UNIVERSITÉ DE MONTRÉAL

CONCEPTION CONJOINTE DES POLITIQUES DE CONTRÔLE DE PRODUCTION, DE QUALITÉ ET DE MAINTENANCE DES SYSTÈMES MANUFACTURIERS EN DÉGRADATION

BASSEM BOUSLAH

DÉPARTEMENT DE MATHÉMATIQUES ET DE GÉNIE INDUSTRIEL

ÉCOLE POLYTECHNIQUE DE MONTRÉAL

THÈSE PRÉSENTÉE EN VUE DE L'OBTENTION

DU DIPLÔME DE PHILOSOPHIÆ DOCTOR

(GÉNIE INDUSTRIEL)

DÉCEMBRE 2015

UNIVERSITÉ DE MONTRÉAL

ÉCOLE POLYTECHNIQUE DE MONTRÉAL

Cette thèse intitulée :

CONCEPTION CONJOINTE DES POLITIQUES
DE CONTRÔLE DE PRODUCTION, DE QUALITÉ ET DE MAINTENANCE
DES SYSTÈMES MANUFACTURIERS EN DÉGRADATION

présentée par : BOUSLAH Bassem

en vue de l'obtention du diplôme de : Philosophiæ Doctor

a été dûment acceptée par le jury d'examen constitué de :

M. OUALI Mohamed-Salah, Doctorat, président

M. PELLERIN Robert, Ph. D., membre et directeur de recherche

M. GHARBI Ali, Ph. D., membre et codirecteur de recherche

Mme. YACOUT Soumaya, D. Sc., membre

M. DEJAX Pierre, Ph. D., membre externe

DÉDICACE

À la mémoire de ma grand-mère,

À mes chers parents,

À ma grande famille BOUSLAH,

À mes amis.

REMERCIEMENTS

C'est un agréable devoir de témoigner ma reconnaissance aux personnes qui m'ont supporté de près ou de loin dans la réalisation de cette thèse.

J'adresse tout d'abord mes sincères remerciements à mes directeurs de recherche, Mr. Robert Pellerin, Professeur et Titulaire de la Chaire de recherche Jarislowsky/SNC-Lavalin, et Mr. Ali Gharbi, Professeur et Responsable de Laboratoire de Conception et Contrôle des Systèmes de Production à l'École de Technologie Supérieure, pour leur encadrement de haute qualité, leurs directives scientifiques, leur disponibilité, leurs conseils judicieux et leur soutien financier.

Je tiens également à remercier, Pr. Mohamed-Salah Ouali, Pr. Soumaya Yacout et Pr. Bernard Clément de l'École Polytechnique de Montréal, et Pr. Pierre Dejax de l'École des Mines de Nantes qui me font l'honneur d'examiner et de juger ma thèse de doctorat.

J'adresse aussi mes remerciements à tous mes collègues chercheurs et doctorants qui travaillaient avec Pr. Robert Pellerin, plus particulièrement, Dr. Nathalie Perrier, Dr. François Berthaut et Mme. Kaouthar Cherkaoui, avec qui j'ai eu beaucoup d'échanges, de collaboration et de discussions stimulantes et enrichissantes. Je remercie également tous les membres de Laboratoire de Conception et Contrôle des Systèmes de Production à l'École de Technologie Supérieure pour leur gentillesse et leur collaboration.

Je tiens aussi à remercier le Ministère de l'Enseignement Supérieur et de la Recherche Scientifique de la Tunisie, représenté par la Mission Universitaire de la Tunisie en Amérique du Nord, qui a financé la plus grande partie de mes études au Canada.

Enfin et tout particulièrement, j'adresse mes plus sincères remerciements à mes parents, à toute ma grande famille et à mes amis qui m'ont toujours encouragé et soutenu le long de mes études doctorales.

RÉSUMÉ

La gestion de la production, le contrôle de la qualité et la planification de la maintenance sont les trois principales fonctions de la gestion des opérations dans les usines manufacturières. Dans la pratique, ces trois fonctions sont souvent gérées séparément, bien qu'elles soient, en réalité, étroitement inter-reliées. Plusieurs recherches ont été menées depuis des décennies afin de concevoir et d'optimiser conjointement les politiques de contrôle de la production, de la qualité et de la maintenance. Cette tendance est motivée par le fait que les politiques d'intégration des trois fonctions permettent d'améliorer la productivité et de réduire considérablement les coûts.

Cependant, dans la quasi-totalité des modèles d'intégration dans la littérature, seulement deux fonctions sont intégrées à la fois. De plus, pour des raisons de simplification, ces modèles sont basés sur certaines hypothèses simplificatrices et irréalistes pour modéliser la dégradation de la qualité des produits et de la fiabilité des machines. Par exemple, ces modèles négligent souvent l'impact des opérations de production sur l'intensité de dégradation, mais aussi la corrélation entre les dégradations de la qualité et de la fiabilité. Par ailleurs, les politiques de contrôle de la qualité utilisées dans ces modèles sont soit les cartes de contrôle, soit le contrôle à 100%. Toutefois, l'intégration des plans d'échantillonnage, qui représentent une branche importante de Contrôle Statistique de la Qualité, avec les politiques de production et de maintenance n'a pas été étudiée encore dans la littérature. Ces plans sont largement utilisés dans l'industrie depuis longtemps afin d'éviter le coût excessif du contrôle à 100% et d'assurer en même un contrôle statistique de la qualité des produits livrés.

Cette thèse s'intéresse au problème de conception conjointe des politiques de contrôle de la production, de la qualité et de la maintenance. L'objectif principal de la recherche est d'intégrer les plans d'échantillonnage avec les politiques de production et de maintenance des systèmes où la qualité et la fiabilité sont les deux sujettes à la dégradation. Nous proposons une approche pratique de modélisation et d'optimisation de ces politiques qui permet de prendre en considération la dynamique complexe de la dégradation telle que dans la réalité des systèmes manufacturiers. En outre, nous étudions les propriétés statistiques des plans d'échantillonnage afin de montrer comment des informations pertinentes fournies par ces plans peuvent être intégrées dans la planification des activités de maintenance préventive afin d'améliorer les performances globales des systèmes manufacturiers.

Les contributions scientifiques réalisées dans le cadre de cette thèse sont présentées sous forme de quatre articles de revue. Le premier article introduit un modèle d'intégration du plan d'échantillonnage simple avec la commande de la production pour un *système de fabrication par lots*. Ce modèle vise essentiellement à étudier les interactions entre les paramètres du plan d'échantillonnage et les paramètres de gestion de la production tels que la taille du lot de production et le stock de sécurité. Ensuite, une extension de ce modèle est proposée dans le deuxième article afin de considérer l'aspect dynamique de la dégradation de la qualité et de la fiabilité en fonction des opérations de production et d'intégrer une politique de maintenance préventive. L'objectif est d'optimiser conjointement les paramètres de contrôle de la production, de la qualité et de la maintenance de façon à minimiser le coût total des opérations, tout en respectant une contrainte sur la qualité après-contrôle. De plus, cet article vise à montrer l'utilité des informations issues du plan d'échantillonnage simple pour la surveillance de la qualité de la production et pour l'organisation des actions de maintenance préventive. Une analyse comparative de l'utilisation de plan d'échantillonnage par rapport au contrôle à 100% est aussi fournie afin de quantifier les gains économiques qui en découleraient. Le troisième article propose une approche d'intégration du plan d'échantillonnage continu de type-1 (CSP-1) avec les politiques de production et de maintenance préventive pour les *systèmes de production continue*. L'objectif est d'étendre l'applicabilité du plan CSP-1 aux processus de production en dégradation, puisqu'il est actuellement applicable seulement aux processus stables. Un autre objectif de cet article est de quantifier les bénéfices de l'utilisation de CSP-1 par rapport au contrôle à 100%, et de montrer aussi comment le couplage de CSP-1 avec la maintenance préventive permet d'améliorer les performances des systèmes en dégradation. Finalement, le quatrième article introduit un modèle de contrôle conjoint de la production, de la qualité et de la maintenance d'une *ligne de production* dont les machines sont sujettes à la dégradation. En plus, les machines peuvent tomber en panne à cause des pièces non-conformes fabriquées dans les processus en amont. L'objectif est de montrer l'importance de la corrélation entre les dégradations de la qualité et de la fiabilité dans la modélisation de la dynamique des systèmes manufacturiers, et d'étudier l'effet de cette corrélation sur les paramètres optimaux du contrôle de la production, de la qualité et de la maintenance. Le second objectif de cet article est de montrer que les activités de maintenance et de contrôle de la qualité à un certain niveau de la ligne de production contribuent aussi à l'amélioration de la fiabilité des machines en aval.

ABSTRACT

Production, quality and maintenance control are the three main functions of operations management in manufacturing plants. Traditionally, they have been treated by scientists and practitioners as separate problems even though they are strongly interrelated. In the past three decades, the integration of production, maintenance and quality control has attracted much attention in the literature. This trend is motivated by the fact that integrated control policies generally result in better manufacturing performance and significant cost savings.

Nevertheless, most of the existing integrated models in the literature integrate only two functions at a time. Moreover, for simplicity, almost all of the integrated models are based on several simplifying assumptions that may make them unrealistic. For example, the complex dynamics of quality and reliability degradations such as the impact of operations speed on degradation intensity and the correlation between quality and reliability degradations have been always overlooked in the literature of integrated models. On the other hand, the quality control policies used in the existing integrated models are either 100% inspection of all parts produced or statistical process control tools such as the control charts. However, acceptance sampling which constitutes an important branch of the Statistical Quality Control has never been integrated with production and maintenance policies. Acceptance sampling plans and procedures have been widely used in industry for a long time to reduce the cost and time of quality inspection and to statistically control the outgoing quality.

This research considers the problem of the joint design of production, quality and maintenance control policies of stochastic manufacturing systems. Specifically, the main objective of this thesis is to integrate sampling inspection techniques with production and maintenance control policies for systems subject to both quality and reliability degradations. We provide a practical modeling framework to adequately pattern the complex dynamics of degradation processes as in the real-life in order to develop new effective integrated control policies. Moreover, we investigate the intrinsic statistical properties of acceptance sampling plans in order to demonstrate how they can be coupled with condition-based maintenance to improve the overall performance of degrading manufacturing systems.

This thesis is comprised of four journal articles. The first article investigates the joint production and quality control of a *batch-processing production system* which is unreliable and imperfect. A single acceptance sampling plan by attributes is used for quality control. The objective of this article is to introduce an integrated model for the joint optimization of the production lot size, the safety stock and the sampling plan parameters which minimize the total cost incurred. This aims to provide a better understanding of the interactions between the optimal production-inventory settings and the optimal sampling plan parameters. As an extension of this model, the second article considers that quality and reliability degradations are operation-dependent. Moreover, a preventive maintenance strategy is incorporated into the integrated control policy. Thus, the objective is to jointly optimize the production, quality and maintenance control parameters. This article investigates the statistical characteristics of the single sampling plan to show the relevance of quality information resulting from such a quality control to the maintenance decision-making. Also, a comparative study is conducted to quantify the economic savings that can be realized by using the sampling plans for degrading systems rather than 100% inspection. The third article addresses the joint economic design of production control, type-1 continuous sampling plan (CSP-1) and preventive maintenance of *continuous-flow manufacturing systems*. The objective is to show how integrated control policies can extend the application of continuous sampling plans to degrading production systems, as they are presently limited only to stable processes. In this article, three quality control policies are considered and compared: 100% inspection, the classical CSP-1 as in the standard procedures and a CSP-1 plan with a stopping rule that is coupled with condition-based maintenance. This aims to quantify the economic savings that can be achieved by using the CSP-1 compared to 100% inspection and to demonstrate how CSP-1 with an inspection stopping rule for degrading processes is more cost-effective than the classical CSP-1. Finally, the fourth article investigates the joint design of production, quality and maintenance control policies for *manufacturing lines*. We consider a small production line composed of two machines subject to quality and reliability degradations. The second machine is also subject to failures caused by defective products manufactured in upstream processes. The main objective of this article is to study the interactions between the optimal production, quality and maintenance control settings and the effect of failures correlation on those settings. Also, we show how maintenance and quality control activities in preceding stages can play an important role in the reliability improvement of the subsequent machines.

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CHAPITRE 1 INTRODUCTION

Les entreprises industrielles modernes font face à de nombreux défis de taille pour assurer leurs pérennités. D'une part, des facteurs de marché comme la concurrence et l'impact des technologies de communication sur le comportement des clients exercent une pression sur le prix, la qualité des produits et le respect des dates de livraison. D'autre part, à l'intérieur de l'entreprise, la gestion des opérations est devenue une tâche fort complexe qui cherche, à la fois, à améliorer la qualité des produits, à minimiser les coûts des opérations et à mieux exploiter les actifs et les installations de production. Ces installations sont généralement sujettes, par nature, aux nombreux phénomènes aléatoires qui affectent la qualité et le coût des produits; ceux-ci perturbent les plans de production et de livraison. L'usure et les pannes des équipements de production, la dégradation de la qualité et les durées aléatoires de maintenance sont des exemples de phénomènes aléatoires souvent observés dans les systèmes manufacturiers. La capacité des politiques de gestion des opérations à minimiser les effets de ces phénomènes sur la productivité, la qualité et le coût total est devenue aujourd'hui un facteur déterminant de la compétitivité et de la croissance des entreprises industrielles.

Dans le secteur manufacturier, la gestion des opérations repose essentiellement sur trois principales fonctions: la gestion de la production, le contrôle de la qualité et la planification des activités de maintenance. Dans la pratique, ces trois fonctions sont généralement gérées séparément par des unités organisationnelles indépendantes, bien qu'elles soient, en réalité, étroitement inter-reliées (Ben-Daya et Rahim, 2001). Plusieurs recherches ont été menées depuis des décennies afin de développer des stratégies de gestion intégrée des opérations qui permettent, à travers une approche holistique, de concevoir et d'optimiser conjointement les politiques de contrôle de la production, de la qualité et de la maintenance. Plusieurs revues de littérature détaillées sur ce sujet ont été publiées dans les dernières années, telles que dans Pandey et al. (2010), Hadidi et al. (2012), Inman et al. (2013) et Colledani et al. (2014). Cette tendance est motivée par le fait que les politiques de gestion intégrée des opérations permettent d'améliorer considérablement la productivité et la qualité des produits par rapport à l'approche traditionnelle qui consiste à gérer chaque aspect de gestion des opérations de façon isolée (Colledani et al., 2012). En outre, la gestion intégrée des opérations aide les entreprises à réduire significativement

les coûts et à réaliser une augmentation des bénéfices allant jusqu'à plus de 40% (Colledani et Tolio, 2011b).

Cependant, la quasi-totalité des modèles existants de gestion intégrée des opérations ne traitent que deux fonctions à la fois parmi la gestion de la production, le contrôle de la qualité et la planification de la maintenance (Hadidi et al., 2012 ; Colledani et al., 2014). De plus, ces modèles sont basés sur un certain nombre d'hypothèses simplificatrices, souvent irréalistes, pour modéliser la dégradation de la qualité des produits et de la fiabilité des machines. Tout d'abord, ces deux phénomènes de dégradation sont rarement étudiés de façon simultanée dans ces modèles. Des aspects importants tels que le lien entre la dégradation de la qualité et de la fiabilité et l'effet d'une possible corrélation entre les deux phénomènes sur les paramètres de contrôle de la production, de la qualité et de la maintenance n'ont jamais été étudiés dans la littérature. Pourtant, plusieurs recherches ont montré qu'ignorer les interactions entre la qualité des produits et la fiabilité des machines dans la modélisation des systèmes de production pourrait conduire à une surestimation significative de la fiabilité globale du système (Chen et Jin, 2005; Sun et al., 2009), ce qui réduit, par conséquent, l'efficacité des politiques de gestion de stock, de contrôle de la qualité et de maintenance proposées. De plus, ces modèles négligent l'aspect dynamique de la dégradation, alors que plusieurs études industrielles dans les systèmes manufacturiers automatisés ont déjà montré l'impact important de la dynamique des opérations de production sur l'intensité de dégradation de la qualité et de la fiabilité (Buzacott et Hanifin, 1978; Khouja et al., 1995; Owen et Blumenfeld, 2008).

Par ailleurs, des efforts considérables ont été déployés par les chercheurs pour intégrer les techniques de Contrôle Statistique de la Qualité (CSQ), notamment les cartes de contrôle, avec les politiques de production et de maintenance. Néanmoins, l'intégration des plans d'échantillonnage, qui représentent une branche importante de CSQ, avec les politiques de production et de maintenance n'a pas été étudiée encore dans la littérature, bien que ces plans soient largement utilisés dans l'industrie depuis longtemps. Ainsi, des recherches récentes menées par Cao et Subramaniam (2013) et Bouslah et al. (2013) ont montré que la conception des plans d'échantillonnage a un impact important sur la productivité, aussi bien sur les décisions optimales de planification de production et de gestion de stock. Dans le cas des systèmes de production sujets à une dégradation de la qualité, plusieurs chercheurs proposent des politiques

de maintenance conditionnelle basées sur le retour d'informations collectées lors du contrôle à 100% de la qualité, puisque ces informations permettent de reconnaître l'état de dégradation de la qualité de production (Tapiero ,1986; Hsu et Kuo, 1995; Radhoui et al., 2010). Toutefois, il n'existe aucun modèle dans la littérature qui explore les propriétés statistiques spécifiques des plans d'échantillonnage afin d'intégrer les informations issues de ces plans dans la planification des activités de la maintenance, ce qui permet d'éviter les coûts excessifs du contrôle à 100%.

