE STOCK DU PRODUIT, CAS DE PANNE PAS DE PRODUCTION BLOC==0

   dBLOC = getss(&BLOC);
   dDem1 = getss(&Dem1);
   dTauxP1 = getss(&TauxP1);
   dUm1 = getss(&Um1);
   dZ2 = getss(&Z2);
   dZ1= getss(&Z1);
   dST1 = getss(&ST1);
   dE = getss(&E);
   dTETA = getss(&TETA);
   dLIMITE = getss(&LIMITE);
   dY = getss(&Y);
   daa = getss(&aa);
   dbb = getss(&bb);

   if (dST1 < dZ1)
          {
                dTauxP1 = dUm1;
          }
   else
                    {
                         if (dST1 == dZ1)
```

```
                                        {
                                             dTauxP1 = dDem1;
                                        }
                                   else
                                 {
                                     dTauxP1 = 0;
                                 }
                           }

// loi uniforme de Teta

 dTETA = (dbb - daa) * x + daa;
 DSTOCK1 = dTauxP1 * dBLOC - dDem1;
   setd(&ST1, &DSTOCK1);
   setd(&E, &DE);

// INTEGRALE DANS LE TEMPS DE STOCK POSITIF ET STOCK NEGATIF


      if (dST1 >= 0)
            {
                value = dST1;
              setss(&SP1, &value);
            }
      else
            {
                 value = 0;
              setss(&SP1, &value);
            }


      if (dST1 < 0)
            {
              value = -dST1;
                 setss(&SN1, &value);
             }
       else
             {
              value = 0;
                 setss(&SN1, &value);
             }

     return;
```

ANNEXE II

MODÈLE DE SIMULATION D'UN SYSTÈME MANUFACTURIER NON-FIABLE M1P1 QUI GÉNÈRE DES ÉMISSIONS AVEC STRATÉGIE DE MAINTENANCE DANS UN CONTEXTE DE DÉGRADATION

Cadre expérimentale (Experiment frame):

```
PROJECT,"M1P1_HPP_CLASS_avec_degradation","Ali_BEN_SALEM",,Yes,No,Yes,No,
No,No,No,No,No,No,No;

CONTINUOUS,   16,,.00001,0.1,,Euler,Warning;

FILES:File1,"C:\Users\absalem\Desktop\HPP.xlsx",MSExcel,,Dispose,,Hold,RECORDSET(
Recordset 1,"ccvv",512),RECORDSET(Recordset 2,"vvcc",512);

VARIABLES: Emission total,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
          AGECR,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
          Beginning,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
          q31,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real),0.05:
          Cor,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real),0:
Time of simulation.WIP,CLEAR(System),CATEGORY("Exclude-
Exclude"),DATATYPE(Real):
          Depass,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
```

```
        DepassTot,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
        Duration,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
        Over,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real),0:
        X0,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):

SEEDS:    1,1,Yes:
        2,2,Yes:
        3,3,Yes:
        4,4,Yes:
        5,5,Yes:
        6,6,Yes:
        7,7,Yes:
        8,8,Yes:
        9,9,Yes:
        10,10,Yes;

PICTURES:    1,Picture.Ball:

CSTATS:    SN1,Negative Stock,,DATABASE(,"Continuous","User Specified","Negative
Stock"):
        SP1,Positive Stock,,DATABASE(,"Continuous","User Specified","Positive stock"):
        ST1,Total Stock,,DATABASE(,"Continuous","User Specified","Total stock");

DSTATS:    X0,X0 Value,,DATABASE(,"Variable","User Specified","X0");

REPLICATE,    25,,HoursToBaseTime(1000000),Yes,Yes,,,,24,Hours,No,No,,,No,No;
```

```
LEVELS:     1,ST1:
            2,SP1:
            3,SN1:
            4,E:
            5,BLOC:
            6,Dem1,2:
            7,TauxP1,:
            8,Um1,3:
            9,Z1:
            10,TETA,:
            11,LIMITE,:
            12,A1,2:
            13,A2,:
            14,K22,0.02:
            15,age,0:
            16,Pro,0:
            17,K11,0.023:
            18,As,:
            19,Q12,:
            20,q120,0.0042:
            21,q121,0.0044:
            22,K33,-0.00005:
            23,alfa1,0.6:
            24,alfa2,0.6;

RATES:      1,DSTOCK1:
            2,DSP1:
            3,DSN1:
            4,DE:
            15,Dage:
```

```
        16,DPro;

ENTITIES:   Entity 1,Picture.Blue Ball,0.0,0.0,0.0,0.0,0.0,0.0,AUTOSTATS(Yes,,):
        Entity 2,Picture.Red Ball,0.0,0.0,0.0,0.0,0.0,0.0,AUTOSTATS(Yes,,);
```

Modèle de simulation:

```
38$                    CREATE,                1,HoursToBaseTime(PERIODE),Entity
1:HoursToBaseTime(PERIODE):NEXT(39$);
39$       ASSIGN:     Create 44.NumberOut=Create 44.NumberOut + 1:NEXT(15$);
15$       BRANCH,     1:
                If,LIMITE >= E,42$,Yes:
                Else,43$,Yes;
42$          ASSIGN:        Decide 11.NumberOut True=Decide 11.NumberOut True +
1:NEXT(17$);
43$          ASSIGN:        Decide 11.NumberOut False=Decide 11.NumberOut False +
1:NEXT(16$);
17$       ASSIGN:     Depass=0:
                DepassTot=DepassTot+Depass:
                Emission total=Emission total + E:NEXT(18$);
18$       ASSIGN:     E=0:NEXT(14$);
14$       ASSIGN:     Dispose 194.NumberOut=Dispose 194.NumberOut + 1;
44$       DISPOSE:    Yes;
16$       ASSIGN:
               DepassTot=DepassTot+Depass:
                Emission total=Emission total + E:NEXT(18$);
45$                       CREATE,                   1,HoursToBaseTime(0.0),Entity
1:HoursToBaseTime(1),1:NEXT(46$);
46$       ASSIGN:     Create 1.NumberOut=Create 1.NumberOut + 1:NEXT(2$);
2$       READ,      File 1,RECORDSET(Recordset 1):
                PERIODE,
```