Reconnaissant le rôle important de la gestion intégrée des opérations dans l'amélioration des performances des entreprises industrielles, cette thèse a pour objectif de développer des nouvelles politiques d'intégration de contrôle de la production, de la qualité et de la maintenance pour différentes configurations de systèmes manufacturiers, à savoir: les systèmes de production par lots, les systèmes de production continue, les systèmes composés d'une seule unité de production et les lignes de production. Dans cette recherche, le contrôle de la qualité est basé essentiellement sur les plans d'échantillonnage dans le but de montrer comment la conception de ces plans dans un contexte d'intégration avec la production et la maintenance permet d'améliorer significativement les performances des systèmes de production en dégradation. En outre, nous proposons une approche pratique de modélisation et d'optimisation de ces politiques qui permet de prendre en considération la dynamique complexe de la dégradation de la qualité et de la fiabilité.

La thèse est organisée en huit chapitres. Le Chapitre 2 présente une revue critique de la littérature portant sur l'intégration de contrôle de la production, de la qualité et de la maintenance, sur la modélisation de la dégradation de la qualité et de la fiabilité et sur les méthodes de conception des plans d'échantillonnage. Le Chapitre 3 présente les objectifs de la thèse, l'organisation générale des travaux de recherche et la démarche scientifique adoptée. Ensuite, les contributions scientifiques réalisées dans le cadre de cette recherche sont présentées sous forme de quatre articles scientifiques dans les chapitres 4, 5, 6 et 7. Ces articles ont été publiés ou soumis dans des revues scientifiques internationales avec comité de lecture.

Le premier article intitulé « *Joint production and quality control of unreliable batch manufacturing systems with rectifying inspection* » a été publié en 2014 dans la revue *International Journal of Production Research*. Cet article introduit un modèle de contrôle conjoint de la production et de la qualité par échantillonnage simple pour un système de

fabrication par lots, non-fiable et imparfait. Ce modèle vise à étudier les interactions entre les paramètres du plan d'échantillonnage et les paramètres de gestion de la production tels que la taille du lot de production et le stock de sécurité. L'objectif est d'introduire une nouvelle approche d'optimisation conjointe des politiques de commande de la production et des plans d'échantillonnage dans un environnement stochastique.

Le second article intitulé « *Integrated production, sampling quality control and maintenance of deteriorating production systems with AOQL constraint* » a été accepté en Août 2015 dans la revue *OMEGA, The International Journal of Management Science*. C'est une extension du premier article en intégrant la maintenance préventive, l'aspect dynamique de la dégradation de la qualité et de la fiabilité en fonction des opérations de production, et une contrainte sur la qualité après-contrôle. L'objectif de ce modèle est d'optimiser conjointement les paramètres de contrôle de la production, de la qualité et de la maintenance de façon à minimiser le coût total des opérations. Cet article explore la dynamique et les propriétés statistiques du plan d'échantillonnage simple afin de monter comment on peut profiter des informations fournies par ces plans pour la surveillance de la qualité de production et pour l'organisation des interventions de maintenance majeure. Aussi, cet article cherche à quantifier les gains économiques en utilisant les plans d'échantillonnage pour les systèmes en dégradation par rapport au contrôle à 100%.

Le troisième article intitulé « *Joint economic design of production, continuous sampling inspection and preventive maintenance of a deteriorating production system* » est présentement sous-révision dans *International Journal of Production Economics*. Cet article traite l'intégration du contrôle de la production, de la qualité et de la maintenance des systèmes de production continue. L'approche d'intégration proposée a pour objectif de montrer comment la conception du plan d'échantillonnage continu de type-1 (CSP-1), dans un contexte de conception conjointe avec les politiques de production et de maintenance, permet d'étendre leur applicabilité aux processus de production en dégradation, puisque ces plans sont actuellement applicables seulement aux processus de production stables. Un autre objectif de l'article est de montrer comment le couplage du contrôle de la qualité par échantillonnage continu avec la planification de la maintenance préventive permet d'améliorer les performances des systèmes de production en dégradation. Une analyse comparative des coûts de trois modèles d'intégration est présentée afin de quantifier les bénéfices de l'utilisation du CSP-1 par rapport au contrôle à 100%, et aussi les

bénéfices du CSP-1 modifié (couplé avec la maintenance préventive) par rapport au CSP-1 classique.

Le quatrième article intitulé « *Joint production, quality and maintenance control of a two-machine line subject to operation-dependent and quality-dependent failures* » a été soumis récemment dans *OMEGA, The International Journal of Management Science*. Cet article introduit un modèle du contrôle conjoint de la production, de la qualité et de la maintenance d'une ligne de production dont les machines sont sujettes à la dégradation. En plus, les machines peuvent tomber en panne à cause des pièces non-conformes fabriquées dans les processus de production en amont. L'objectif de ce modèle est de montrer l'importance de la corrélation entre la dégradation de la qualité des produits et la dégradation de la fiabilité des machines dans la modélisation de la dynamique des systèmes manufacturiers, et d'étudier l'effet de cette corrélation sur les paramètres optimaux du contrôle de la production, de la qualité et de la maintenance. Le second objectif de cet article est de démontrer que le contrôle de la qualité dans les lignes de production ne permet pas seulement d'améliorer la qualité des produits, mais il contribue aussi à l'amélioration de la fiabilité des machines.

Finalement, le Chapitre 8 présente une discussion générale des travaux de recherche, une conclusion de la thèse et les perspectives futures de recherche.

CHAPITRE 2 REVUE CRITIQUE DE LA LITTÉRATURE

Ce chapitre présente une analyse critique de la littérature scientifique traitant le problème d'intégration du contrôle de la production, de la qualité et de la maintenance des systèmes manufacturiers en dégradation. En premier lieu, nous présentons les différents niveaux d'intégration de ces trois fonctions dans la littérature. En second lieu, nous discutons les différents modèles utilisés dans la littérature pour modéliser la dégradation des systèmes manufacturiers, ainsi que les limitations de ces modèles. En troisième lieu, nous présentons une revue critique sur les techniques de contrôle de la qualité utilisées dans la littérature. Dans cette partie, nous abordons plus particulièrement les limitations des méthodes de conception des plans d'échantillonnage.

2.1 Intégration des politiques de contrôle de la production, de la qualité et de la maintenance

L'intégration des politiques de contrôle de la production, de la qualité et de la maintenance a fait l'objet de plusieurs recherches scientifiques depuis des décennies. Dans une revue de la littérature récente sur ce thème de recherche, Hadidi et al. (2012) classent les modèles de gestion intégrée des opérations en deux catégories, en faisant une différence entre le concept d'interdépendance et le concept d'intégration: le concept d'interdépendance concerne les modèles qui cherchent à optimiser une seule fonction parmi le contrôle de la production, de la qualité et de la maintenance, en considérant les autres fonctions comme des contraintes. Une contrainte ici veut dire que les politiques et les paramètres de contrôle de ces fonctions sont imposés et considérés comme des données (à ne pas optimiser). D'autre part, le concept d'intégration concerne les modèles où, au moins, deux fonctions parmi le contrôle de la production, de la qualité et de la maintenance sont à concevoir et à optimiser conjointement.

En se basant sur la définition de l'intégration telle que proposé par Hadidi et al. (2012), nous trouvons que la majorité des modèles d'intégration dans la littérature s'intéresse seulement à deux fonctions à la fois. Par exemple, plusieurs modèles d'intégration des politiques de la production et de la maintenance préventive ont été proposés depuis les années 1990 sans considérer l'aspect qualité. Une revue de littérature détaillée sur ces travaux est présentée par Budai et al., 2008. Dans les dernières années, plusieurs recherches sur l'intégration des politiques

de la production et de la maintenance ont été publiées dans la littérature, telle que l'intégration des politiques de maintenance préventive avec la Quantité Économique de Production (par exemple, Sana, 2012; Liao, 2013), l'intégration de la planification de la production et de la maintenance préventive opportuniste (par exemple, Xia et al., 2012, 2015) et la commande conjointe du taux de production et de la maintenance préventive (par exemple, Berthaut et al., 2010, 2011; Assid et al., 2015b).

De l'autre coté, la recherche sur l'intégration de contrôle de la production et de la qualité sans considérer l'aspect maintenance remonte aux années 1970 et 1980 (deux revues détaillées de la littérature sur ces travaux ont été présentées par Goyal et al. (1993) et Inman et al. (2003)). Ces travaux de recherche portent généralement sur les effets mutuels du choix des politiques et des paramètres du contrôle de la production et de la qualité. Par exemple, plusieurs recherches ont été effectuées afin d'étudier les effets du taux de production, de la planification des opérations de mise-en-course, de la conception des systèmes de production et du choix des technologies de fabrication sur la qualité des produits (par exemple, Liu et al., 2009; Sana, 2010a; Jeang, 2012; Pal et al., 2013). Ainsi, d'autres recherches ont étudié les effets de l'emplacement des stations de contrôle de la qualité, et de niveau et de la politique de contrôle de la qualité dans chaque station sur le flux de production, le stock en-cours, le délai de production et la productivité (par exemple, Kim et Gershwin, 2005, 2008; Colledani et Tolio, 2011; Colledani et al., 2015). De plus, nous remarquons qu'il y a un intérêt grandissant d'intégrer les techniques de Contrôle Statistique de la Qualité surtout les cartes de contrôle et l'analyse de capabilité des processus avec les politiques de production (par exemple, Hajji et al., 2011; Pan et al., 2011, 2012; Colledani et Tolio, 2012). Cependant, les plans d'échantillonnage, qui représentent une branche importante du Contrôle Statistique de la Qualité, n'ont pas encore été intégrés avec les politiques de production (plus de détails sont fournis dans la Section 2.3).

Dans sa récente revue de littérature sur l'intégration du contrôle de la production et de la qualité, Inman et al. (2013) ont constaté que, malgré le progrès important de la recherche sur ce sujet, l'intégration simultanée du contrôle de la production et de la qualité avec les politiques de maintenance préventive n'a pas été suffisamment étudiée dans la littérature. Dans les deux revues de littérature de Hadidi et al. (2012) et Colledani et al. (2014), on compte moins d'une dizaine d'articles qui s'adressent à l'intégration simultanée du contrôle de la production, de la qualité et de la maintenance.

2.2 Dégradation de la qualité et de la fiabilité dans les systèmes manufacturiers

La modélisation de la dégradation de la qualité et de la fiabilité dans les systèmes manufacturiers est un élément clé qui détermine jusqu'à quel point on peut imiter la réalité de la dynamique complexe de ces systèmes, mais aussi jusqu'à quel point les politiques développées avec une telle modélisation peuvent être mises en pratique. Dans la littérature, la quasi-totalité des modèles d'intégration de contrôle de la production, de la qualité et de la maintenance sont basés sur un certain nombre d'hypothèses simplificatrices et irréalistes dans la modélisation de la dégradation des systèmes manufacturiers. Dans cette section, nous discutons certains aspects importants de la dégradation de la qualité et de la fiabilité qui ont été démontrés à partir de plusieurs études de cas réelles, mais qui ont été souvent négligés dans la littérature.

2.2.1 Modélisation de la dégradation de la qualité

La dégradation de la qualité est un phénomène inhérent des systèmes manufacturiers. Le mode de dégradation de la qualité le plus utilisé dans la littérature est celui qui consiste à décrire le processus de production par deux états: l'état 'sous-contrôle' au début de chaque nouveau cycle de production où tous les produits fabriqués sont conformes, et l'état 'hors-contrôle' à partir du moment où le processus commence à générer des produits non-conformes. Le passage de l'état 'sous-contrôle' à l'état 'hors-contrôle' est supposé être aléatoire, souvent suivant une distribution exponentielle pour des raisons de simplification de la modélisation. Rosenblatt et Lee (1986) sont probablement les premiers qui ont étudié différentes formes de dégradation de la qualité sur la planification de la production. Ces auteurs ont proposé quatre modes de dégradation, une fois le système est passé à l'état 'hors-contrôle', à savoir : (i) production d'une proportion *constante* de produits non-conformes (pas de dégradation), (ii) dégradation linéaire de la qualité en fonction du temps, (iii) dégradation exponentielle de la qualité en fonction du temps, et (iv) dégradation multi-niveaux de la qualité avec un passage aléatoire d'un niveau à un autre plus élevé. L'étude de Rosenblatt et Lee (1986) sur l'impact de ces différents modes de dégradation de la qualité sur la Quantité Économique de Production a fait l'objet de plusieurs extensions dans la littérature. Pourtant, la majorité de ces extensions sont basées sur le premier modèle de Rosenblatt et Lee (1986) qui ignore l'aspect dynamique de la dégradation de la qualité. Il y a quelques exceptions.

Khouja et Mehrez (1994) ont considéré que le taux de production est flexible et qu'il peut affecter l'intensité de dégradation de la qualité (passage de l'état 'sous contrôle' à l'état 'hors contrôle'). En fait, cette hypothèse s'appuie sur plusieurs études industrielles qui ont montré que l'accélération du taux de production augmente la dégradation de la qualité. Par exemple, dans le cas des systèmes d'assemblage robotiques, Felix Offodile et Ugwu (1991) ont montré que l'augmentation de la vitesse de mouvement du bras d'assemblage d'un robot entraîne une diminution de la *répétabilité*. La *répétabilité* est définie par la capacité du robot de retourner au même point cible au début de chaque cycle d'assemblage. Cette mesure est critique pour la qualité des produits: Albertson (1983) et Mehrez et Felix Offodile (1994) ont montré que la dégradation de la *répétabilité* entraîne une augmentation du pourcentage des items non-conformes produits par le robot. L'effet direct du taux de production sur la qualité des produits a été aussi observé dans d'autres contextes industriels tels que dans l'industrie automobile et dans les processus d'usinage et de découpage des métaux (Owen et Blumenfeld, 2008). Malgré que l'effet du taux de production sur l'intensité de dégradation de la qualité ait été démontré dans plusieurs études industrielles, la quasi-totalité des modèles d'intégration dans la littérature ont complètement négligé cette relation de dépendance (à l'exception des modèles suivants: Khouja et Mehrez (1994), Sana (2010), Njike et al. (2011, 2012) et Rivera-Gomez et al. (2013)).

2.2.2 Modélisation de la dégradation de la fiabilité

Dans la littérature, la dégradation de la fiabilité d'une machine peut être dépendante des opérations de production (c'est-à-dire, en fonction de l'usage de la machine) ou dépendante du temps (indépendamment de l'usage de la machine). D'où, les pannes des machines ont été souvent classées en deux catégories :

(i) *Les pannes dépendantes des opérations*: une panne de ce type peut survenir seulement quand la machine est opérationnelle. La panne se produit généralement à cause de l'usure de la machine qui dépend de sa part du taux de production, du volume de production durant un cycle donné ou du nombre de cycles de production.

(ii) *Les pannes dépendantes du temps*: une panne de ce type peut survenir même durant les périodes d'arrêt forcé de la machine (machine bloquée ou non-alimentée). Le taux de pannes augmente avec l'avancement du temps et elle est due aux phénomènes autres que l'usure.

Dans une étude industrielle approfondie des arrêts des lignes de production dans l'industrie automobile (cas de *Chrysler Corporation*), Hanifin (1975) a montré que 84% des pannes sont dépendantes des opérations et que seulement 16% des pannes sont dépendantes du temps. Ainsi, selon Buzacott et Hanifin (1978), il est plus réaliste d'utiliser les modèles de pannes dépendantes des opérations pour modéliser la fiabilité des systèmes de production, puisque ces pannes surviennent beaucoup plus fréquemment en pratique que les pannes dépendantes du temps. Pourtant, la plupart des modèles de gestion intégrée des opérations dans la littérature utilisent les modèles de pannes dépendantes du temps pour des raisons de simplification. En fait, il est beaucoup plus complexe de modéliser les pannes dépendantes des opérations que celles dépendantes du temps, car dans le premier type de pannes, il fallait compter, en particulier, seulement les temps où la machine est opérationnelle dans la modélisation de la dégradation de la fiabilité (Matta et Simone, 2015). Dans une analyse comparative des deux modèles de pannes, Mourani et al. (2007) ont montré que la modélisation d'une machine sujette aux pannes dépendantes des opérations dans une ligne de production par un modèle de pannes dépendantes du temps peut conduire à une sous-estimation significative de la capacité globale de production (allant jusqu'à plus de 16% dans certains cas).

2.2.3 Impact de la qualité sur la fiabilité des équipements de production

Les deux modèles de pannes susmentionnés dans la section prétendante (les pannes dépendantes des opérations et du temps) sont utiles pour modéliser seulement les pannes décorrélées (*uncorrelated failures*). Ce sont les pannes complètement indépendantes de la dynamique et des pannes des autres machines du système de production (Gershwin, 1994). Cependant, dans la réalité des systèmes manufacturiers, les machines peuvent être sujettes aux pannes de nature complexe qui dépendent de l'état des autres machines telles que les pannes causées par les produits défectueux fabriqués par les machines en amont (Colledani et al., 2014).

Dans la littérature de gestion intégrée des opérations, l'effet de la qualité des produits sur la fiabilité des machines en aval a toujours été négligé dans la modélisation de la dégradation des machines (Colledani et al., 2014). Pourtant, ce type de pannes est souvent observé dans les lignes de production. Par exemple, une étude industrielle intéressante sur les pannes dans les lignes d'assemblage des carrosseries des voitures chez *General Motors* a montré que les tôles de dimensions non-conformes fabriqués dans les processus en amont sont à l'origine de 44% de

toutes les pannes *catastrophiques* de ces équipements (Yang et al., 2000; Chen et al., 2004). L'effet de la qualité des produits semi-finis sur la fiabilité des machines est aussi observé dans l'industrie alimentaire (Akbarov et al., 2008) et les processus d'usinage (Chen et Ji, 2005; Sun et al., 2009). Une discussion complète sur les *pannes dépendantes de la qualité* et leurs effets sur la fiabilité des machines est présentée dans la Section 7.2. Cette discussion est appuyée sur des exemples industriels réels afin de mieux comprendre l'ampleur et l'effet de ces pannes sur les systèmes manufacturiers.

2.3 Contrôle de la qualité des systèmes de production imparfaits

2.3.1 Politiques de contrôle de la qualité utilisées dans la littérature

Dans un contexte de production où la qualité est variable ou même en dégradation, la mise en place d'une stratégie de contrôle de la qualité est essentielle pour répondre aux spécifications de la qualité, protéger la clientèle contre la 'mauvaise' qualité et réduire les coûts de la non-qualité. Les techniques de contrôle de la qualité les plus utilisées dans la littérature peuvent être classées en deux grandes catégories: le contrôle à 100% de tous les produits et les techniques de Contrôle Statistique de la Qualité.

2.3.1.1 Le contrôle à 100%

Le contrôle à 100% est généralement utilisé dans les situations où la qualité est très critique pour la clientèle de telle façon que délivrer un produit défectueux est économiquement très pénalisant pour le manufacturier (Montgomery, 2008). Dans la littérature d'intégration de la production, de la qualité et de la maintenance, le contrôle à 100% est généralement adopté pour assurer la livraison des produits sans défauts. Par exemple, les premiers modèles d'intégration de la production et de la qualité tels que dans les travaux de Rosenblatt et Lee (1986), Porteus (1986), Khouja et Mehrez (1994) et Salameh et Jaber (2000), ainsi que la plupart de leurs extensions (Khan et al., 2011), ont supposé que tous les items produits sont inspectés. En réalité, l'hypothèse du contrôle à 100% est souvent utilisée afin de simplifier l'analyse et la modélisation des systèmes de production imparfaits, contrairement aux techniques de Contrôle Statistique de la Qualité qui ajoutent plus de complexité à la modélisation et à la résolution des modèles intégrés (variables de décision additionnelles tels que les paramètres de ces techniques et contraintes de plus telle que la contrainte sur la qualité après-contrôle, etc.). En pratique, le contrôle à 100% est

généralement très coûteux. En plus, le contrôle à 100% n'est pas toujours assez efficace pour capturer et éliminer les produits non-conformes. Selon Juran (1999), le taux d'efficacité du contrôle à 100% d'un grand nombre de produits est en réalité environ de 80% (cela veut dire, que seulement 80% des produits non-conformes sont détectés par le contrôle à 100%). Aussi, malgré que certains industriels préfèrent profiter des technologies d'automatisation du contrôle de la qualité à 100%, une telle stratégie pourrait entraver, à long terme, les efforts nécessaires d'amélioration continue (Juran, 1999).

2.3.1.2 Techniques de Contrôle Statistique de la Qualité

Le Contrôle Statistique de la Qualité est une branche importante de la Qualité Totale (*Total Quality Management*), qui consiste à collecter, analyser et interpréter les données pour l'organisation des activités de contrôle de la qualité (Besterfield, 2009). Les deux techniques de Contrôle Statistique de la Qualité les plus répandues dans l'industrie et aussi largement étudiées dans la littérature sont les techniques de Contrôle (Maîtrise) Statistique des Processus surtout (les cartes de contrôle et les plans d'échantillonnage).

2.3.1.2.1 Les cartes de contrôle

W.A. Shewart (1934) a montré que le problème de non-conformité des produits est dû essentiellement à la variabilité du processus de production et il a introduit des cartes de contrôle pour suivre l'évolution des grandeurs physiques qui expriment cette variabilité. Quand une déviation par rapport aux tolérances prédéfinies est observée, celle-ci indique que le processus de production a passé de l'état stationnaire '*sous-contrôle*' à l'état '*hors-contrôle*' et que les causes '*assignables*' de la variabilité du processus doivent être identifiées et éliminées afin de le restaurer à son état stationnaire '*sous-contrôle*'. Rahim (1994) est probablement le premier auteur qui a intégré les cartes de contrôle de type $\bar{x}$ dans un contexte de production. Son modèle permet de déterminer simultanément la Quantité Économique de Production et la conception économique de la carte de contrôle (taille de l'échantillon, intervalle de temps d'échantillonnage et les limites de contrôle). Rahim et Ben-Daya (1998) ont étendu le modèle de Rahim (1994) en considérant un temps d'arrêt non négligeable du système de production dans le cas de fausses alarmes de déviation du processus de production. Le modèle de Rahim (1994) a été étendu aussi par Ben-Daya (1999) et Ben-Daya et Makhdoum (1998) qui ont intégré différentes politiques de maintenance préventive imparfaite afin de réduire le taux de passage à l'état '*hors-contrôle*'.

Dans les dernières années, plusieurs modèles d'intégration de la maintenance et des cartes de contrôle ont été proposés afin d'étudier divers aspects liés au choix de la politique de maintenance préventive (Yeung et al., 2008; Panagiotidou et George Nenes, 2010; Zhang et al., 2015), sur la conception des cartes de contrôle (Panagiotidou et George Nenes, 2009; Charongrattanasakul et Pongpullponsak, 2011), sur la détérioration de la qualité (Pan et al., 2012) et sur le contrôle de la qualité dans les lignes de production (Colledani et Tolio, 2011a; Liu et al., 2013).

2.3.1.2.2 Les plans d'échantillonnage

Le contrôle de la qualité par échantillonnage est essentiellement utilisé dans les situations suivantes : le contrôle de la qualité est destructif, le coût de contrôle à 100% est très élevé, ou le contrôle à 100% n'est pas techniquement faisable tel que dans le cas où les tests d'inspection de la qualité sont longs (Montgomery, 2008; Schilling et Neubauer, 2009). Les premiers plans d'échantillonnage des lots (dans le cas des systèmes d'approvisionnement ou de production par lots) et les plans d'échantillonnage continu (dans le cas d'une production continue) ont été développés, respectivement, par H. F. Dodge et H. G. Romig en 1928, et H. F. Dodge en 1943, afin de substituer le contrôle à 100% de tous les produits. Plusieurs normes et méthodes de conception des plans d'échantillonnage ont été proposées dans la littérature (voir la section suivante 2.3.2). Toutefois, contrairement aux cartes de contrôle, l'intégration des plans d'échantillonnage avec les politiques de production et de la maintenance préventive n'a pas été explorée encore dans la littérature. On compte un très petit nombre d'initiatives dans cette direction de recherche. Par exemple, Bouslah et al. (2013) ont proposé un modèle d'optimisation simultanée de la taille du lot de production et du stock de sécurité d'un système de production non-fiable et imparfait en considérant un plan d'échantillonnage simple pour le contrôle de la qualité. Les auteurs ont montré que le choix des paramètres du plan d'échantillonnage a un impact très significatif sur la politique optimale de production (taille optimale du lot de production et le stock de sécurité optimal). Quand aux plans d'échantillonnage continu, on trouve Tapiero et Hsu (1988), Tsiotras et Tapiero (1992) et Cao et Subramaniam (2013) qui ont étudié l'impact du plan d'échantillonnage continu de type-1 (CSP-1) sur les performances des lignes de production (le stock en-cours, la productivité, la qualité moyenne après contrôle, etc.)

2.3.2 Méthodes de conception des plans d'échantillonnage dans la littérature

2.3.2.1 Normes standards de conception des plans d'échantillonnage

Tel que mentionné dans la section précédente, il existe deux types de plans d'échantillonnage : les plans d'échantillonnage des lots dans le cas d'une production par lots et les plans d'échantillonnage continu dans le cas d'une production continue. Plusieurs normes sont utilisées dans la pratique pour la conception de ces deux types de plans d'échantillonnage, à savoir :

- Les tables d'échantillonnage de la série des standards MIL-STD-105, et les procédures des normes ANSI/ASQC Z1.4 et ISO 2859-1 sont les plus utilisées dans l'industrie pour la conception des plans d'échantillonnage simple, double et multiple avec un contrôle de la qualité par attributs. Ces tables sont indexées d'après le Niveau de Qualité Acceptable (NQA, ou AQL en anglais) qui représente le critère de base de conception de ces plans. Le NQA est le pourcentage de produits non-conformes qu'on peut tolérer dans un lot qui aura une forte probabilité d'acceptation lors du contrôle de la qualité par échantillonnage.
- Les tables de Dodge-Romig (1959) permettent de concevoir deux autres types de plans d'échantillonnage simple et double avec un contrôle par attributs: les plans AOQL et les plans LTPD. Le critère AOQL (*Average Outgoing Quality Limit*) représente la limite de la qualité moyenne après contrôle : c'est le pourcentage maximum d'items non-conformes qui se trouveront à long terme dans les lots après contrôle de la qualité. Le critère LTPD (*Lot Tolerance Percent Defective*) représente le niveau limite de qualité toléré : c'est le pourcentage d'items non-conformes dans un lot qui devrait avoir une très faible probabilité d'être accepté.
- Les tables de la série de standards MIL-STD-1235 sont utilisées pour la conception des plans d'échantillonnage continu de type CSP-1, CSP-2, CSP-F, CSP-V et CSP-T. Ces tables sont indexées d'après la limite de la qualité moyenne après contrôle (AOQL) et le niveau de qualité acceptable (AQL).
- Les tables des standards de MIL-STD-414, ANSI/ASQC Z1.9 et ISO 3951-1 sont utilisées pour concevoir les plans d'échantillonnage (des lots) avec mesures. Ces tables sont indexées d'après le niveau de qualité acceptable.

2.3.2.2 Conception économique des plans d'échantillonnages

Les normes standards susmentionnées négligent complètement l'impact économique dans le choix des paramètres du plan d'échantillonnage. De nombreuses recherches ont été menées depuis longtemps pour une conception plus économique des plans d'échantillonnage à proposer aux manufacturiers. Par exemple, Hald (1960) a proposé l'un des premiers modèles d'optimisation du plan d'échantillonnage simple par attributs qui minimise les coûts de qualité (coût d'échantillonnage et les coûts d'acceptation et de rejet des lots) en considérant que la proportion d'items non-conformes produite suit une distribution de probabilité connue. Pfanzagl (1963) a présenté une analyse de sensibilité du modèle de Hald (1960), et il a proposé une extension pour la conception économique du plan d'échantillonnage double. Plusieurs extensions de ces travaux ont été proposées dans la littérature pour intégrer différents aspects tels que la relation entre la qualité entrante, l'état du processus de production et la qualité après contrôle (Ercan et al., 1974), l'effet du coût d'échantillonnage sur le choix des paramètres du plan d'échantillonnage (Moskowitz et Berry, 1976; Moskowitz et al., 1979), l'optimisation multicritère telle que l'optimisation du coût de contrôle de la qualité et la qualité moyenne après contrôle (Ravindran et al., 1986) et l'effet des erreurs d'inspection de la qualité sur la conception économique des plans d'échantillonnage (Ferrell et Chhoker, 2002). Quand à la conception économique des plans d'échantillonnage continu, on trouve Cassady et al. (2000) qui ont développé un modèle qui permet de calculer le coût d'utilisation d'un plan d'échantillonnage donné de type CSP-1. Chen et Chou (2002, 2003) ont utilisé le modèle de Cassady et al. (2000) afin d'optimiser les paramètres de CSP-1 tout en considérant une contrainte sur la limite de la qualité moyenne après contrôle (AOQL). Haji et Haji (2004) ont proposé une conception économique de CSP-1 en utilisant le *théorème de renouvellement*. D'autres extensions de la conception économique de CSP-1 ont été aussi présentées par Lin et Yu (2009) et Eleftheriou et Farmakis (2011). Une revue plus détaillée de la conception économique des plans d'échantillonnage par lots et continu est aussi présentée dans les sections 4.1 et 6.1, respectivement.

2.3.3 Limites des méthodes de conception des plans d'échantillonnage

2.3.3.1 Limites des normes standards de conception des plans d'échantillonnages

Les normes de conception des plans d'échantillonnage, telles que les tables militaires et les tables recommandées par l'*American National Standards Institute* et l'Organisation Internationale de Normalisation, et les tables LTPD et AOQL de Dodge-Romig ne considèrent pas l'aspect économique du contrôle de la qualité. Nikolaidis et Nenes (2009) ont présenté une évaluation économique intéressante des tables du plan d'échantillonnage simple de la norme standard ISO 2859-1. Les auteurs se sont appuyés sur des exemples numériques pour montrer que ces normes sont loin d'être économiques et que le coût d'une conception d'un plan d'échantillonnage simple avec ces normes peut aller, en moyenne, jusqu'à 230% plus cher que le coût d'un plan d'échantillonnage conçu à partir d'une approche économique. Dans un contexte contemporain où la minimisation des coûts représente une priorité pour les entreprises manufacturières, l'utilisation des approches économiques de conception des plans d'échantillonnage au lieu des normes standards semble être inévitable.

En outre, nous avons constaté d'autres limites des tables standards de conception des plans d'échantillonnage, à savoir :

1. Une conception d'un plan d'échantillonnage simple ou double par attributs en utilisant les tables MIL-STD-105E, ANSI/ASQC Z1.4 et ISO 2859-1 exige la connaissance de la taille du lot de production et le niveau de qualité acceptable (AQL). Ces tables ne sont pas pratiques dans le cas où la taille du lot de production est dynamique ou dans le cas d'une politique d'avortement de la production des lots interrompus par des pannes (Groenevelt et al., 1992b). De plus, le critère AQL ne permet que de considérer le risque du fabricant (risque de ne pas accepter un lot de qualité acceptable) : le niveau limite de qualité toléré (LTPD) qui définit le risque des clients (risque d'accepter un lot contenant un tel niveau de LTPD) est complètement négligé dans les tables MIL-STD-105E, ANSI/ASQC Z1.4 et ISO 2859-1.

2. Une conception d'un plan d'échantillonnage simple ou double par attributs en utilisant les tables AOQL et LTPD de Dodge-Romig dépend essentiellement de l'information sur le pourcentage moyen d'items non-conformes produits. Cette information n'est pas toujours disponible surtout au début de chaque nouveau cycle de production (par exemple, après une

opération de maintenance) où la quantité des données sur la qualité des lots n'est pas suffisante pour faire une bonne estimation de la qualité moyenne des lots. Par exemple, Montgomery (2008) propose d'analyser la qualité des 25 premiers lots produits. Dans ce cas, on ne sait pas exactement comment utiliser les tables de Dodge-Romig pour contrôler la qualité de ces 25 lots, c'est-à-dire avant même la détermination de la qualité moyenne de ces lots. La situation est encore plus problématique dans le cas où la qualité des produits se détériore d'une façon aléatoire et progressive. Dans ce cas, l'estimation de la qualité moyenne devrait être mise à jour d'une façon continue.

3. L'un des apports pertinents des normes ANSI/ASQC Z1.4 et ISO 2859-1 par rapport aux standards militaires MIL-STD-105 réside dans le fait d'adapter la sévérité du contrôle avec l'état de la qualité des lots. Par exemple, dans le cas où le nombre de lots rejetés consécutivement dans un mode de contrôle renfoncé (sévère) atteint un certain seuil (5 ou 10 dépendamment de la norme utilisée), alors le contrôle de la qualité doit être arrêté pour une révision des conditions de production. Pourtant, les regèles de modification de la sévérité du contrôle de la qualité dans ces normes (passage du contrôle réduit au contrôle normal, du contrôle normal au contrôle renforcé, et vice-versa) sont choisies arbitrairement, sans aucune considération pratique telle que l'état de la qualité de production, l'impact économique, etc.

4. Contrairement aux conceptions du plan d'échantillonnage des lots tel que dans les normes ANSI/ASQC Z1.4 et ISO 2859-1, une conception d'un plan d'échantillonnage continu telle que dans la série des standards militaires MIL-STD-1235 ne donne aucune indication sur le point de déclenchement d'une révision/restauration des conditions de production quand le contrôle à 100% de tous les produits demeure longtemps: une telle situation survient lorsque la qualité ne s'améliore plus depuis le début du contrôle à 100%.