```
                LIMITE,
                X0,
                AGECR,
                Z1:NEXT(11$);
11$      VBA:       1,vba:NEXT(0$);
0$      ASSIGN:     Time of simulation.NumberIn=Time of simulation.NumberIn + 1:
                Time of simulation.WIP=Time of simulation.WIP+1;
78$      STACK,      1:Save:NEXT(50$);
50$      DELAY:      TFIN,,NVA:NEXT(59$);
59$      TALLY:      Time of simulation.TotalTimePerEntity,Diff.StartTime,1;
60$      TALLY:      Time of simulation.TotalCostPerEntity,
                Diff.WaitCost + Diff.VACost + Diff.NVACost + Diff.TranCost +
Diff.OtherCost,1;
83$       ASSIGN:      Time of simulation.NVATime=Time of simulation.NVATime +
Diff.NVATime;
84$      TALLY:      Time of simulation.NVATimePerEntity,Diff.NVATime,1;
88$       ASSIGN:      Time of simulation.NVACost=Time of simulation.NVACost +
Diff.NVACost;
85$      TALLY:      Time of simulation.NVACostPerEntity,Diff.NVACost,1;
98$      STACK,      1:Destroy:NEXT(97$);
97$       ASSIGN:      Time of simulation.NumberOut=Time of simulation.NumberOut +
1:
                Time of simulation.WIP=Time of simulation.WIP-1:NEXT(12$);
12$      VBA:       2,vba:NEXT(13$);
13$      WRITE,      File 1,RECORDSET(Recordset 2):
                Z1,
                CAVG(Total Stock),
                CAVG(Positive Stock),
                CAVG(Negative Stock),
                Duration,
```

```
                Pro,
                E,
                Emission total,
                Cor,
                Over,
                Depass,
                DepassTot:NEXT(1$);
1$        ASSIGN:     Dispose 1.NumberOut=Dispose 1.NumberOut + 1;
100$      DISPOSE:    Yes;
101$              CREATE,             1,HoursToBaseTime(0.0),Entity
2:HoursToBaseTime(1),1:NEXT(102$);
102$      ASSIGN:     Create 2.NumberOut=Create 2.NumberOut + 1:NEXT(6$);
6$        ASSIGN:     ST1=0:
                Picture=Picture.Ball:
                BLOC=1:
                age=0:
                TETA=A1:
                n=0:NEXT(3$);
3$        ASSIGN:     MTTF.NumberIn=MTTF.NumberIn + 1:
                MTTF.WIP=MTTF.WIP+1;
134$      STACK,      1:Save:NEXT(106$);
115$      TALLY:      MTTF.TotalTimePerEntity,Diff.StartTime,1;
116$          TALLY:        MTTF.TotalCostPerEntity,Diff.WaitCost + Diff.VACost +
Diff.NVACost + Diff.TranCost + Diff.OtherCost,
                1;
139$      ASSIGN:     MTTF.VATime=MTTF.VATime + Diff.VATime;
140$      TALLY:      MTTF.VATimePerEntity,Diff.VATime,1;
144$      ASSIGN:     MTTF.VACost=MTTF.VACost + Diff.VACost;
141$      TALLY:      MTTF.VACostPerEntity,Diff.VACost,1;
154$      STACK,      1:Destroy:NEXT(153$);
```

```
153$        ASSIGN:       MTTF.NumberOut=MTTF.NumberOut + 1:
                          MTTF.WIP=MTTF.WIP-1:NEXT(35$);
35$         BRANCH,       1:
                          If,BLOC == 1,156$,Yes:
                          Else,157$,Yes;
156$            ASSIGN:          Decide 9.NumberOut True=Decide 9.NumberOut True +
1:NEXT(4$);
157$            ASSIGN:          Decide 9.NumberOut False=Decide 9.NumberOut False +
1:NEXT(3$);
4$          ASSIGN:       BLOC=0:
                          n=n+1:NEXT(5$);
5$          ASSIGN:       MTTR.NumberIn=MTTR.NumberIn + 1:
                          MTTR.WIP=MTTR.WIP+1;
187$        STACK,        1:Save:NEXT(159$);
168$        TALLY:        MTTR.TotalTimePerEntity,Diff.StartTime,1;
169$            TALLY:          MTTR.TotalCostPerEntity,Diff.WaitCost + Diff.VACost +
Diff.NVACost + Diff.TranCost + Diff.OtherCost,
                          1;
192$        ASSIGN:       MTTR.VATime=MTTR.VATime + Diff.VATime;
193$        TALLY:        MTTR.VATimePerEntity,Diff.VATime,1;
197$        ASSIGN:       MTTR.VACost=MTTR.VACost + Diff.VACost;
194$        TALLY:        MTTR.VACostPerEntity,Diff.VACost,1;
207$        STACK,        1:Destroy:NEXT(206$);
206$        ASSIGN:       MTTR.NumberOut=MTTR.NumberOut + 1:
                          MTTR.WIP=MTTR.WIP-1:NEXT(23$);
23$         ASSIGN:       Cor=Cor+1:
                          BLOC=1:NEXT(3$);
7$          DETECT:       ST1,Positive,Z1,0.001:NEXT(8$);
8$          ASSIGN:       Dispose 2.NumberOut=Dispose 2.NumberOut + 1;
209$        DISPOSE:      Yes;
```