2.3.3.2 Limites des modèles de conception économique des plans d'échantillonnages

La quasi-totalité des modèles de conception économique ne considère que les coûts du contrôle de la qualité et néglige complètement l'impact d'une telle conception sur la production, l'état de stock, le délai de fabrication du produit fini, etc. En pratique, le contrôle de la qualité est étroitement relié avec les autres fonctions de la gestion des opérations telles que l'approvisionnement, la production, la maintenance, etc. Par exemple, Peters et al. (1988), Ben-Daya et al. (2006) et Ben-Daya et Noman (2008b) ont intégré la conception économique du plan

d'échantillonnage simple dans un contexte d'approvisionnement. Dans ces travaux, les auteurs ont déterminé simultanément la quantité économique de commande, le point de réapprovisionnement optimal et les paramètres optimaux du plan d'échantillonnage. Dans un contexte de production, Lee et Tagaras (1992) ont proposé une heuristique qui permet de déterminer simultanément la conception économique de plusieurs plans d'échantillonnage simple dans divers points d'un système de production complexe composé de plusieurs machines. Bouslah et al. (2013) ont étudié l'impact du choix des paramètres du plan d'échantillonnage simple sur la taille optimale du lot de production et le stock de sécurité optimal. Dans la littérature, il n'existe aucun modèle de conception économique des plans d'échantillonnage qui prend en considération l'impact d'une telle stratégie de contrôle de la qualité sur la production (taille du lot de production, stock de sécurité, etc.) et la maintenance (stratégie et fréquence de maintenance, etc.), et vice-versa, l'impact des politiques de production et de maintenance sur la conception de ces plans.

2.3.3.3 Intégration des plans d'échantillonnage avec le contrôle de la production et de la maintenance

L'intégration de la planification de la production et de la maintenance préventive avec le contrôle de qualité en utilisant les cartes de contrôle a été largement étudiée dans la littérature telle que dans Ben-Daya et Makhdoum (1998), Ben-Daya (1999), Ben-Daya et Rahim (2000), Yeung et al. (2007), Zhou et Zhu (2008), Chen et al. (2011), Pan et al. (2012), Liu et al. (2013), Zhang et al. (2014, 2015), etc. Cependant, il n'existe aucun modèle dans la littérature qui intègre simultanément la production, la maintenance préventive et le contrôle de la qualité avec les plans d'échantillonnage.

L'intégration des plans d'échantillonnage avec les politiques de contrôle de la production et de la maintenance présente un axe de recherche intéressant pour les raisons suivantes :

(i) Les plans d'échantillonnage sont largement utilisés dans l'industrie depuis longtemps pour réduire les coûts excessifs du contrôle à 100% (Montgomery, 2008).

(ii) Les plans d'échantillonnage possèdent des propriétés statistiques très spécifiques (Schilling et Neubauer, 2009). Ces propriétés influencent directement les performances globales des entreprises manufacturières tels que le niveau de la qualité perçue par la clientèle (qualité

moyenne après contrôle), le stock en-cours, la productivité, les coûts de qualité, etc. (Cao et Subramaniam, 2013).

(iii) Le choix des paramètres de conception de ces plans a un impact important sur les décisions optimales de la gestion manufacturière (Bouslah et al., 2013).

Dans un contexte d'intégration du contrôle des activités de la maintenance et de la qualité, plusieurs chercheurs, comme Hsu et Kuo (1995), Radhoui et al., (2009, 2010) et Pan et al., (2012), ont montré l'utilité des informations issues du contrôle de la qualité dans l'organisation des interventions de la maintenance préventive. Dans ces travaux, le contrôle de la qualité est effectué soit par un contrôle à 100%, soit par des cartes de contrôle. On peut donc conclure qu'il n'existe aucun modèle qui montre comment les informations issues des plans d'échantillonnage peuvent être utilisées pour l'organisation des activités de la maintenance préventive, alors que, à cause de leurs propriétés statistiques spécifiques, ces plans fournissent assez d'informations pertinentes sur l'état et la tendance de la qualité de production sans faire nécessairement le contrôle à 100% de tous les produits.

CHAPITRE 3 ORGANISATION GÉNÉRALE DE LA THÈSE

Ce chapitre présente les objectifs de recherche de cette thèse à la lumière de l'analyse critique de la littérature présentée dans le chapitre précédent. Ensuite, nous présentons les travaux de recherche réalisés dans le cadre de cette thèse. Ce chapitre présente aussi la démarche de recherche scientifique et les hypothèses générales de modélisation utilisées dans ces travaux.

3.1 Objectifs et hypothèses de recherche

Considérant les limites des modèles d'intégration et des méthodes de conception des plans d'échantillonnage dans la littérature, cette thèse vise principalement à développer des nouvelles politiques d'intégration des politiques de production, de maintenance et de contrôle de la qualité par échantillonnage pour les systèmes manufacturiers en dégradation. Cet objectif comporte cinq sous-objectifs, à savoir:

1. Développer une nouvelle approche de conception des plans d'échantillonnage dans un contexte d'intégration avec les politiques de production et de maintenance préventive.
2. Modéliser adéquatement la dynamique complexe de la dégradation de la qualité des produits et de la fiabilité de machines telle que dans la réalité des systèmes manufacturiers. Ceci implique la modélisation des relations de dépendance entre la dégradation de la qualité et de la fiabilité, le vieillissement des machines et le taux de production. Aussi, cet objectif comporte la modélisation des pannes corrélées telles que les pannes dépendantes de la qualité. Le but est d'assurer que les politiques d'intégration à développer peuvent être mises en pratique.
3. Étudier les interactions et les interdépendances entre les paramètres de contrôle de la production, de la qualité et de la maintenance, et analyser leurs impacts sur les performances des systèmes manufacturiers (essentiellement, le coût total des opérations, la qualité des produits livrés et la fiabilité des machines). Cet objectif comporte l'étude de l'impact des politiques de contrôle de la production, de la qualité et de la maintenance utilisées à un certain niveau du système de production sur les machines et les équipements de fabrication en aval.

4. Montrer la pertinence et l'utilité des informations issues du contrôle de la qualité avec les plans d'échantillonnage pour les décisions de maintenance préventive. Ceci implique également de montrer comment ces informations peuvent être incorporées dans les méthodes classiques de maintenance.
5. Quantifier les gains économiques qui découleraient de l'utilisation des plans d'échantillonnage pour les systèmes de production en dégradation par rapport au contrôle à 100% qui est largement utilisé dans la littérature.

Les objectifs susmentionnés reposent sur cinq principales hypothèses à valider dans le cadre de cette recherche, à savoir:

- **Hypothèse 1:** Il est possible d'utiliser les plans d'échantillonnage pour les systèmes de production avec une dégradation de la qualité, tout en assurant la satisfaction des exigences imposées sur la qualité après-contrôle.
- **Hypothèse 2:** Le niveau de la qualité finale après-contrôle est le résultat de la configuration de tous les paramètres de contrôle de la production, de la qualité et de la maintenance du système manufacturier (autrement dit, le niveau de la qualité perçue par les clients finaux ne dépend pas seulement des paramètres de contrôle de la qualité).
- **Hypothèse 3:** Il existe des seuils optimaux et uniques de certaines mesures issues du contrôle de la qualité avec les plans d'échantillonnage qui peuvent être considérés comme des seuils pour la maintenance préventive conditionnelle.
- **Hypothèse 4:** Il existe un niveau minimal de contrôle de la qualité à effectuer pour fournir la moindre quantité de retour d'informations pour la maintenance préventive conditionnelle.
- **Hypothèse 5:** L'amélioration de la qualité des produits semi-finis dans les lignes de production permet d'améliorer significativement la fiabilité des équipements de production en aval.

3.2 Organisation de la thèse

Les travaux de recherche réalisés dans le cadre de cette thèse sont présentés sous forme de quatre articles scientifiques. Ces quatre articles sont présentés dans les chapitres suivants, 4, 5, 6 et 7.

Dans le premier article « *Joint production and quality control of unreliable batch manufacturing systems with rectifying inspection* », nous avons développé un premier modèle d'intégration d'une politique de commande de la production avec un plan d'échantillonnage simple pour un système de production par lots. Le système de production est non-fiable et il produit une proportion aléatoire de produits non-conformes. La durée de la maintenance corrective est aléatoire suivant une distribution générale. Les durées d'inspection et de rectification des produits non-conformes sont non-négligeables. L'objectif de ce modèle est d'optimiser conjointement, la taille du lot de production, le stock de sécurité optimal et les paramètres optimaux du plan d'échantillonnage simple qui minimisent le coût total. Une approche de résolution basée sur une combinaison de modélisation mathématique, de simulation et d'optimisation avec la méthodologie de surface de réponse a été utilisée afin de solutionner ce problème stochastique et non-linéaire. Les résultats numériques obtenus montrent que les interactions entre les paramètres de contrôle de la production et de la qualité sont significatives, ce qui confirme l'importance de l'optimisation conjointe de ces paramètres. De plus, les expérimentations montrent que la conception économique du plan d'échantillonnage est sensible aux coûts de stockage, de la pénurie et du transport des lots, et à la fiabilité du système. Selon une analyse comparative récente de la littérature sur l'intégration de la qualité dans les modèles de la Quantité Économique de Production menée (Karimi-Nasab et Sabri-Laghaie, 2014), notre premier article paraît être l'unique dans la littérature qui intègre simultanément la conception du plan d'échantillonnage, le problème de la Quantité Économique de Production et la commande optimale de la production.

Dans le deuxième article « *Integrated production, sampling quality control and maintenance of deteriorating production systems with AOQL constraint* », nous avons considéré que la qualité des produits et la fiabilité du système se dégradent d'une façon dynamique en fonction des opérations de production. Nous avons intégré aussi, par rapport au modèle du premier article, une stratégie de maintenance préventive qui consiste à effectuer une maintenance 'imparfaite' durant les activités de mise-en-course de la production, et une maintenance 'parfaite' dès que le pourcentage des produits défectueux dans un lot rejeté, suite au contrôle de la qualité, dépasse un certain seuil prédéterminé. En se basant sur des arguments scientifiques, nous avons montré la pertinence de cette stratégie de maintenance bien que le retour d'information sur le pourcentage des produits défectueux n'est pas toujours disponible, puisque sa disponibilité dépend de l'acceptation ou de rejet des lots produits. L'objectif de ce modèle est d'optimiser conjointement

la taille du lot de production, le stock de sécurité, les paramètres du plan d'échantillonnage simple et le seuil de la maintenance préventive conditionnelle. La solution optimale doit satisfaire une contrainte sur la qualité après-contrôle imposée par la clientèle. Une analyse comparative des performances de notre modèle par rapport aux modèles intégrés similaires basés sur le contrôle à 100% tel que dans la littérature (par exemple, Radhoui et al., 2009, 2010) a montré qu'il est possible de réduire significativement le coût total en utilisant les plans d'échantillonnage et que le gain économique peut aller dans certaines situations jusqu'à plus de 20%.

Dans le troisième article « *Joint economic design of production, continuous sampling inspection and preventive maintenance of a deteriorating production system* », nous avons étudié l'intégration simultanée du contrôle de la production, de la qualité et de la maintenance des systèmes de production continue. Ce sont les systèmes qui ne nécessitent pas, généralement, des opérations de mise-en-course, contrairement aux systèmes de production par lots. Trois modèles d'intégration ont été modélisés et comparés: le premier consiste à intégrer le contrôle de la production et de la maintenance préventive périodique avec un contrôle à 100% de la qualité, le deuxième modèle utilise plutôt un plan d'échantillonnage continu de type-1 (CSP-1) au lieu du contrôle à 100%, et le troisième modèle propose une version modifiée de CSP-1 qui permet de coupler la procédure du contrôle de la qualité avec les décisions de la maintenance préventive. Le premier objectif de cet article est de montrer que la conception conjointe de CSP-1 et de la maintenance préventive permet d'étendre l'applicabilité de ces plans d'échantillonnage aux processus de production dont la qualité est en dégradation, puisque leur applicabilité est limitée actuellement aux processus de production 'sous-contrôle' (Schilling et Neubauer, 2009). Dans le même contexte, le deuxième objectif de l'article consiste à quantifier les gains économiques qui découleraient de l'utilisation des plans d'échantillonnage continu au lieu du contrôle à 100%. Le troisième objectif de cette recherche est de montrer comment le couplage de CSP-1 et de la maintenance préventive, tel que dans le troisième modèle de cet article, permet d'améliorer les performances du système de production et de réaliser des gains économiques additionnels par rapport au CSP-1 classique.

Enfin, dans le quatrième article « *Joint production, quality and maintenance control of a two-machine line subject to operation-dependent and quality-dependent failures*», nous avons étudié une ligne de production composée de deux machines dont les dégradations de la qualité et de la fiabilité sont dépendantes des opérations. La deuxième machine est sujette aussi aux pannes

dépendantes de la qualité. Le problème de contrôle de la qualité ici consiste à déterminer l'emplacement optimal des stations d'inspection et le niveau de contrôle de la qualité à chaque station. L'objectif de l'article est donc de déterminer conjointement les paramètres de contrôle de la production, de la qualité et de la maintenance qui minimisent le coût total des opérations, tout en respectant la contrainte imposée sur la qualité après-contrôle. En outre, nous avons analysé à travers plusieurs exemples numériques l'effet de la corrélation entre la dégradation de la qualité des produits et la dégradation de la fiabilité des machines sur la fiabilité globale de la ligne de production et sur les paramètres optimaux de contrôle de la production, de la qualité et de la maintenance. Un résultat intéressant de cette recherche est de montrer que les activités de maintenance et de contrôle de la qualité à un certain niveau de la ligne de production pourraient influencer les performances des machines en aval.

3.3 Démarche de recherche

La démarche de recherche adoptée dans cette thèse afin de modéliser et résoudre les problèmes de conception et d'optimisation conjointe des modèles intégrés proposés dans les quatre articles, se résume par la méthodologie suivante (Figure 3.1) :

- ***Étape* 1 -** *Définition de l'objectif et des hypothèses du problème sous étude* : Cette étape consiste à comprendre la problématique, l'objectif de l'étude et les hypothèses de modélisation considérées.
- ***Étape* 2 -** *Formulation analytique du problème sous étude* : Cette étape consiste à identifier les variables de décision et à formuler la fonction-objectif et les contraintes du problème.
- ***Étape* 3 -** *Examiner si le problème d'optimisation peut être résolu analytiquement ou non* : *Si* la formulation analytique aboutit à déterminer une expression analytique explicite de la fonction-objectif et des contraintes, et que le problème peut être résolu analytiquement (par exemple, le gradient de la fonction-objectif est analytiquement calculable), *alors* résoudre le problème d'optimisation en utilisant l'approche analytique convenable. *Sinon*, passer à l'étape 4.
- ***Étape* 4 -** *Vérifier*, *Si* la fonction-objectif est analytiquement calculable, *alors* le problème d'optimisation peut être résolu par une approche numérique, telle que la discrétisation de l'espace de variation des variables de décision et les méthodes d'estimation numérique du

gradient (Bazaraa et al., 2006), ou en utilisant les méta-heuristiques telles que les algorithmes génétiques, la Recherche Tabu, le Recuit Simulé, etc. (Doerner et al., 2007). *Sinon*, passer à l'étape 5.

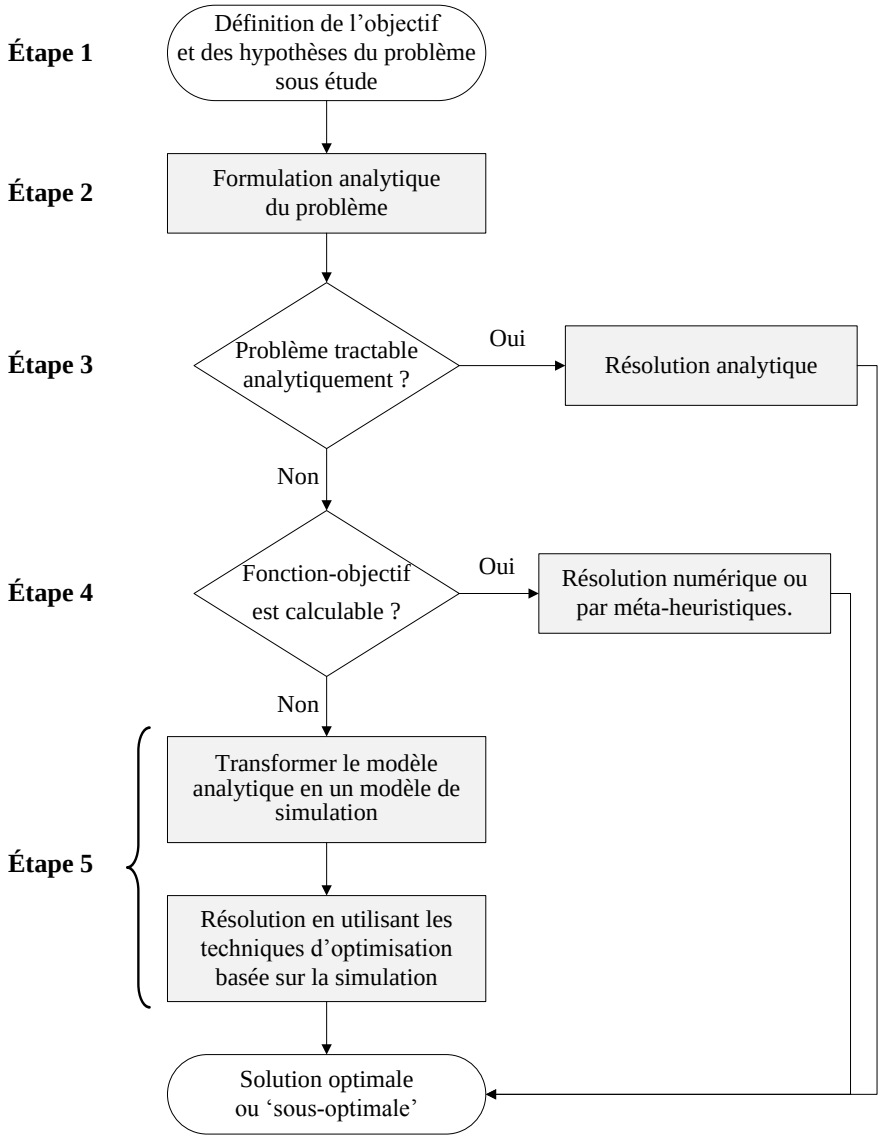


Figure 3-1 : Approche générale de résolution

- ***Étape* 5 -** *Utiliser une approche d'optimisation basée sur la simulation*: Cette étape comporte deux sous-étapes : *La première* consiste à développer et à valider un modèle de simulation avec le logiciel ARENA, à partir de la modélisation analytique du problème. La transformation du modèle analytique en un modèle de simulation se fait de la façon suivante: les équations et les événements discrets se modélisent à l'aide de la simulation à

événements discrets avec le langage SIMAN alors que les équations différentielles et les systèmes continues se modélisent à l'aide des routines en C++ (Pegden et al., 1995). *La deuxième sous-étape* consiste à utiliser des techniques d'optimisation basées sur la simulation, telles que la Méthodologie de Surface de Réponse, les méta-heuristiques et les méthodes de recherche basées sur le gradient afin de déterminer la solution optimale/sous-optimale (Negahban et Smith, 2014; Gosavi, 2014, 2015; Fu, 2015).

3.4 Hypothèses générales considérées dans la recherche

Certaines hypothèses générales sont considérées, sans perdre de généralité, dans les quatre articles scientifiques, à savoir :

1. Le système manufacturier est mono-produit.
2. Le taux de la demande est constant.
3. Le taux de production est flexible. Il peut être varié à tout moment. C'est le cas de la plupart des systèmes de production modernes (Giri et al., 2005).
4. La matière première est toujours disponible pour la production.
5. La matière première est toujours de bonne qualité.
6. La pénurie est permise.
7. Les fonctions de dégradation de la qualité des produits et de la fiabilité des équipements de production sont supposées connues.
8. Les temps de maintenance corrective et préventive sont aléatoires et suivent des distributions générales connues a priori.
9. Les temps de mise-en-course de la production et de contrôle de la qualité sont constants.
10. Les coûts unitaires de stockage, de pénurie, de non-qualité, de mise-en-course de la production et de maintenance sont connus. Les fonctions-coûts sont supposées linéaires.

Dans la pratique, les fonctions de dégradation de la qualité et de la fiabilité et les distributions des temps de maintenance peuvent être déterminées à partir des données réelles en utilisant des techniques mathématiques, numériques et statistiques telles que dans Meeker et Escobar (1998) et Lai and Xie (2006).

CHAPITRE 4 ARTICLE 1: JOINT PRODUCTION AND QUALITY CONTROL OF UNRELIABLE BATCH MANUFACTURING SYSTEMS WITH RECTIFIYING INSPECTION

Article publié dans

International Journal of Production Research

Vol. 52, No. 14, 2014, p. 4103-4117

DOI: 10.1080/00207543.2012.746481

Rédigé par:

Bassem BOUSLAH
Department of Mathematics and Industrial Engineering,
École Polytechnique de Montréal
{*bassem.bouslah@polymtl.ca*}

Ali GHARBI
Automated Production Engineering Department,
École de Technologie Supérieure
{*ali.gharbi@etsmtl.ca*}

Robert PELLERIN
Department of Mathematics and Industrial Engineering,
École Polytechnique de Montréal
{*robert.pellerin@polymtl.ca*}

Abstract

Production control policy and economic sampling plan design problems have been studied separately in previous research. This paper considers a joint production control policy and economic single sampling plan design for an unreliable batch manufacturing system. The production is controlled by a modified hedging point policy which consists in building and maintaining a safety stock of finished product to avoid shortages during corrective maintenance. The main objective of this paper is to determine simultaneously the economic production quantity, the optimal safety stock level and the economic sampling plan design which minimize the expected overall cost. A stochastic mathematical model is developed and solved using a simulation optimization approach based on the response surface methodology. Simulation is used to imitate the complex dynamic and stochastic behaviour of processes as in the real-life industrial systems. The obtained results show clearly strong interactions between production quantity, inventory state and sampling plan design which confirm the necessity of jointly considering production and quality control parameters in an integrated model. Moreover, it is shown a significant impact of production system reliability on the economic sampling plan design and therefore on the quality of finished product delivered to consumers. Numerical example and sensitivity analyses are presented for illustrative purposes.

Keywords - Unreliable manufacturing system, sampling plan, economic production quantity, simulation, response surface methodology.

4.1 Introduction

In the literature, batch manufacturing systems are controlled using the economic production quantity (EPQ) model. The classical EPQ model has been widely extended by many researchers to control various real-life manufacturing situations such as production equipment failures and quality imperfection. The impact of stochastic machine breakdowns and corrective maintenance on the economic batch size and the optimal safety stock decisions has been investigated in the pioneered works of Groenevelt et *al*. (1992a, 1992b) which provided a framework for many extensions of EPQ model to unreliable production systems as in Kim et *al*. (1997) and Chung (2003). On the other hand, Porteus (1986) and Rosenblatt and Lee (1986) were the first who studied the effect of quality imperfection on the EPQ model. In both studies, the researchers

assumed that the deterioration of production system is a random process characterized by two states: ‘in-control’ state when all items produced are conforming of quality and ‘out-of-control’ state when some percentage of items produced are defectives. Lee and Rosenblatt (1987) incorporated maintenance by inspection feature into EPQ model to monitor the production process deterioration. They focused on simultaneously determining of the optimal batch size and the optimal inspection schedule. Many subsequent extensions have been undertaken based on Rosenblatt and Lee’s models such as in Kim and Hong (1999) and Chung and Hou (2003). In recent years, the joint production system breakdowns and process quality deterioration problems have been investigated in EPQ model by Chiu et *al*. (2007), Liao et *al*. (2009), Chakraborty et *al*. (2009) and Sana and Chaudhuri (2010).

In most existing EPQ models, the researchers did not specify how the product-quality control is performed. Most of them used inspection schedules to mainly control the production process deterioration and not to consistently control the quality of product. In addition, they did not indicate how the nonconforming items produced between two successive inspections can be discovered and treated. Also, many authors assumed that the inspection is made instantly during batch processing and the inspection delay is negligible. However, inspection is in itself an important part of quality assurance that should be fairly represented in the EPQ model. In real-life manufacturing organisations, it is recommended to use statistical quality control techniques, such as control charts or acceptance sampling plans, especially when the cost of 100% inspection is higher than the cost of delivering a certain proportion of nonconforming items (Besterfield, 2009). Only few researchers have integrated statistical quality control techniques into EPQ models such as Rahim and Ben-Daya (1998) who presented an integrated model for a continuous production process for joint economic determination of production quantity, inspection schedule and $\bar{x}$-control chart design.

To the author’s knowledge, quality control using lot-by-lot single acceptance sampling plan by attributes has not been investigated in the production context, although extensive research in its different aspects and properties has been carried out (Wetherill and Chiu, 1975). In fact, one can find several researches which have attempted to design economically the single sampling plan but without considering production and system reliability factors. Among these, Ercan et *al*. (1974) developed a mathematical model to derive minimum cost single acceptance sampling plans by attribute recognizing the interrelations among average incoming quality limit, process quality

level and average outgoing quality limit. Moskowitz and Berry (1976) presented a Bayesian algorithm for determining optimal single acceptance plan parameter values when discrete distributions are used to measure product quality, and when the sampling cost is either a linear or strictly convex function. Moreover, Moskowitz et *al*. (1979) developed a two-stage optimization algorithm for determining the optimal economic single sample acceptance plan when the prior distribution of lot quality and the sampling distribution are discrete. The proposed algorithm gives a minimal improvement in solution quality compared to the Bayesian algorithm, but the minimum cost plan is obtained much faster. Ravindran et *al*. (1986) presented two nonlinear integer goal programming models (with a constant/prior probability distribution of the lot fraction defective) for the determination of optimal acceptance sampling plan which explicitly considered the two conflicting criteria of average lot inspection cost and average outgoing quality. Much later, Ferrell and Chhoker (2002) developed mathematical models that can be used to design both 100% inspection and single sampling plans, with and without inspector error when a Taguchi-like loss function is used to describe the cost associated with any deviation between the actual value of a product's quality characteristic and its target value. The above models, which are mainly designed to control received commodity from suppliers, are commonly developed to minimize an expected total cost including inspection, batches acceptance and rejection costs. Finally, economic single acceptance sampling plan have been integrated with economic ordering quantity (EOQ) model by Peters et *al*. (1988), Ben-Daya et *al*. (2006) and Ben-Daya and Noman (2008).

In this paper, we propose a joint economic production and quality control design model for unreliable manufacturing systems, which has the following three features: the production is controlled by a modified hedging point policy (HPP), the quality control is performed by a single acceptance sampling by attributes, and the batch sizing, the hedging level and the sample size are decision variables. Our choice to use the HPP for the production-inventory control is motivated by its flexibility, feedback and optimality properties (Bielecki and Kumar, 1988; Bouslah et *al*., 2012). The single sampling plan by attributes is the most commonly applied sampling procedure in industry because of its simplicity compared to double, multiple and sequential sampling (Wetherill and Chiu, 1975). The problem is formulated as a stochastic mathematical model considering all production and quality control tasks with non-negligible processing delays. Given that the proposed optimization problem is complex and no analytical solution is available, we developed a simulation model to imitate the real dynamic and stochastic behaviour of the

manufacturing system. Then, we used simulation with optimization techniques (design of experiments and response surface methodology) to jointly optimize production and quality decision variables which minimize the total incurred cost including quality control costs, holding and backlog costs and transportation cost of batches produced.

The remainder of this paper is organized as follows. Section 4.2 presents the notation. Section 4.3 describes the problem under study. The optimization problem formulation is presented in Section 4.4. Section 4.5 explains the resolution approach. An illustrative numerical example of the resolution approach with a thorough sensitivity analysis is given in Section 4.6. Finally, Section 7 concludes this paper.

4.2 Notation

The following are the notations used in this paper:

$q(t)$	Batch-in-process level at time t (units)
$x(\mathrm{t})$	Inventory level at time t
$y(\mathrm{t})$	Inventory position at time t
$u(.)$	Production rate (units/time)
u^i	Production rate of the ith batch (units/time)
u_{max}	Maximum production rate (units/time)
d	Constant demand rate (units/time)
$p(.)$	Proportion of nonconforming items (random variable)
p^i	Proportion of nonconforming items in the ith batch (random variable)
n	Sample size (decision variable)
c	Acceptance number on the second sample (decision variable)
Q	Production batch size (units) (decision variable)
Z	Hedging level of inventory position (decision variable)
θ_i	Production start time of the ith batch
δ_i	Production end time of the ith batch
N_∞	Long-term cumulative total number of batches produced
TTF	Time To Failures (random variable)
TTR	Time To Repair (random variable)

τ_{insp} Inspection delay per unit (time/unit)

τ_{rect} Rectification delay per unit (time/unit)

C^{+} Unit holding cost ($/unit)

C^{-} Unit backlog cost ($/unit)

C_{tr} Cost of batch transportation ($/load)

C_{insp} Unit inspection cost ($/unit)

C_{rect} Unit rectification cost ($/unit)

C_{rep} Unit replacement cost ($/unit)

4.3 Problem description

4.3.1 Production system

Consider an imperfect production system subject to stochastic breakdowns and repairs and supplying a downstream stock $x(.)$. The production system produces one single item in batches of size Q in order to meet a constant and continuous demand d. The batch-in-process is stored in a downstream area of the system (as illustrated in Figure 4.1) until the production of the actual batch is completed. The system availability state can be described at each time t by a stochastic process $\{\alpha(t)\}$ taking values in $\{0,1\}$. $\alpha(t) = 1$, if the production system is available at time t, and, $\alpha(t) = 0$, if not. When a failure occurs during the production cycle, the production of interrupted batches is always resumed after repair. Let $q(t)$ be a piecewise continuous variable which describes the batch processing progress at time t. Let $0 \le q(t) \le Q$ be the capacity constraint of the batch-in-process level.

Because the production process is imperfect, a certain random proportion $p(.)$ of nonconforming items is always produced. We assume that the proportion of nonconforming items $p(.)$ varies from batch to batch. As in Salameh and Jaber (2000), we consider that the number of nonconforming items in each ith batch is equal to $p^{i}Q$ proportionally to the batch size Q, where p^{i} is the proportion of nonconforming items in the ith batch following a prior known probability distribution of $p(.)$. Once produced, a quality control is performed on the batch to decide whether it is acceptable or not.

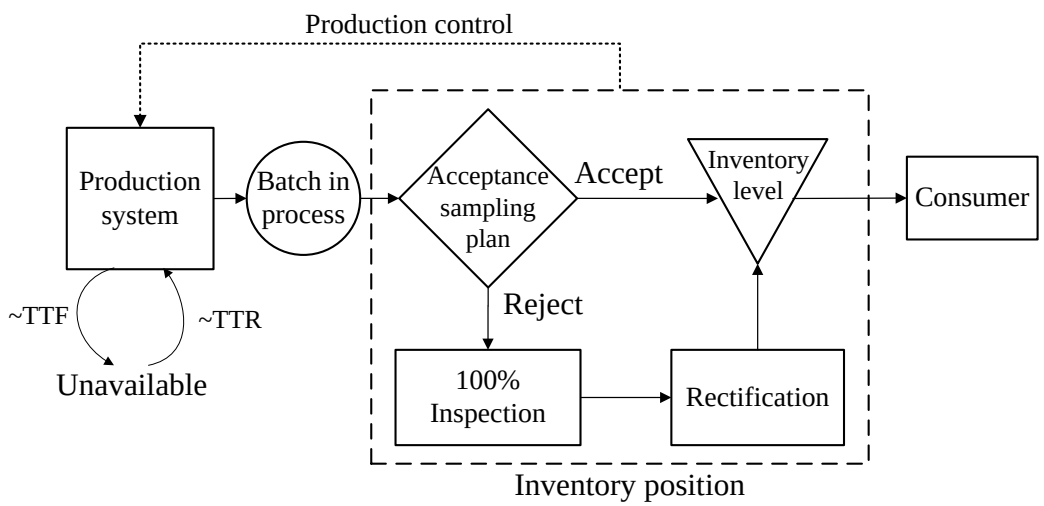


Figure 4-1: Unreliable and imperfect production system with quality control.

4.3.2 Quality Control Policy

The quality control policy consists of a lot-by-lot single acceptance sampling plan with parameters *n* and *c*. A sample of size *n* is drawn randomly from the batch, and inspected item-by-item by attributes. The sample inspection duration is equal to $n\,\tau_{insp}$. If the number of nonconforming items in the sample does not exceed the acceptance number c, the batch is accepted and the k nonconforming items are replaced, from a stock of known good items, before the transport of the entire batch to the final stock area. Otherwise, the batch is rejected. We assume in our study that all inspection operations are performed with free error. Rejected batches are 100% inspected and all nonconforming items are sorted by inspection personnel. The duration of this operation is equal to $(Q-n)\,\tau_{insp}$. Then, the nonconforming items are rectified. The delay of rectification of the nonconforming items discovered in the *i*th batch is equal to $p^i Q\,\tau_{rect}$. After that, the entire batch is transported to the serviceable stock. Let ξ_i be the arrival time of the *i*th batch to the on-hand serviceable inventory *x*(.). Then, $\xi_i = \delta_i + n\,\tau_{insp}$, if the *i*th batch is accepted, and $\xi_i = \delta_i + Q\,\tau_{insp} + p^i Q\,\tau_{rect}$, if not. We assume that always we have $\xi_i \le \delta_{i+1}\left(i = 1..N\right)$ which means that the quality control operations of the *i*th batch is finished before the end of the production cycle of the next (*i*+*1*)th batch.

The probability P_a of accepting the *i*th batch containing k nonconforming items can be calculated using the binomial probability distribution (Besterfield, 2009), as follows:

$$P_a\left(p^i \mid n,c\right)=\sum_{k=0}^{c}\frac{n!}{k!(n-k)!}\left(p^i\right)^k\left(1-p^i\right)^{n-k} \tag{1}$$

As the accepted batches do not receive 100% inspection, some nonconforming items will remain in the outgoing batches and therefore transmitted to the consumer. The long-term average proportion of nonconforming items existing in the final stock, also named the Average Outgoing Quality *AOQ*, can be calculated using the following formulae (Schilling and Neubauer, 2009):

$$AOQ=\frac{E[p]\cdot P_a\left(E[p]\right)\cdot\left(Q-n\right)}{Q} \tag{2}$$

We assume that all nonconforming items transmitted to the consumer are returned and replaced by good ones. While the demand/backlog is filled, the replaced quantity at each time *t* can be considered proportional to the demand rate *d*. Consequently, the instantaneous real demand rate becomes equal to $d/\left(1-\beta(t)AOQ\right)$, where, $\beta(t)$ measures the instantaneous service level of the demand/backlog. $\beta(t)=1$, if $x(t)>0$ or $\alpha(t)=1$, and $\beta(t)=0$, otherwise.