```
9$          DETECT:     ST1,Either,0,0.001:NEXT(10$);
10$         ASSIGN:     Dispose 3.NumberOut=Dispose 3.NumberOut + 1;
210$        DISPOSE:     Yes;
19$         DETECT:      E,Positive,LIMITE,0.001:NEXT(20$);
20$         ASSIGN:     Dispose 22.NumberOut=Dispose 22.NumberOut + 1;
211$        DISPOSE:     Yes;
21$         DETECT:      E,Negative,LIMITE,0.001:NEXT(22$);
22$         ASSIGN:     Dispose 27.NumberOut=Dispose 27.NumberOut + 1;
212$        DISPOSE:     Yes;
27$         DETECT:      age,Positive,AGECR,0.001:NEXT(29$);
29$         ASSIGN:     Picture=Picture.Red Ball:NEXT(24$);
24$         ASSIGN:     BLOC=0:NEXT(25$);
25$         ASSIGN:     MTTRO.NumberIn=MTTRO.NumberIn + 1:
                  MTTRO.WIP=MTTRO.WIP+1;
242$        STACK,      1:Save:NEXT(214$);
214$        DELAY:       EXPO(1/q31, X0+2),,VA:NEXT(223$);
223$        TALLY:      MTTRO.TotalTimePerEntity,Diff.StartTime,1;
224$        TALLY:      MTTRO.TotalCostPerEntity,
                  Diff.WaitCost  +  Diff.VACost  +  Diff.NVACost  +  Diff.TranCost  +
Diff.OtherCost,1;
247$        ASSIGN:      MTTRO.VATime=MTTRO.VATime + Diff.VATime;
248$        TALLY:      MTTRO.VATimePerEntity,Diff.VATime,1;
252$        ASSIGN:      MTTRO.VACost=MTTRO.VACost + Diff.VACost;
249$        TALLY:      MTTRO.VACostPerEntity,Diff.VACost,1;
262$        STACK,      1:Destroy:NEXT(261$);
261$        ASSIGN:      MTTRO.NumberOut=MTTRO.NumberOut + 1:
26$         ASSIGN:     Over=Over+1:
                  age=0:
                  TETA=A1:
                  BLOC=1:NEXT(34$);
```

```
34$       SIGNAL:     1:NEXT(28$);
28$       ASSIGN:     Dispose 2214.NumberOut=Dispose 2214.NumberOut + 1;
264$       DISPOSE:    Yes;
30$       DETECT:     age,Positive,AGECR,0.001:NEXT(31$);
31$       ASSIGN:     Dispose 201.NumberOut=Dispose 201.NumberOut + 1;
265$       DISPOSE:    Yes;
32$       DETECT:     age,Negative,AGECR,0.001:NEXT(33$);
33$       ASSIGN:     Dispose 202.NumberOut=Dispose 202.NumberOut + 1;
266$       DISPOSE:    Yes;
36$       DETECT:     ST1,Either,As,0.001:NEXT(37$);
37$       ASSIGN:     Dispose 241.NumberOut=Dispose 241.NumberOut + 1;
267$       DISPOSE:    Yes;
```

Routine C++:

```
extern "C" void cdecl cstate  ()
{
   SMREAL          DSTOCK1;
   SMREAL          DE;
   SMREAL          DPro;
   SMREAL          Dage;
   SMREAL          dST1;
   SMREAL          value;
   SMREAL          dBLOC;
   SMREAL          dDem1;
   SMREAL          dTauxP1;
   SMREAL          dUm1;
   SMREAL          dZ1;
   SMREAL          dE;
   SMREAL          dTETA;
   SMREAL          dLIMITE;
   SMREAL          dA1;
   SMREAL          dA2;
   SMREAL          dK22;
   SMREAL          dage;
   SMREAL          dPro;
   SMREAL          dK11;
   SMREAL          dQ12;
```

```
   SMREAL         dq120;
   SMREAL         dq121;
   SMREAL         dK33;
   SMREAL         dalfa1;
   SMREAL         dalfa2;

   static SMINT  ST1     =1;
   static SMINT  SP1      =2;
   static SMINT  SN1     =3;
   static SMINT  BLOC    =5;
   static SMINT  Dem1     =6;
   static SMINT  TauxP1  =7;
   static SMINT  Um1     =8;
   static SMINT  Z1      =9;
   static SMINT  TETA      =10;
   static SMINT  LIMITE     =11;
   static SMINT  A1     =12;
   static SMINT  A2     =13;
   static SMINT  K22     =14;
   static SMINT  age     =15;
   static SMINT  Pro     =16;
   static SMINT  K11     =17;
   static SMINT  As     =18;
   static SMINT  Q12     =19;
   static SMINT  q120     =20;
   static SMINT  q121     =21;
   static SMINT  K33     =22;
   static SMINT  alfa1     =23;
   static SMINT  alfa2     =24;

// METRE AJOUR LE STOCK DU PRODUIT, CAS DE PANNE PAS DE
PRODUCTION BLOC==0

   dBLOC = getss(&BLOC);
   dDem1 = getss(&Dem1);
   dTauxP1 = getss(&TauxP1);
   dUm1 = getss(&Um1);
   dZ1= getss(&Z1);
   dST1 = getss(&ST1);
   dE = getss(&E);
   dTETA = getss(&TETA);
   dLIMITE = getss(&LIMITE);
   dA1 = getss(&A1);
   dA2 = getss(&A2);
   dK22 = getss(&K22);
   dage = getss(&age);
```

```
   dPro = getss(&Pro);
   dK11 = getss(&K11);
   dK33 = getss(&K33);
   dq120 = getss(&q120);
   dq121 = getss(&q121);
   dQ12 = getss(&Q12);
   dalfa1 = getss(&alfa1);
   dalfa2 = getss(&alfa2);


   if (dST1 < dZ1)
          {
                dTauxP1 = dUm1;
          }
   else
                    {
                         if (dST1 == dZ1)

                                 {
                                      dTauxP1 = dDem1;
                                 }
                            else
                          {
                              dTauxP1 = 0;
                                }


// Indice d'émission

 dTETA = dA1 * exp(dK22 * dalfa1 * dage);
 setss(&TETA, &dTETA);

 // stock d'inventaire

 DSTOCK1 = dTauxP1 * dBLOC - dDem1;
   setd(&ST1, &DSTOCK1);

// Production

 DPro = dTauxP1 * dBLOC;
   setd(&Pro, &DPro);

// Age de la machine

 Dage = dK11 * dBLOC * dTauxP1 ;
   setd(&age, &Dage);
```

```
// Emission

 DE = dTauxP1 * dBLOC * dTETA;
   setd(&E, &DE);