4.3.3 Production Control Policy

In the literature, it was shown that the optimal production control policy for continuous-flow unreliable manufacturing systems is of a hedging point policy (HPP) type (Bielecki and Kumar, 1988). For unreliable batch manufacturing systems with delays which cannot be considered as continuous-flow systems, Bouslah et *al*. (2012) showed that the optimal feedback control policy can be closely approximated by a base-stock policy expressed by a modified HPP. When the batches produced need to be transported for a non-negligible delay to the serviceable stock, the authors assumed that the feedback inventory control is based on the concept of the inventory position which includes the on-hand inventory in the final stock and the total pending quantities in transportation as in Mourani et *al*. (2008) and Li et *al*. (2009). In our study, we define the inventory position $y(t)$ at each time *t* as the sum of the stock (inventory/backlog) level $x(t)$ and the total amount of batches under sampling, 100% inspection and rectification. Considering the effect of the outgoing quality on the real demand rate, the modified HPP is formulated as follows:

$$u^i\left(t \in \underset{i=1,2,..,\infty}{]\theta_i,\theta_{i+1}]},\alpha\right)=\begin{cases}\alpha(t)\,u_{\max} & \text{if}\left(y(\theta_i^+)<Z\right)\\ \dfrac{\alpha(t)\,d}{1-AOQ} & \text{if}\left(y(\theta_i^+)=Z\right)\\ 0 & \text{if}\left(y(\delta_i^+)>Z\right)\end{cases} \tag{3}$$

In fact, the production rate $u^i(.)$ of the ith batch can take three possible levels depending on the inventory position state and the instantaneous system availability, as follows:

1. If the inventory position at the beginning of the the ith production cycle ($t=\theta_i$) is strictly below the threshold level Z, and while the production system is available ($\alpha(t)=1$), the corresponding ith batch is manufactured at the maximum production rate u_{max}. Such a case happens when the production is restarting just after a corrective maintenance.

2. If the inventory position at the beginning of the ith production cycle is exactly equal to the threshold level Z, and while the production system is available ($\alpha(t)=1$), the production rate of the ith batch is set to the demand rate $d/(1-AOQ)$ in order to maintain the on-hand inventory position.

3. If the inventory position at a time $t \in]\theta_i,\theta_{i+1}]$ becomes strictly greater than the threshold level Z the manufacturing is stopped ($u(.)=0$) until the inventory position takes back the threshold level Z by the effect of the demand. Also, when the production system becomes unavailable ($\alpha(t)=0$), the production is stopped immediately.

4.4 Optimization problem formulation

The dynamics of production $q(.)$, inventory position $y(.)$ and final inventory level $x(.)$ can be described respectively by the following difference and differential equations:

$$\begin{aligned}
&\frac{dq(t)}{dt}=u(t,\alpha),\ q(0)=q,\ \forall t\in]\theta_i,\delta_i[,\\
&q\left(\delta_i^+\right)=q\left(\delta_i^-\right)-Q,\\
&\frac{dy(t)}{dt}=\frac{-d}{1-\beta(t)AOQ},\ y(0)=y,\forall t\in]\delta_i,\delta_{i+1}[,\\
&y\left(\delta_i^+\right)=y\left(\delta_i^-\right)+Q,\\
&\frac{dx(t)}{dt}=\frac{-d}{1-\beta(t)AOQ},\ x(0)=x,\forall t\in]\xi_i,\xi_{i+1}[,\\
&x\left(\xi_i^+\right)=x\left(\xi_i^-\right)+Q,\\
&\forall i=1,..,N
\end{aligned} \tag{4}$$

where, q, x and y denote respectively the WIP level, the inventory position and the finished product inventory level at initial time. δ_i^- and δ_i^+ denote the left and right boundaries of the ith production cycle end time δ_i, and ξ_i^- and ξ_i^+ denote the left and right boundaries of the arrival time ξi of the ith batch to the final stock $x(.)$.

Figure 4.2 depicts graphically the dynamic of production (batch-in-process level $q(t)$), and the evolution of the serviceable inventory level $x(t)$ as function of instantaneous system availability $\alpha(t)$, production cycle length, and acceptance or not of batches produced.

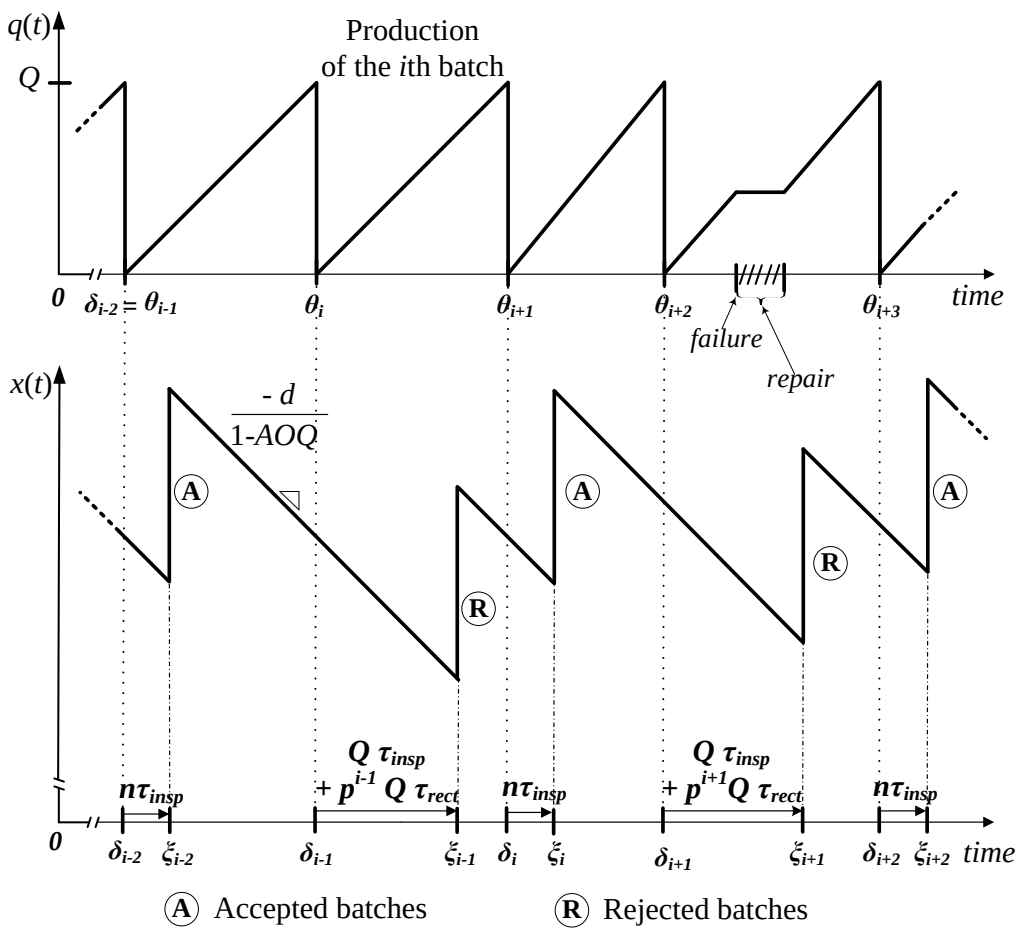


Figure 4-2: Production and inventory level dynamics.

Our objective is to determine the optimal batch size Q, the optimal hedging level Z and the economic sampling plan design (n, c) which minimize the long-term expected total cost ETC(.) per unit time including; the average total holding cost which includes the storage of the work-in-process (batch-in-process, batches under sampling, 100% inspection and rectification) and the final inventory stock $x(.)$, the average backlog cost, the average cost of sampling, the average

costs of 100% inspection and rectification of the rejected batches, the average cost of transportation, and the average cost of replacement of nonconforming items sold to the consumer. Note that the consumer satisfaction is considered in the expected total cost function by penalizing the backlog (product availability in the producer serviceable inventory) and the replacement of returned nonconforming items (quality of product).

Any admissible solution (Q, Z, n, c) must satisfy the following constraints:

$$\begin{aligned} &0 < Q \le \min\left\{Q_{\max}^{bip}, Q_{\max}^{insp}\right\} \\ &0 < Z \le Z_{\max} \\ &0 < c \le n \le n_{\max} \\ &Q, Z, n, c : \text{integers} \end{aligned} \tag{5}$$

where, $Q_{\max}^{bip}$ is the maximum batch-in-process storage capacity, $Q_{\max}^{insp}$ is the maximum inspection area capacity, Z_{max} is the maximum storage capacity of the inventory position and n_{max} is the maximum sample size. The constraint of the maximum sample size was used by Ravindran et *al*. (1986) and in practice it represents the capacity constraint of resources allowed to sampling.

Therefore, the optimization model associated to the problem under study can be described as follows:

$$\begin{cases} \text{Minimize } ETC(Q,Z,n,c) = C^{+}\left(E[q]+E[y^{+}]\right)+C^{-}E[x^{-}] & \text{(inventory and backlog costs)} \\ \qquad\qquad + C_{insp}\, n\, E[N_{\infty}] & \text{(sampling cost)} \\ \qquad\qquad + \left(1-P_a\left(E[p]\right)\right)C_{insp}\left(Q-n\right)E[N_{\infty}] & \text{(100\% inspection cost)} \\ \qquad\qquad + \left(1-P_a\left(E[p]\right)\right)C_{rect}\, E[p]\, Q\, E[N_{\infty}] & \text{(rectification cost)} \\ \qquad\qquad + P_a\left(E[p]\right)C_{rep}\, E[p]\left(Q-n\right)E[N_{\infty}] & \text{(replacement cost)} \\ \qquad\qquad + C_{tr}\, E[N_{\infty}] & \text{(transportation cost)} \\ \text{Subject to} \quad \text{Constraints (1)-(2)-(3)-(4)-(5)} \end{cases}$$

where, $E[q] = \lim_{T\to+\infty} \frac{1}{T}\int_0^T q(t)\,dt$, $E[y^{+}] = \lim_{T\to+\infty} \frac{1}{T}\int_0^T \max(0,\ y(t))\,dt$, $E[x^{-}] = \lim_{T\to+\infty} \frac{1}{T}\int_0^T \max(0, -x(t))\,dt$, $E[N_{\infty}]$ is the long-term expected number of batches produced per unit time, and $E[p]$ is the expected proportion of nonconforming items.

The decision variables (Q, Z, n, c) are integer numbers. Moreover, the expected total cost function $ETC(.)$ is nonlinear due to the $E[q]$, $E[y^+]$, $E[x^-]$ and $P_a(.)$ terms. Also, the constraints (3) and (4) are nonlinear and stochastic. Hence, this model is a stochastic, nonlinear and integer programming problem which is difficult and complex. However, the expected total cost $ETC(.)$ is convex in Q and Z. In fact, the sum of the inventory, backlog and transportation costs is a convex function in Q and Z as shown in Bouslah et *al*. (2012), while 100% inspection, rectification and replacement costs are linear with respect to Q. In addition, when the sampling cost is assumed to be linear or strictly convex function in the sample size n, the existence of a global optimum sampling plan (n^*, c^*) which minimizes the sum of all quality related costs was proved by Moskowitz and Berry (1976) and Moskowitz et *al*. (1979). These objective function $ETC(.)$ properties are exploited in developing the resolution approach procedure.

4.5 Resolution approach

4.5.1 Resolution approach procedure

In this section, we propose a resolution approach which combines an enumeration procedure with respect to the acceptance number c and a simulation based-optimization approach to optimize the expected total cost $ETC_c(Q,Z,n)$ for each given acceptance number. The enumeration procedure approach has been used by Peters et *al*. (1988) and Ben-Daya and Noman (2008) to determine the optimal single sampling plan design for supplier quality control. However, the simulation based-optimization approach which combines simulation, design of experiments, statistical analysis and response surface methodology has been widely employed in literature to design manufacturing control policies as in Safizadeh and Thornton (1984) and Gharbi and Kenne (2000). To implement the resolution approach we developed and validated a simulation model representing the real dynamic of the system as described in Section 4.4. The simulation model is used to calculate the expected total cost for given (Q, Z, n, c). The proposed procedure can be summarized by the following steps:

Step 0. Set $c = 0$.

Step 1. For a fixed acceptance number c, determine $\psi_c(Q,Z,n)$ a quadratic approximation function of the expected total cost $ETC_c(Q,Z,n)$ using a combination of design of experiments,

regression analysis and response surface methodology. Optimize $\psi_c(Q,Z,n)$ under constraints (5). Find Q_c^*, Z_c^* and n_c^* and calculate $\psi_c\left(Q_c^*,Z_c^*,n_c^*\right)$. If $c=0$, set $c=1$.

Step 2. If $\psi_c\left(Q_c^*,Z_c^*,n_c^*\right) \le \psi_{c-1}\left(Q_{c-1}^*,Z_{c-1}^*,n_{c-1}^*\right)$ and $n_c^* \le n_{\max}$, set $c=c+1$. Go to step 1.

Step 3. If $n_c^* > n_{\max}$, the optimal control batch size, the optimal hedging level, the optimal sample size and acceptance number are respectively $Q_{c-1}^*, Z_{c-1}^*,\ n_{c-1}^*$ and $c-1$. Otherwise, find the optimal solution Q_c^*, Z_c^*, n_c^* and c^* such that

$$\psi_{c-1}\left(Q_{c-1}^*,Z_{c-1}^*,n_{c-1}^*\right) \ge \psi_c\left(Q_c^*,Z_c^*,n_c^*\right) \le \psi_{c+1}\left(Q_{c+1}^*,Z_{c+1}^*,n_{c+1}^*\right).$$

In step 1, we use, for given acceptance number *c*, an experimental design plan to define how the control factors (*Q*, *Z*, *n*) should be varied in order to determine the effects of the design factors and their interactions (i.e. analysis of variance ANOVA) on the incurred total cost. Then, the effects (design factors and their interactions) are considered as input to a regression analysis which is used in conjunction with the response surface methodology, to fit the relationship between the cost and the input factors (Montgomery, 2008). Given the convexity of the $ETC_c(Q,Z,n)$, as mentioned in Section 4.4, it can be approximated by a second-order function precisely when the experimental region of (*Q*, *Z*, *n*) is chosen correspondingly to the region of the global optimum. We denote by $\psi_c(.)$ the continuous function of *Q*, *Z* and *n* for a fixed acceptance number *c*, fitting a second-order regression model and relating the response variable $ETC_c(.)$ to the design factors. This function is called the response surface and takes the following equation:

$$\psi_c(Q,Z,n) = \beta_0 + \beta_1 Q + \beta_2 Z + \beta_3 n + \beta_{12} QZ + \beta_{13} Qn + \beta_{23} Zn + \beta_{11} Q^2 + \beta_{22} Z^2 + \beta_{33} n^2 + \varepsilon \qquad (7)$$

where, β_0, β_i (i = 1, 3), β_{12}, β_{13}, β_{23}, β_{ii} (i = 1, 3) are unknown parameters to be estimated from the collected simulation data, and ε is a random error.

4.5.2 Simulation model

A combined discrete-continuous model was developed using the SIMAN simulation language with C++ subroutines (Pegden et *al*., 1995), and then executed through the ARENA simulation software. The advantage of using a combined discrete-continuous model is to reduce the

execution time (Lavoie et *al*., 2007), and to model accurately the real production and inventory dynamics of the manufacturing system.

The simulation model can be described following the sequence of numbers appearing in Figure 4.3, as follows:

⓪ INITIALIZATION: setting the values of the parameters (u_{max}, d, c, τ_{insp}, τ_{rect}), the simulation run-time T_∞, the decision variables (Q, Z, n), the unit partial costs (C^+, C^-, C_{insp}, C_{rect}, C_{rep}, C_{tr}), the initial states (q, x, y) and the probability distributions of the proportion of defective items p(.), Time To Failures *TTF* and Time To Repair *TTR*. The simulation run-time T_∞ is set long enough to guarantee that the random events during the simulation run are observed sufficiently and that the steady-state of the model is reached. Note that the model is developed to accept any probability distribution for the *p*, *TTF* and *TTR*.

① The DEMAND RATE is used as an input of the state equations. In order to represent the real system operation, we define the instantaneous real demand rate as $d/\left(1-AOQ(t)\right)$, where, $AOQ(t)$ is the instantaneous average outgoing quality. The $AOQ(t)$ can be calculated using the following formula:

$$AOQ(t)=\frac{\sum_{i=0/a^i=1}^{N(t)} p^i(Q-n)}{\left(N(t)+1\right)Q} \tag{8}$$

where, a^i=1, if the batch is accepted, and a^i=0, if not. $N(t)$ is the cumulative number of batches arrived to the serviceable inventory x(.) at time each t.

② The STATE EQUATIONS are described by the differential equations of (4) and are modeled with a C++ language insert. When a batch is released at the end of production cycle or a batch enters into the serviceable inventory x(.), a signal is send to the C++ routines to update the values of the variables q(.), y(.) and x(.) using the difference equations of (4).

③ The PRODUCTION CONTROL POLICY is implemented using equation (3). At the end of each production cycle, the control policy is triggered to determine the production rate of the next production cycle depending on the current position inventory and the system availability.

④ The PRODUCTION block models the processing delay which is calculated by dividing the batch size Q by the production rate u^i(.). When the batch production is completed, the original entity is sent back to the PRODUCTION CONTROL POLICY block and a duplicated entity is

created and sent to an UPDATE block where the batch-in-process level is impulsively annulled and the batch size is added to the inventory position.

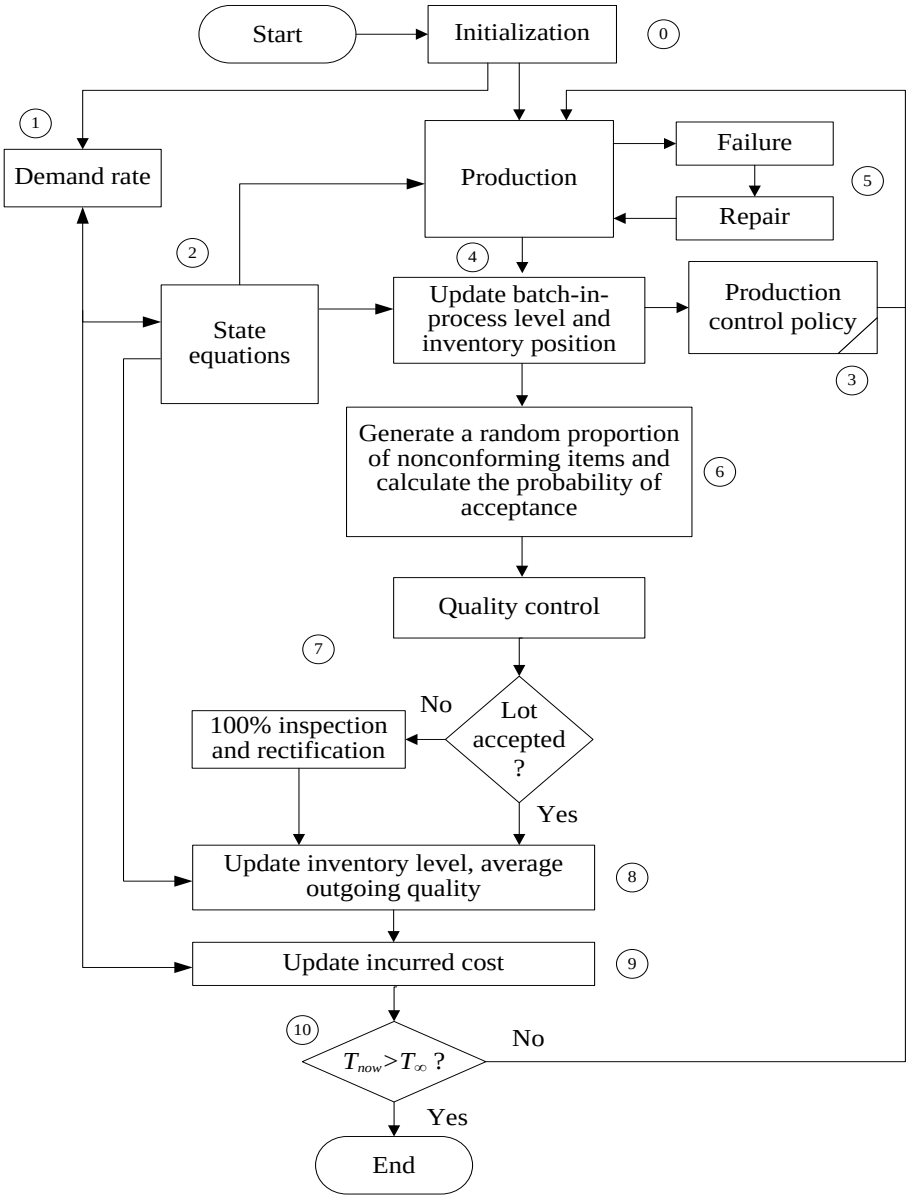


Figure 4-3: Simulation block diagram.

⑤ The blocks FAILURE and REPAIR model respectively the failure and repair events as a close loop following the *TTF* and *TTR* distributions.

⑥ A random proportion of nonconforming items p^i is attributed to each batch produced following the $p(.)$ probability distribution, and the associated probability of acceptance $P_a(.)$ is calculated using Eq. (1).

⑦ Then, the entity (batch produced) holds in QUALITY CONTROL block for sampling during $n \times \tau_{insp}$. The decision to accept or reject the batch is modeled by a probabilistic branch function of SIMAN using the probability of acceptance $P_a(.)$ attributed to each batch. Rejected batches hold in an additional block for 100% inspection and rectification during $Q\,\tau_{insp} + p^i Q\,\tau_{rect}$.

⑧ When a batch arrives to the serviceable final stock, the corresponding entity impulsively updates the inventory level as in (4). The average outgoing quantity $AOQ(.)$ is also updated using Eq. (8).

⑨ This block updates instantly the incurred cost according to the instantaneous values of the different variables and the unit costs.

⑩ Simulation run-time control: if the current time T_{now} exceeds the predefined simulation run-time T_{∞}, the simulation run is stopped.

4.5.3 Validation of the simulation model

To validate that the conceptual simulation model represents accurately the system under study, we graphically verify that the dynamics of production and inventory operates correctly according to Eq. (3) and Eqs. (5). Figure 4.4 represents a sample of the trajectories evolution of the production rate, the inventory position and the inventory during simulation run. The graphic shows how the production rate value changes in response to changes in the inventory position and the system availability states as intended. The impact of batches rejection on the inventory level dynamic is clearly shown by a significant time lag between the inventory level and the inventory position trajectories due to the 100% inspection and rectification operations. In addition, we verified the behaviour of the observed operating characteristic (OC) curve (obtained by simulation) of various given sampling plans comparing with their associated theoretical OC curves (obtained using Eq. (1)). We always found that the observed OC curve coincides with the theoretical OC curve which confirms the accuracy of the quality control modeling in the simulation model.

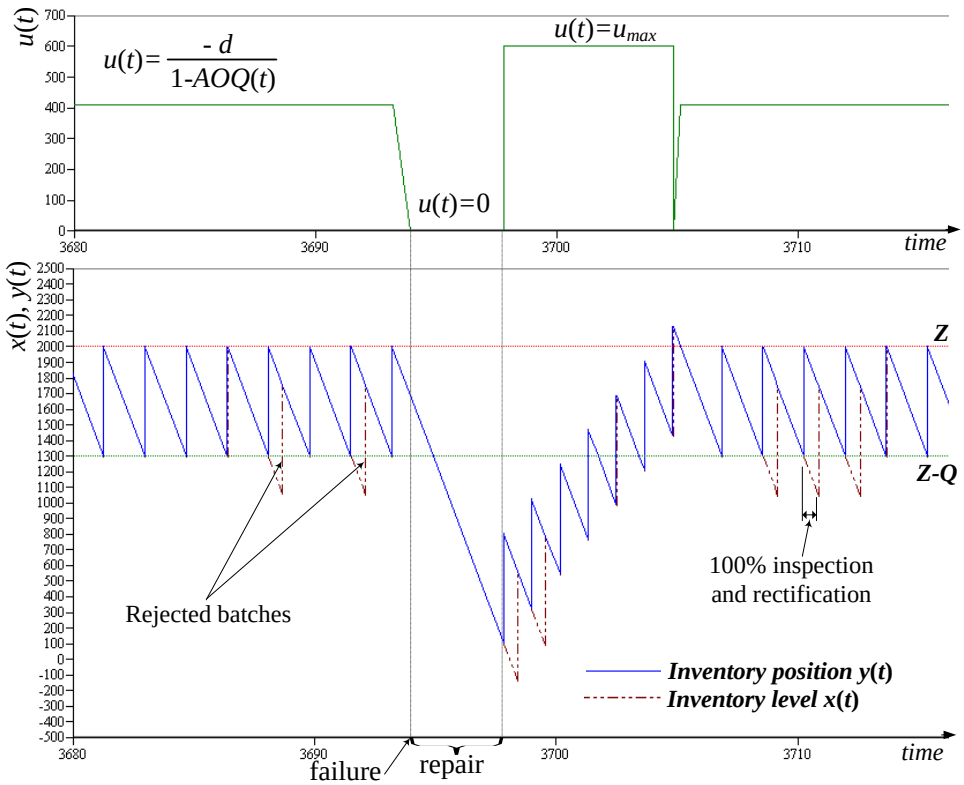


Figure 4-4: Production rate and inventory position/level evolutions during simulation run.

4.6 Numerical example and results analysis

In this section, we present a numerical example to illustrate the resolution approach procedure and to conduct a sensitivity analysis of the optimal solution with respect to the model parameters. Let us consider the following parameters in appropriate units: u_{max}=600, d=400, n_{max}=130, Z_{max}=4500, $Q_{\max}^{bip} = Q_{\max}^{insp}$=1500, τ_{insp} =5×10^{-4}, τ_{rect} =10^{-3}, C^{+}=0.1, C^{-}=1.5, C_{tr}=250, C_{insp}=0.25, C_{rect}=5, C_{rep}=12.5. The stochastic variables are as follows: p~*Uniform*(0.02,0.04), *TTF*~*LogNormal*(50,5) and *TTR*~*Gamma*(0.5,10). The expected proportion of nonconforming items $E[p]$ is equal to 0.03. We define the expected system availability rate as $E[\alpha] = MTTF/(MTTF + MTTR)$ where *MTTF* is the mean time to failure and *MTTR* is the mean time to repair. From the above *TTF* and *TTR* distributions, the expected system availability rate $E[\alpha]$ is equal to 90.91%.

For given acceptance number c, simulation runs are carried out according to a three factors Box-Behnken experimental plan (15 runs) with four replications for each combination of factors (Q, Z, n). This type of design is desired because of its rotatable feature and its efficiently in terms

of number of required runs (Montgomery, 2008). In order to ensure that the steady-state is reached, the duration of each simulation run is set to 500,000 units of time. The simulated data is carried out using statistical software (STATISTICA) to seek a second order regression model fitting the response variable $ETC_c(Q, Z, n)$.

Table 4.1: Results of the application of the resolution procedure.

c	$R^2_{adjusted}$	Q^*	Z^*	n^*	$\psi_c\left(Q^*, Z^*, n^*\right)$
0	0.9842	1176	2658	5	534.61
1	0.9826	1154	2664	12	533.12
2	0.9831	1148	2665	26	532.42
3	0.9829	1138	2665	51	531.29
4	0.9824	1127	2680	92	530.32
5	0.9804	1104	2681	143	529.04

Table 4.1 presents the results obtained from the application of the resolution approach procedure to the present numerical example. We remark that the R-squared adjusted value for all acceptance number is always greater than 98.00%. This states that more than 98.00% of the observed variability in the expected total costs is explained by the models. This confirms that the expected total cost $ETC_c(Q, Z, n)$ for each fixed acceptance number c can be closely fitted by second-order model (Montgomery, 2008). It should be mentioned here that ANOVA analysis of fitting models for all acceptance number showed that the linear and quadratic effects of the factors (Q, Z, n) and their interactions, $Q.Z$, $Q.n$ and $Z.n$, are significant for the response variable at a 0.05 level of significance. Figure 4.5 shows the Pareto chart of standardized effects for the Box-Behnken design when the acceptance number is equal to 4.

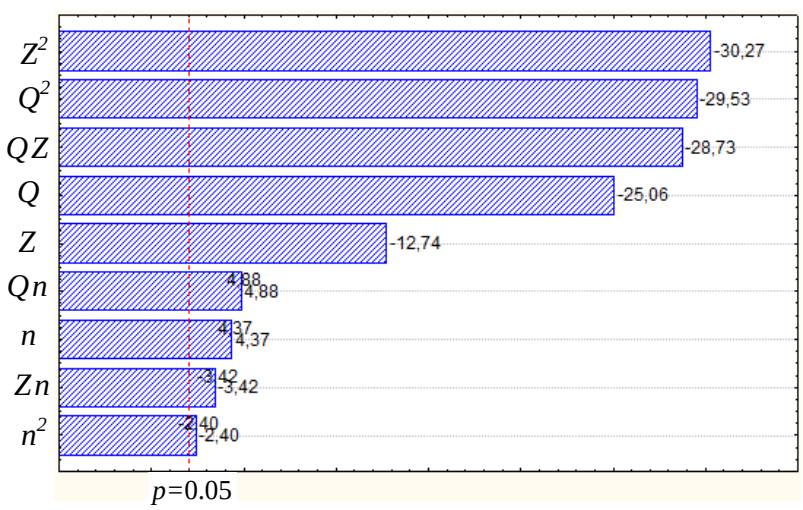


Figure 4-5: Pareto chart of standardized effects for the three factors Box-Behnken experimental design (c = 4).

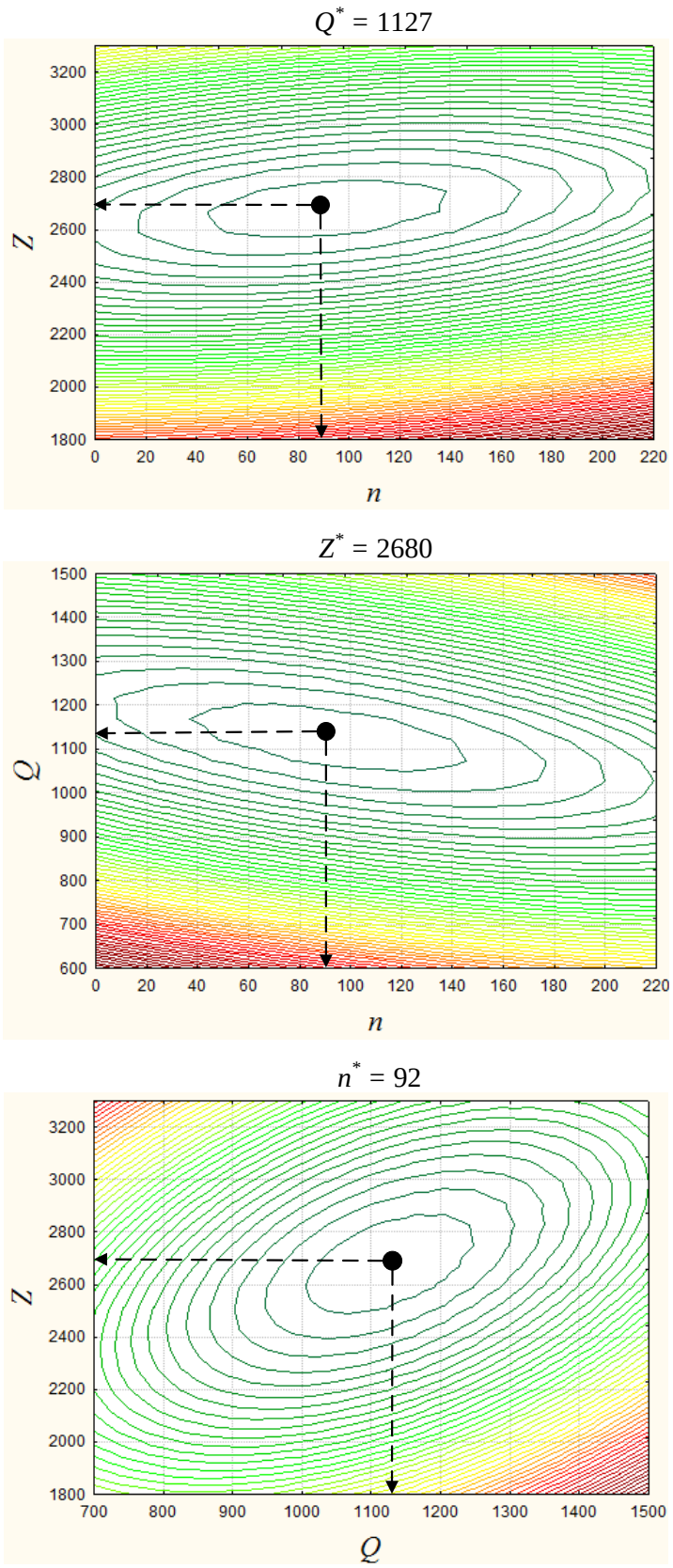


Figure 4-6: Contour plots of the $ETC_c(.)$ predicted from the quadratic model (c = 4).

From Table 4.1, the optimal acceptance number c^* is 4 because it corresponds to the minimum expected total cost that satisfies the constraint $n \le n_{\max}$. For all acceptance number greater than c^*, the optimal sample size n^* exceeds the maximum sample size $n_{\max}$. Using STATISTICA the related second order cost function is given by:

$$\begin{aligned}\psi_4(Q,Z,n) &= 865.69 - 107.54\times10^{-3}Q - 201.98\times10^{-3}Z - 89.25\times10^{-3}n - 94.23\times10^{-6}QZ \\ &+240.23\times10^{-6}Qn - 89.78\times10^{-6}Zn + 150.01\times10^{-6}Q^2 + 59.02\times10^{-6}Z^2 + 322.97\times10^{-6}n^2\end{aligned} \quad (9)$$

The optimization of the quadratic function $\psi_4(Q,Z,n)$ gives a minimum expected total cost 530.32 located at Q^* = 1127, Z^* = 2680 and n^* = 92 as shown in Figure 4.6. Also, from Table 4.1, we remark that the differences between the $\psi_c(Q^*,Z^*,n^*)$ for all acceptance number c ($c \neq c^*$) and $\psi_{c^*}(Q^*,Z^*,n^*)$ are less than 1%. This can be explained by the possible existence of several local minima around the global optimum of the expected total cost as shown by Moskowitz and Berry (1976) and Peters et *al*. (1988).