// INTEGRALE DANS LE TEMPS DE STOCK POSITIF ET STOCK NEGATIF


      if (dST1 >= 0)
            {
                value = dST1;
              setss(&SP1, &value);
            }
      else
            {
                 value = 0;
              setss(&SP1, &value);
            }


      if (dST1 < 0)
            {
              value = -dST1;
                 setss(&SN1, &value);
             }
       else
             {
              value = 0;
                 setss(&SN1, &value);
             }


     return;
}
```

ANNEXE III

MODÈLE DE SIMULATION D’UN SYSTÈME MANUFACTURIER NON-FIABLE M1P1 QUI GÉNÈRE DES ÉMISSIONS AVEC STRATÉGIE DE SOUS-TRAITANCE

Cadre expérimentale (Experiment frame):

```
PROJECT,"M1P1_HPP_CLASS_avec_Sous_Traitance","Ali_Ben_Salem",,Yes,No,Yes,No,
No,No,No,No,No,No,No;

CONTINUOUS,   6,,.0001,0.1,,Euler,Warning;

FILESFile1,"C:\Users\absalem\Desktop\HPPclass.xlsx",MSExcel,,Dispose,,Hold,RECORDS
ET(Recordset 1,"xcv",512),RECORDSET(Recordset 2,"xxcv",512);

VARIABLES: Emission total,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
           Beginning,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
           Ending,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
           Sc,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
           Duration,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
           X0,CLEAR(System),CATEGORY("User Specified-User
Specified"),DATATYPE(Real):
           MTTF.VATime,CLEAR(Statistics),CATEGORY("Exclude"):
           Dispose 27.NumberOut,CLEAR(Statistics),CATEGORY("Exclude");

SEEDS:        1,,Yes:
```

```
          2,,Yes:
          3,,Yes:
          4,,Yes:
          5,,Yes:
          6,,Yes:
          7,,Yes:
          8,,Yes:
          9,,Yes:
          10,,Yes;

QUEUES:      Hold 1.Queue,FIFO,,AUTOSTATS(Yes,,):
          Hold 2.Queue,FIFO,,AUTOSTATS(Yes,,);

CSTATS:       SN1,Negative Stock,,DATABASE(,"Continuous","User Specified","Negative
Stock"):
          SP1,Positive Stock,,DATABASE(,"Continuous","User Specified","Positive stock"):
          ST1,Total Stock,,DATABASE(,"Continuous","User Specified","Total stock");

DSTATS:      X0,X0 Value,,DATABASE(,"Variable","User Specified","X0");

REPLICATE,    45,,HoursToBaseTime(500000),Yes,Yes,,,,24,Hours,No,No,,,No,No;

LEVELS:      1,ST1:
          2,SP1:
          3,SN1:
          4,E:
          5,Pr:
          6,Sou:
          7,BLOC:
          8,Dem1,100:
```

```
          9,TauxP1,:
          10,Um1,125:
          11,Usou,:
          12,Z1:
          13,TETA,:
          14,LIMITE,:
          15,aa,0.5:
          16,bb,2:
          17,Y;

RATES:    1,DSTOCK1:
          2,DSP1:
          3,DSN1:
          4,DE:
          5,DPr:
          6,DSou;

ENTITIES:   Entity 1,Picture.Blue Ball,0.0,0.0,0.0,0.0,0.0,0.0,AUTOSTATS(Yes,,):
          Entity 2,Picture.Red Ball,0.0,0.0,0.0,0.0,0.0,0.0,AUTOSTATS(Yes,,);
```

Modèle de simulation:

```
44$       CREATE,1,  Hours  To    Base   Time(PERIODE),
Entity1:HoursToBaseTime(PERIODE):NEXT(45$);
45$         ASSIGN:      Create 44.NumberOut=Create 44.NumberOut + 1:NEXT(16$);
16$         BRANCH,      1:
                    If,LIMITE >= E,48$,Yes:
                    Else,49$,Yes;
48$             ASSIGN:          Decide 11.NumberOut True=Decide 11.NumberOut True +
1:NEXT(18$);
```

```
49$          ASSIGN:         Decide 11.NumberOut False=Decide 11.NumberOut False +
1:NEXT(17$);
18$       ASSIGN:      Depass=0:
                  DepassTot=DepassTot+Depass:
                  Emission total=Emission total + E:NEXT(19$);
19$       ASSIGN:      E=0:NEXT(15$);
15$       ASSIGN:      Dispose 194.NumberOut=Dispose 194.NumberOut + 1;
50$       DISPOSE:      Yes;
17$       ASSIGN:      Depass=E-Limite:
                  DepassTot=DepassTot+Depass:
                  Emission total=Emission total + E:NEXT(19$);
51$                      CREATE,                     1,HoursToBaseTime(0.0),Entity
1:HoursToBaseTime(1),1:NEXT(52$);
52$       ASSIGN:      Create 1.NumberOut=Create 1.NumberOut + 1:NEXT(2$);
2$        READ,        File 1,RECORDSET(Recordset 1):
                  PERIODE,
                  LIMITE,
                  X0,
                  Y,
                  Sc,
                  Z1:NEXT(12$);

12$       VBA:        1,vba:NEXT(0$);


0$        ASSIGN:      Time of simulation.NumberIn=Time of simulation.NumberIn + 1:
                  Time of simulation.WIP=Time of simulation.WIP+1;
84$       STACK,       1:Save:NEXT(56$);
56$       DELAY:       TFIN,,NVA:NEXT(65$);
65$       TALLY:       Time of simulation.TotalTimePerEntity,Diff.StartTime,1;
```

```
66$          TALLY:        Time of simulation.TotalCostPerEntity,
                           Diff.WaitCost  +  Diff.VACost  +  Diff.NVACost  +  Diff.TranCost  +
Diff.OtherCost,1;
89$            ASSIGN:        Time of simulation.NVATime=Time of simulation.NVATime +
Diff.NVATime;
90$          TALLY:        Time of simulation.NVATimePerEntity,Diff.NVATime,1;
94$             ASSIGN:         Time of simulation.NVACost=Time of simulation.NVACost +
Diff.NVACost;
91$          TALLY:        Time of simulation.NVACostPerEntity,Diff.NVACost,1;
104$         STACK,        1:Destroy:NEXT(103$);
103$          ASSIGN:       Time of simulation.NumberOut=Time of simulation.NumberOut +
1:
                           Time of simulation.WIP=Time of simulation.WIP-1:NEXT(13$);
13$          VBA:          2,vba:NEXT(14$);
14$          WRITE,        File 1,RECORDSET(Recordset 2):
                           Z1,
                           Sc,
                           CAVG(Total Stock),
                           CAVG(Positive Stock),
                           CAVG(Negative Stock),
                           Duration,
                           E,
                           Pr,
                           Sou,
                           Emission total,
                           Depass,
                           DepassTot:NEXT(1$);
1$           ASSIGN:       Dispose 1.NumberOut=Dispose 1.NumberOut + 1;
107$                             CREATE,                        1,HoursToBaseTime(0.0),Entity
2:HoursToBaseTime(1),1:NEXT(108$);
```

```
108$      ASSIGN:      Create 2.NumberOut=Create 2.NumberOut + 1:NEXT(7$);
7$        ASSIGN:      ST1=0:NEXT(3$);
3$        ASSIGN:      BLOC=1:NEXT(4$);
4$        ASSIGN:      MTTF.NumberIn=MTTF.NumberIn + 1:
                 MTTF.WIP=MTTF.WIP+1;
140$      STACK,       1:Save:NEXT(112$);
112$      DELAY:       EXPO(7, X0),,VA:NEXT(121$);
121$      TALLY:       MTTF.TotalTimePerEntity,Diff.StartTime,1;
122$          TALLY:           MTTF.TotalCostPerEntity,Diff.WaitCost + Diff.VACost +
Diff.NVACost + Diff.TranCost + Diff.OtherCost,
                 1;
145$      ASSIGN:      MTTF.VATime=MTTF.VATime + Diff.VATime;
146$      TALLY:       MTTF.VATimePerEntity,Diff.VATime,1;
150$      ASSIGN:      MTTF.VACost=MTTF.VACost + Diff.VACost;
147$      TALLY:       MTTF.VACostPerEntity,Diff.VACost,1;
160$      STACK,       1:Destroy:NEXT(159$);
159$      ASSIGN:      MTTF.NumberOut=MTTF.NumberOut + 1:
                 MTTF.WIP=MTTF.WIP-1:NEXT(5$);
5$        ASSIGN:      BLOC=0:NEXT(6$);
6$        ASSIGN:      MTTR.NumberIn=MTTR.NumberIn + 1:
                 MTTR.WIP=MTTR.WIP+1;
191$      STACK,       1:Save:NEXT(163$);

163$      DELAY:       EXPO(0.4, X0+1),,VA:NEXT(172$);
172$      TALLY:       MTTR.TotalTimePerEntity,Diff.StartTime,1;
173$          TALLY:           MTTR.TotalCostPerEntity,Diff.WaitCost + Diff.VACost +
Diff.NVACost + Diff.TranCost + Diff.OtherCost,
                 1;
196$      ASSIGN:      MTTR.VATime=MTTR.VATime + Diff.VATime;
197$      TALLY:       MTTR.VATimePerEntity,Diff.VATime,1;
```

```
201$        ASSIGN:       MTTR.VACost=MTTR.VACost + Diff.VACost;
198$        TALLY:        MTTR.VACostPerEntity,Diff.VACost,1;
211$        STACK,        1:Destroy:NEXT(210$);
210$        ASSIGN:       MTTR.NumberOut=MTTR.NumberOut + 1:
                     MTTR.WIP=MTTR.WIP-1:NEXT(3$);
8$          DETECT:       ST1,Positive,Z1,0.001:NEXT(9$);
9$          ASSIGN:       Dispose 2.NumberOut=Dispose 2.NumberOut + 1;
213$        DISPOSE:      Yes;
10$         DETECT:       ST1,Positive,0,0.001:NEXT(11$);
11$         ASSIGN:       Dispose 3.NumberOut=Dispose 3.NumberOut + 1;
214$        DISPOSE:      Yes;
20$         DETECT:       E,Positive,LIMITE,0.001:NEXT(21$);
21$         ASSIGN:       Dispose 22.NumberOut=Dispose 22.NumberOut + 1;
215$        DISPOSE:      Yes;
22$         DETECT:       E,Negative,LIMITE,0.001:NEXT(23$);
23$         ASSIGN:       Dispose 27.NumberOut=Dispose 27.NumberOut + 1;
216$        DISPOSE:      Yes;
24$         DETECT:       E,Positive,Y,0.001:NEXT(28$);
28$         ASSIGN:       E=Y:
                     Usou=Dem1:NEXT(29$);
29$         BRANCH,       1:
                     If,ST1 >= Sc,217$,Yes:
                     Else,218$,Yes;
217$            ASSIGN:          Decide 2.NumberOut True=Decide 2.NumberOut True +
1:NEXT(30$);
218$            ASSIGN:          Decide 2.NumberOut False=Decide 2.NumberOut False +
1:NEXT(34$);
30$         ASSIGN:       Usou=0:
                     TauxP1=0:NEXT(32$);
32$         QUEUE,        Hold 1.Queue;
```

```
            SCAN:        ST1 <= Sc:NEXT(31$);
31$          ASSIGN:      TauxP1=0:
                     Usou=Dem1:NEXT(25$);
25$          ASSIGN:      Dispose 2212.NumberOut=Dispose 2212.NumberOut + 1;
219$         DISPOSE:     Yes;
34$          ASSIGN:      TauxP1=Um1:
                     Usou=0:NEXT(42$);
42$          QUEUE,       Hold 2.Queue;
            SCAN:        ST1 >= Sc:NEXT(31$);
26$          DETECT:      E,Negative,Y,0.001:NEXT(27$);
27$          ASSIGN:      Dispose 2701.NumberOut=Dispose 2701.NumberOut + 1;
220$         DISPOSE:     Yes;
35$          DETECT:      ST1,Negative,0,0.001:NEXT(36$);
36$          ASSIGN:      Dispose 52.NumberOut=Dispose 52.NumberOut + 1;
221$         DISPOSE:     Yes;
222$                        CREATE,                    1,HoursToBaseTime(0.0),Entity
1:HoursToBaseTime(1):NEXT(223$);
223$         ASSIGN:      Create 9.NumberOut=Create 9.NumberOut + 1:NEXT(37$);
37$          ASSIGN:      Dispose 30.NumberOut=Dispose 30.NumberOut + 1;
226$         DISPOSE:     Yes;
38$          DETECT:      ST1,Positive,Sc,0.001:NEXT(39$);
39$          ASSIGN:      Dispose 31.NumberOut=Dispose 31.NumberOut + 1;
227$         DISPOSE:     Yes;
40$          DETECT:      ST1,Negative,Sc,0.001:NEXT(41$);
41$          ASSIGN:      Dispose 32.NumberOut=Dispose 32.NumberOut + 1;
228$         DISPOSE:     Yes;
```

Routine C++:

```
extern "C" void cdecl cstate  ()
{
```

```
SMREAL        DSTOCK1;
SMREAL        DPr;
SMREAL        DSou;
SMREAL        DE;
SMREAL        dE;
SMREAL        dST1;
SMREAL        value;
SMREAL        dBLOC;
SMREAL        dDem1;
SMREAL        dTauxP1;
SMREAL        dUm1;
SMREAL        dUsou;
SMREAL       dTETA;
SMREAL       dLIMITE;
SMREAL       dZ1;
SMREAL       dPr;
SMREAL       dSou;
SMREAL       dY;
SMREAL       daa;
SMREAL       dbb;
SMREAL        x;


static SMINT  ST1     =1;
static SMINT  SP1   =2;
static SMINT  SN1     =3;
static SMINT  E     =4;
static SMINT  Pr      =5;
static SMINT  Sou      =6;
static SMINT  BLOC    =7;
static SMINT  Dem1  =8;
static SMINT  TauxP1  =9;
static SMINT  Um1     =10;
static SMINT  Usou     =11;
static SMINT  Z1      =12;
static SMINT  TETA      =13;
static SMINT  LIMITE     =14;
static SMINT  aa     =15;
static SMINT  bb     =16;
static SMINT  Y     =17;


// METRE AJOUR LE STOCK DU PRODUIT, CAS DE PANNE PAS DE PRODUCTION
BLOC==0
```

```
   dBLOC = getss(&BLOC);
   dDem1 = getss(&Dem1);
   dTauxP1 = getss(&TauxP1);
   dUm1 = getss(&Um1);
   dUsou = getss(&Usou);
   dZ1= getss(&Z1);
   dST1 = getss(&ST1);
   dPr = getss(&Pr);
   dSou = getss(&Sou);
   dY = getss(&Y);
   daa = getss(&aa);
   dbb = getss(&bb);
   dTETA = getss(&TETA);
   dLIMITE = getss(&LIMITE);


if (dE <= dY)
 {
   if (dST1 < dZ1)
           {
                 dTauxP1 = dUm1;
           }
   else
                     {
                          if (dST1 == dZ1)

                                    {
                                         dTauxP1 = dDem1;
                                    }
                              else
                          {
                              dTauxP1 = 0;
                                   }
                     }
 // loi uniforme

dTETA = (dbb - daa) * x + daa;
   DSTOCK1 = dTauxP1 * dBLOC - dDem1;
   setd(&ST1, &DSTOCK1);

   DPr = dTauxP1 * dBLOC;
   setd(&Pr, &DPr);

   DE = dTauxP1 * dBLOC * dTETA;
```

```
   setd(&E, &DE);
 }
else
{
   if (dE > dY)
    {
       DSTOCK1 = dUsou - dDem1;
         setd(&ST1, &DSTOCK1);
       DSou = dUsou;
         setd(&Sou, &DSou);
    }
}

// INTEGRALE DANS LE TEMPS DE STOCK POSITIF ET STOCK NEGATIF


      if (dST1 >= 0)
             {
                 value = dST1;
              setss(&SP1, &value);
             }
      else
             {
                  value = 0;
              setss(&SP1, &value);
             }


      if (dST1 < 0)
            {
              value = -dST1;
                  setss(&SN1, &value);
             }
        else
             {
              value = 0;
                  setss(&SN1, &value);
             }

     return;
}
```

BIBLIOGRAPHIE

Agrawal, A., Harhalakis, G., Minis, I., & Nagi, R. (1996). 'Just-in-time'production of large assemblies. *IIE transactions*, 28(8), p. 653-667.

Akella, R., & Kumar, P.R. (1986). Optimal Control of Production Rate in a Failure Prone Manufacturing System. IEEE Transactions on Automatic Control, 31(2), p. 116-126.

Arora, S., & Gangopadhyay, S. (1995). Toward a theoretical model of voluntary overcompliance. Journal of economic behavior & organization, 28(3), p. 289-309.

Arora, S., & Cason, T. N. (1996). Why do firms volunteer to exceed environmental regulations? Understanding participation in EPA's 33/50 program. Land economics, p. 413-432.

Aronsson, G. (1971). Pontryagin's Maximum Principle and a Minimax Problem. *Mathematica Scandinavica*, 29, p. 55-71.

Assid, M., Gharbi, A., & Hajji, A. (2014). Joint production and setup control policies: an extensive study addressing implementation issues via quantitative and qualitative criteria. *The International Journal of Advanced Manufacturing Technology*, p. 1-18.

Bai, S.X. and Elhafsi, M. (1997). Scheduling of an unreliable manufacturing system with non resumable set-ups. *Computers Ind. Eng*., 32, p. 909-925.

Basnet, C., & Mize, J. H. (1995). A rule-based, object-oriented framework for operating flexible manufacturing systems. *The International Journal of Production Research*, 33(5), p. 1417-1431.

Bielecki, T., et P. R. Kumar. (1988). Optimality of zero-inventory policies for unreliable manufacturing systems. *Operations Research*, 36(4), p. 532-541.

Berthaut, F., Gharbi, A., Kenné, J. P., & Boulet, J. F. (2010). Improved joint preventive maintenance and hedging point policy. *International Journal of Production Economics*, 127(1), p. 60-72.

Blackman, A., & Boyd, J. (2002). Tailored Regulation: Will Voluntary Site-Specific Environmental Performance Standards Improve Welfare?. *Southern Economic Journal*, p. 309-326.

Bonney, M. Jaber, M.J. (2011). Environmentally responsible inventory models: Non-classical models for a non-classical era. International Journal of Production Economics, 133 (1), p. 43–53.

Bouchery, Y., Ghaffari, A., Jemai, Z., & Dallery, Y. (2012). Including sustainability criteria into inventory models. European Journal of Operational Research, 222(2), p. 229-240.

Bouslah, B., Gharbi, A., Pellerin, R., & Hajji, A. (2013). Optimal production control policy in unreliable batch processing manufacturing systems with transportation delay. International Journal of Production Research, 51(1), p. 264-280.

Boukas, E. K., & Haurie, A. (1990). Manufacturing flow control and preventing maintenance: a stochastic control approach. Automatic Control, IEEE Transactions on, 35(9), p. 1024-1031.

Bellman, R. (1956). Dynamic programming and Lagrange multipliers. Proceedings of the National Academy of Sciences of the United States of America, 42(10), p. 767.

Bironneau, L. (2000). Le choix des méthodes et outils de pilotage de la production en milieu industriel. France, Centre de Recherche Rennais en Economic et Gestion, Institut de Gestion de Rennes, Universite de Rennes 1.

Bhattacharya, A. K., & Coleman, J. L. (1994). Linking manufacturing strategy to the design of a customized hybrid production control system. Computer Integrated Manufacturing Systems, 7(2), 134-141.

Brouhle, K., Griffiths, C., & Wolverton, A. (2005). The use of voluntary approaches for environmental policymaking in the US (p. 107-134). Springer Netherlands.

Brouhle, K., Griffiths, C., Wolverton, A. (2009). Evaluating the role of EPA policy levers: An examination of a voluntary program and regulatory threat in the metal-finishing industry. Journal of Environmental Economics and Management, 57, p. 166–181.

Caramanis, M., & Sharifnia, A. (1991). Near optimal manufacturing flow controller design. International Journal of Flexible Manufacturing Systems, 3(3-4), p. 321-336.

Carter, C. R., & Rogers, D. S. (2008). A framework of sustainable supply chain management: moving toward new theory. International journal of physical distribution & logistics management, 38(5), 360-387.

Chaabane, A., Ramudhin, A., & Paquet, M. (2012). Design of sustainable supply chains under the emission trading scheme. International Journal of Production Economics, 135(1), p. 37-49.

Chen, C. and Monahan, G.E. (2010). Environmental safety stock: The impacts of regulatory and voluntary control policies on production planning, inventory control, and environmental performance. European Journal of Operational Research, 207, p. 1280–1292.

Chen, X., Benjaafar, S. and Elomri, A, (2013). The carbon- constrained EOQ. Operations Research Letters, 41, p. 172–179.

Chiodini, V. (1986). Knowledge based system for dynamic manufacturing replanning. Real-Time Optimization in Automated Manufacturing Facilities, Proceedings of a Symposium., Gaitherburg, MD, USA, NBS, Gaithersburg, MD, USA.

Corbett, C. J., & Kirsch, D. A. (2001). International diffusion of ISO 14000 certification. Production and Operations Management, 10(3), p. 327-342.

Dehayem Nodem, F. I., Kenné, J. P., & Gharbi, A. (2011). Simultaneous control of production, repair/replacement and preventive maintenance of deteriorating manufacturing systems. International Journal of Production Economics, 134(1), 271-282.

Dobos, I. (1998). Production- inventory control under environmental constraints, International Journal of Production Economics, 56, p. 123- 131.

Dobos, I. (1999). Production strategies under environmental constraints in an Arrow-Karlin model. International Journal of Production Economics, 59, p. 337-340.

Dobos, I. (2001). Production strategies under environmental constraints: Continuous-time model with concave costs. International Journal of Production Economics, 71, p. 323-330.

Drake, D., Kleindorfer, P. R., & Van Wassenhove, L. N. (2012). Technology choice and capacity portfolios under emissions regulation. Harvard Business School Working Paper, Harvard University.

Elhafsi, M. and S. X. Bai (1996). Optimal production control of a dynamic two-product manufacturing system with setup costs and setup times. Joumal of Global Optimization, 9(2): p. 183-216.

Elkington, J. (1998). Partnerships from cannibals with forks: The triple bottom line of 21st century business. Environmental Quality Management, 8(1), p. 37-51.

Gershwin, S. B., & Gershwin, S. B. (1994). Manufacturing systems engineering(p. 71). Englewood Cliffs, New Jersey: PTR Prentice Hall.

Gharbi, A., & Kenne, J. P. (2003). Optimal production control problem in stochastic multiple-product multiple-machine manufacturing systems. IIE transactions, 35(10), p. 941-952.

Gharbi, A., & Kenne, J. (2000). Production and preventive maintenance rates control for a manufacturing system: an experimental design approach. International Journal of Production Economics, 65(3), p. 275-287.

Gharbi, A., Kenne, J.-P., and Hajji, A. (2006). Operational Level-Based Policies in Production Rate Control of Unreliable Manufacturing Systems With Setups. International Journal of Production Research, 44 (3), p. 545-567.

Gharbi, A., Hajji, A., & Dhouib, K. (2011). Production rate control of an unreliable manufacturing cell with adjustable capacity. International Journal of Production Research, 49(21), p. 6539-6557.

Hajji, A., Gharbi, A., Kenne, J.P. (2009). Joint Replenishment and Manufacturing Activities Control in a Two Stage Unreliable Supply Chain. International Journal of Production Research, 47 (12), p. 3231–3251.

Jaber, M. Y., Glock, C. H., & El Saadany, A. M. (2013). Supply chain coordination with emissions reduction incentives. International Journal of Production Research, 51(1), p. 69-82.

Jain, R.K. (1993). Regulatory framework: United States, Canada, and Mexico. In: Kolluru, R.V. (Ed.), Environmental Strategies Handbook. McGraw-Hill, Inc., New York, p. 67– 117.

Kenne, J. P., & Gharbi, A. (2000). Production planning problem in manufacturing systems with general failure and repair time distributions. Production Planning & Control, 11(6), 581-588.

Kenne, J. P., & Gharbi, A. (2001). A simulation optimization approach in production planning of failure prone manufacturing systems. Journal of intelligent manufacturing, 12(5-6), p. 421-431.

Khanna, M., Quimio, W. R. H., & Bojilova, D. (1998). Toxics release information: a policy tool for environmental protection. Journal of Environmental Economics and Management, 36(3), p. 243-266.

Kushner, H.J , et P.G Dupuis. (1992). Numerical Methods for Stochastic control problem in continous Time, 2. New York: Springer, 475 p.

Lavoie, P., Gharbi, A. and Kenne, J.-P. (2010). A comparative study of pull control mechanisms for unreliable homogenous transfer lines. International Journal of Production Economics, 124 (1), p. 241-251.

Lee W.L. and Yik, F.W.H. (2004). Regulatory and voluntary approaches for enhancing building energy efficiency. Progress in Energy and Combustion Science, 30, p. 477–499.

Li, S., & Gu, M. (2012). The effect of emission permit trading with banking on firm's production–inventory strategies. International Journal of Production Economics, 137(2), p. 304-308.

Li, S. (2013). Optimal control of the production–inventory system with deteriorating items and tradable emission permits. International Journal of Systems Science, (ahead-of-print), p. 1-12.

Li, S. (2014). Optimal control of production-maintenance system with deteriorating items emission tax and pollution R&D investment. International Journal of Production Research, 52 (60), p. 1787-1807.

Liberatore, G., Nicosia, S., & Valigi, P. (1995). Dynamic allocation of kanbans in a manufacturing system using perturbation analysis. In Emerging Technologies and Factory Automation. ETFA'95, Proceedings., INRIA/IEEE Symposium on. 2, p. 595-603). IEEE.

Marcus, P.A., Willig, J.T. (1997). Moving Ahead with ISO 14000: Improving Environmental Management and Advancing Sustainable Development. John Wiley & Sons, New York.

Merton, Robert C. (1971). Optimum consumption and portfolio rules in a continuous-time model. Journal of Economic Theory, 3(4), p. 373-413.

Neto, Q.F.J., G. Walther, J. Bloemhof, J. A. E. E. van Nunen et T. Spengler. (2007). From closed-loop to sustainable supply chains: The WEEE case. International Journal of Production Research, 48(3), p. 4463 – 4481.

Older G.J. and Suri R. (1980). Time optimal of part-routing in a manufacturing system with failure prone machines. In Proc. 19th IEEE Conf Decis. Confr., Alburquerque, NM, p. 722-727.

Pearce, D.W., Turner, R.K. (1990). Economics of Natural Resources and the Environment. John Hopkins University Press, Baltimore, MD.

Quirion, P. (2010). Complying with the Kyoto Protocol under uncertainty: Taxes or tradable permits?. Energy Policy, 38(9), p. 5166-5173.

Rishel, R. (1975). Control of systems with jump Markov disturbances. Automatic Control, IEEE Transactions on, 20(2), 241-244.

Rivera-Gómez, H., Gharbi, A., & Kenne, J. P. (2013). Production and quality control policies for deteriorating manufacturing system. International Journal of Production Research, 51(11), p. 3443-3462.

Radhoui, M., Rezg, N., and Chelbi, A. (2009). Integrated Model of Preventive Maintenance, Quality Control and Buffer Sizing for Unreliable and Imperfect Production Systems. International Journal of Production Research, 47 (2), p. 389–402.

Sethi, S. P., Zhang, Q., & Zhou, X. Y. (1997). Hierarchical production controls in a stochastic two-machine flow shop with a finite internal buffer. Robotics and Automation, IEEE Transactions on, 13(1), p. 1-13.

Seuring, S., & Müller, M. (2008). From a literature review to a conceptual framework for sustainable supply chain management. Journal of cleaner production, 16(15), p. 1699-1710.

Sethi, S. P., & Zhang, H. (1999). Average-cost optimal policies for an unreliable flexible multiproduct machine. International journal of flexible manufacturing systems, 11(2), p. 147-157.

Shin, R. W., & Chen, Y. C. (2000). Seizing global opportunities for accomplishing agencies'missions: the case of ISO 14000. Public Administration Quarterly, 24(1).

Sharifnia, A. (1988). Production control of a manufacturing system with multiple machine states. Automatic Control, IEEE Transactions on, 33(7), p. 620-625.

Soner, H. Mete, H. Fleming Wendell et P. Sethi Suresh. (1985). A stochastic production planning problem with random demand. In Decision and Control, 1985 24th IEEE Conference on, 24, p. 1345-1346.

Tamani, K. (2008). Développement d'une méthodologie de pilotage intelligent par régulation de flux adaptée aux systèmes de production (Doctoral dissertation). Thèse de doctorat en électronique, électrotechnique, automatique de l’Université de Savoie, Annecy, Université de Savoie, 208 p.

Toptal, A., Özlü, H., & Konur, D. (2014). Joint decisions on inventory replenishment and emission reduction investment under different emission regulations. International Journal of Production Research, 52(1), p. 243-269.

Thesen, A. (1999). Some simple, but efficient, push and pull heuristics for production sequencing for certain flexible manufacturing systems. International Journal of Production Research, 37(7), p. 1525-1539.

Wallace, D. (1995). Environmental policy and industrial innovation: Strategies in Europe, the USA and Japan. Earthscan.

Williams, D., & Wirth, A. (1996). A new heuristic for a single machine scheduling problem with set-up times. Journal of the Operational Research Society, 47(1), p. 175-180.