A sensitivity analysis of the production and quality control policies is conducted with respect to model parameters (costs, inspection delay, system availability and proportion of nonconforming items) by varying their values above and below its baseline value. Ten sets of experiments are achieved in order to understand how the optimal control parameters (Q^*, Z^*, n^*, c^*) vary with changes of the model parameters and to show the applicability of the resolution approach for ranges of system parameters. The results are summarized in Table 4.2, where the variation of the optimal control parameters (Q^*, Z^*, n^*, c^*), the optimal expected total cost ETC(.) and the 'optimal' probability of acceptance $P_a^* = P_a(E[p] \mid n^*, c^*)$ are highlighted (i.e., respectively ΔQ^*, ΔZ^*, Δn^*, Δc^*, ΔETC^*, and $\Delta P_a{}^*$). Note that the probability of acceptance P_a^* is used to measure the sampling plan severity. When the probability of acceptance increases the sampling plan severity becomes reduced. Inversely, when the probability of acceptance increases the sampling plan severity becomes tightened.

- *Variation of the inventory cost* (Set I): When the inventory cost C^+ increases, the optimal hedging threshold Z^* decreases in order to avoid further inventory costs. Consequently, the optimal batch size Q^* decreases to reduce production, 100% inspection and rectification delays and therefore ensures a better supply to the serviceable inventory x(.). The optimal sampling plan

severity becomes reduced in order to minimize the holding cost of rejected batches during the 100% inspection and rectification operations. Note that the decrease in inventory cost produces the opposite effects.

- *Variation of backlog cost* (Set II): When the backlog cost C^- increases, the production-inventory control policy reacts by increasing the hedging level Z^* (i.e., increasing the safety stock limit) to provide a better protection to the system against shortages. The optimal batch size Q^* decreases slightly to reduce batch processing delays which improves the supply of the serviceable inventory. The optimal sampling plan becomes more tightened which means that more batches are rejected. This can be explained as follows: first, remind that the demand rate is time-varying depending on the instantaneous service level of the demand/backlog (Section 4.3.2). Because the safety stock limit increases, the long-term service level increases as the sales increase also. Given that the quantity of nonconforming items returned from consumer is proportional to sales, and in order to avoid further replacement cost, the quality control policy reacts by tightening the batches acceptance. The decrease in backlog cost produces the opposite effects.
- *Variation of transportation cost* (Set III): When the transportation cost C_{tr} is higher, the frequency of batches transportation needs to be reduced in order to minimize the total transportation cost. Consequently, the optimal batch size Q^* increases, and leads to a systematic increase in the optimal hedging level Z^* in order to protect the system from backlogs. The optimal sampling plan severity becomes reduced in order to reduce batches rejection and give preference to keep the serviceable inventory at a high level. The opposite effects are well observed when the transportation cost decreases.
- *Variation of inspection cost* (Set IV): When the inspection cost C_{insp} increases, the optimal sampling plan severity becomes reduced in order to minimize rejection of batches produced and therefore reduce the 100% inspection cost. The optimal hedging level Z^* slightly decreases due to the decrease of the long-term average 100% inspection and rectification delays. As a result, the optimal batch size Q^* increases. Note that the decrease in inspection cost conducts to the opposite effects.

Table 4.2: Sensitivity analysis for model parameters.

Sets	Parameters	Changes	Q^*	Z^*	n^*	c^*	ETC^*	P_a^*	$\Delta Q^*(\%)$	$\Delta Z^*(\%)$	$\Delta ETC^*(\%)$	$\Delta P_a^*(\%)$
Basic	-	-	**1127**	**2680**	**92**	**4**	**530.32**	**0.859**	-	-	-	-
Set I	C^+	-50%	1275	3233	122	4	399.82	0.696	+13.13%	+20.63%	-24.61%	-18.98%
		+50%	953	2162	110	5	634.39	0.886	-15.44%	-19.33%	+19.62%	+3.14%
Set II	C^-	-50%	1141	1877	123	6	481.42	0.922	+1.24%	-29.96%	-9.22%	+7.35%
		+50%	1100	2945	112	4	551.97	0.753	-2.40%	+9.89%	+4.08%	-12.34%
Set III	C_{tr}	-50%	777	2418	77	3	479.41	0.799	-31.06%	-9.78%	-9.60%	-6.93%
		+50%	1261	2776	95	5	571.39	0.933	+11.89%	+3.58%	+7.74%	+8.66%
Set IV	C_{insp}	-25%	1042	2738	117	1	519.7	0.131	-7.54%	+2.16%	-2.00%	-84.77%
		+25%	1139	2641	130	11	532.15	0.999	+1.06%	-1.46%	+0.35%	+16.35%
Set V	C_{rect}	-50%	1068	2744	105	1	518.3	0.173	-5.24%	+2.39%	-2.27%	-79.81%
		+50%	1141	2647	127	9	532.32	0.995	+1.24%	-1.23%	+0.38%	+15.82%
Set VI	C_{rep}	-12%	1141	2655	112	9	511.82	0.998	+1.24%	-0.93%	-3.49%	+16.17%
		+12%	1057	2702	117	2	543.57	0.315	-6.21%	+0.82%	+2.50%	-63.36%
Set VII	τ_{insp}	-50%	1116	2651	105	3	528.61	0.613	-0.98%	-1.08%	-0.32%	-28.62%
		+50%	1134	2670	91	7	530.58	0.994	+0.62%	-0.37%	+0.05%	+15.70%
Set VIII	*MTTR*	-50%	959	1559	128	4	418.92	0.660	-14.9%	-41.83%	-21.00%	-23.16%
		+50%	1176	4011	113	7	638.79	0.979	+4.35%	+49.66%	+20.45%	+13.97%
Set IX	*MTTF*	-50%	1118	3045	102	6	532.51	0.966	-0.80%	+13.62%	+0.42%	+12.45%
		+50%	1209	2196	130	3	518.65	0.451	+7.27%	-18.06%	-2.20%	-47.50%
Set X	$E[p]$	-15%	1144	2650	104	10	503.64	1.000	+1.51%	-1.12%	-5.03%	+16.41%
		+15%	1040	2703	130	3	550.65	0.329	-7.72%	+0.86%	+3.83%	-61.66%

- *Variation of rectification cost* (Set V): Similarly to the inspection cost, the increase in the rectification cost C_{rect} results in reducing the severity of the optimal sampling plan in order to minimize rejection of batches and consequently reduce the long-term rectification cost. The optimal hedging level Z^* slightly decreases because the long-term decrease of batch processing delays after production. This causes an increase of the optimal batch size.
- *Variation of replacement cost* (Set VI): When the replacement cost C_{rep} of returned nonconforming items increases, more 100% inspection and rectification operations are needed to reduce the outgoing quality which explains the severity tightening of the optimal sampling plan. Consequently, smaller batch size should be produced to ensure a regular supply of the serviceable inventory. The decrease in replacement cost conducts to the opposite effects.
- *Variation of inspection delay* (Set VII): When the inspection delay increases, the 'optimal' probability of acceptance P_a^* increases in order to reduce the long-term average 100% inspection delay. Therefore, the optimal hedging level Z^* decreases slightly and results in a minor increase of the optimal batch size. The decrease in inspection delay produces the opposite effects.
- *Variation of system availability* (Set VIII and IX): First, recall that when the Mean Time To Failures *MTTF* increases (decreases) or the Mean Time To Repair *MTTR* decreases (increases), the average availability system increases (decreases). When the system availability decreases (*MTTF* decreases or *MTTR* increases), the optimal hedging level Z^* increases in order to protect the serviceable inventory against the risk of shortages becoming higher. As a result, the economic sampling plan severity is reduced in order to save 100% inspection and rectification delays for rejected batches and give better supply to the serviceable inventory. Note that an increase in the *MTTF* or a decrease in the *MTTR* produces the opposite effects.
- *Variation of proportion of nonconforming items (*Set X): A small increase in the average of the proportion of nonconforming items distribution conducts to a significant decrease in the probability of acceptance in order to avoid further replacement cost due the outgoing quality. As more batches will be rejected, the joint production and quality control policies react by reducing the optimal batch size Q^* in order to minimize all processing delays (of production, 100% inspection and rectification) and give more protection to serviceable stock against shortages. The opposite effects are observed when the proportion of defective items decreases.

4.7 Conclusion

The joint production-inventory control policies and statistical quality control techniques have not been sufficiently studied in the literature although they are strongly interrelated. Inman et *al*. (2003) argued that production systems have a significant impact on quality and they observed a lack of research in the intersection of quality and production system design. This paper contributes to research on the joint design of production and quality control of unreliable batch manufacturing systems, where the production control policy consists of a modified hedging policy and quality control is performed by a single sampling plan by attributes. A stochastic mathematical model has been developed to describe the dynamic of production and inventory, to define the system constraints and to calculate the overall incurred cost. Since the optimal solution cannot be obtained analytically due to the nonlinearity and the complexity of the optimization model, we proposed a resolution approach based on integrated enumeration procedure with respect to the acceptance number and a simulation optimization approach to optimize jointly the batch size, the hedging level and the sample size. From an illustrative numerical example and a thorough sensitivity analysis, we showed an important impact of inventory, backlog and transportation costs on the design of the economic sampling plan, and, vice versa, the quality costs have a considerable impact on the economic batch size. Also, we showed a significant impact of the system reliability on the optimal batch size, the optimal safety stock and the economic sampling plan design. An interesting result derived from this study is when the production system becomes more unreliable the outgoing quality increases and consumer satisfaction will be critical towards the quality of final product. Future research can be undertaken to investigate the joint preventive maintenance which improve system reliability, economic production quantity, optimal safety stock and economic sampling plan design. Another area for further research is the consideration of consumer’s quality level and consumer’s risk constraints in the economic sampling plan design.

CHAPITRE 5 ARTICLE 2: INTEGRATED PRODUCTION, SAMPLING QUALITY CONTROL AND MAINTENANCE OF DETERIORATING PRODUCTION SYSTEMS WITH AOQL CONSTRAINT

Article publié dans

OMEGA, The International Journal of Management Science

DOI: 10.1016/j.omega.2015.07.012

Rédigé par:

Bassem BOUSLAH
Department of Mathematics and Industrial Engineering,
École Polytechnique de Montréal
{*bassem.bouslah@polymtl.ca*}

Ali GHARBI
Automated Production Engineering Department,
École de Technologie Supérieure
{*ali.gharbi@etsmtl.ca*}

Robert PELLERIN
Department of Mathematics and Industrial Engineering,
École Polytechnique de Montréal
{*robert.pellerin@polymtl.ca*}

Abstract

This paper considers the problem of integrated production, preventive maintenance and quality control for a stochastic production system subject to both reliability and quality deteriorations. A make-to-stock production strategy is used to provide protection to the serviceable stock against uncertainties. The quality control is performed using a single acceptance sampling plan by attributes. The preventive maintenance strategy consists in carrying out an imperfect maintenance as a part of the setup activity at the beginning of each lot production, while a major maintenance (overhaul) is undertaken once the proportion of defectives in a rejected lot reaches or exceeds a given threshold. The main objective of this study is to jointly optimize the production lot size, the inventory threshold, the sampling plan parameters and the overhaul threshold by minimizing the total incurred cost. To meet customer requirements, the optimization problem is subject to a specified constraint on the average outgoing quality limit (AOQL). A stochastic mathematical model is developed and solved using a simulation-based optimization approach. Numerical examples and thorough sensitivity analyses are provided to illustrate the efficiency of the proposed integrated model. Compared with the 100% inspection policy which is widely used in the literature on integrated production, maintenance and quality control, the results obtained show that an economic design of acceptance sampling in such an integrated context can lead to important cost savings of more than 20%.

Keywords - Dynamic process deterioration, production/inventory control, lot sizing, acceptance sampling plan, preventive maintenance, simulation-based optimization.

5.1 Introduction

Over in the past few decades, a lot of effort has been devoted to integrating production planning, quality control and maintenance scheduling and to investigating the hidden interactions between these three aspects. In a recent literature review on this topic, Hadidi et al. (2012) drew a distinction between the concepts of interrelation and integration between the three fundamental functions: interrelated models are those in which the decision variables of only one function is considered, taking into account the remaining functions as constraints, while integrated models are those in which two or the three functions are modelled and optimized simultaneously. Based on Hadidi et al.'s definitions, we find that most of the

integrated models in the literature consider only two functions at a time. For example, many models integrating only production and preventive maintenance (PM) have been proposed since the second half of the 1990s, without considering the quality aspect (see the literature review by Budai et al., 2008). Recent advances in integrated production and PM include the joint determination of the Economic Production Quantity (EPQ) and PM policy (e.g., Sana, 2012; Liao, 2013), joint production and opportunistic PM scheduling (e.g., Xia et al., 2012, 2015) and simultaneous control of production and PM rates (e.g., Berthaut et al., 2011; Assid et al., 2015b). On the other hand, research on integrating only the production and quality control policies dates back to the 1970s and 1980s (see the literature review by Goyal et al., 1993). More recently, Inman et al. (2013) surveyed the advances on the interface between quality and production system design in the past two decades. Research during this period has been concerned with the mutual effects of production and quality settings, such as the impact of production complexity and technology, operations speed, setup planning and tolerance design on the deterioration of process quality (e.g., Sana, 2010a; Pal et al., 2013; Liu et al., 2009; Jeang, 2012) and, conversely, the impact of quality inspection planning on production flow (e.g., Kim and Gershwin, 2008), etc. In addition, there is a growing interest in the integration of production control design with Statistical Quality Control (SQC) techniques such as control charts (e.g., Colledani and Tolio, 2011), process capability (e.g., Hajji et al., 2011a), and sampling plans (Bouslah et al., 2013, 2014). Nevertheless, Inman et al. (2013) have reported that there are still a large number of sub-areas in quality control (including reliability and maintenance scheduling) that have not been fully integrated with production, and they recommended further investigation of the traditional quality control system design in the production context.

Indeed, only a limited number of papers in the literature deal with the simultaneous integration of the three functions. We can classify these papers into two categories, based on the quality control policy used. The first category includes studies integrating production and PM design with a 100% inspection policy of all items produced. For example, Liao et al. (2009) and Wee and Widyadana (2013) integrated PM programs with the EPQ model for an imperfect production process where all defective items produced must be reworked. Radhoui et al. (2009, 2010) suggested an integrated PM and production control policy for an unreliable imperfect

process producing a random proportion of non-conforming items. They assumed that each lot produced is subject to an automated quality control of negligible duration and cost. The second category of integrated models corresponds to studies using the SQC tools rather than 100% inspection. For example, Ben-Daya and Makhdoum (1998) and Ben-Daya (1999) presented various integrated models for the joint determination of the EPQ, the economic control chart design and the optimal PM level. Nevertheless, some other important aspects of the SQC, such as the acceptance sampling plans have not yet been integrated simultaneously with production and PM planning. Acceptance sampling plans have been widely used in industry for a long time to control the outgoing quality especially in situations where 100% inspection of all items produced is technically or economically impractical (Schilling and Neubauer, 2009). In addition, they have significant impacts on production and inventory, as shown by Bouslah et al. (2013). Unlike 100% inspection and control charts, the interactions between acceptance sampling plans and PM policies have not yet been investigated in the literature.

In the literature on integrated models, many attempts have been made by researchers to adequately pattern the product quality and equipment reliability deteriorations. For example, Rosenblatt and Lee (1986) studied three dynamic patterns of process deterioration (linear, exponential and multi-state) on the EPQ. Moreover, many industrial and academic studies have shown the significant impact of production rate on deterioration intensity, as in Felix Offodile and Ugwu (1991), Khouja and Mehrez (1994) and Sana (2010b). However, for simplicity, most of the existing integrated models neglect the dynamic aspect of process performance deterioration and the impact of production settings on the deterioration intensity. Generally, the researchers assume that the proportion of defective items produced during ‘out-of-control’ periods is constant or follows a prior known distribution.

Furthermore, almost all of the integrated models do not simultaneously consider the quality and reliability deterioration phenomena (Chakraborty et al., 2009). When both phenomena are observed, the PM plays a double role: increasing the reliability of the production equipment and restoring the product quality to the desired level (Ben-Daya and Duffua, 1995; Rivera-Gomez et al., 2013). Because of the direct impact of deterioration on the production system availability and on the output quality, it is more appropriate to base the PM decision on the actual deterioration state rather than on equipment age (Grall et al., 2002). An inference on the

deterioration state could be based on the equipment condition or on the product quality characteristic (Colledani and Tolio, 2012). Condition-based maintenance has attracted a great deal of attention over the past two decades, in conjunction with the technological advances in condition monitoring techniques such as vibration, corrosion, thermography and acoustics analysis (Rao, 1996; Davies, 1998). On the other hand, in situations where quality is directly affected by the degradation of the production system, the quality information feedback, which does not require a costly and high technology for data acquisition and analysis, such as in condition monitoring techniques, could represent an alternative solution to recognise the system degradation. Maintenance based on quality information feedback is becoming increasingly attractive as a field of research, especially in the context of maintenance and quality control integration. Tapiero (1986) was among the first to formulate a feedback stochastic control maintenance problem based on the products quality, assuming that quality is a known function of the machine's degradation state. Hsu and Kuo (1995) studied the performance of an inspection and maintenance policy that begins 100% inspection of a production lot after producing a given number of items and then initiates a preventive/corrective maintenance activity when the fraction of defective parts reaches a given threshold. Similarly, Radhoui et al. (2009, 2010) also used the 100% inspection policy to determine the proportion of non-conforming items of each lot produced and then compare this proportion to some given thresholds to make decisions on PM and overhaul actions. Recently, Panagiotidou and Tagaras (2010), Pan et al. (2012) and Zhang et al. (2015) suggested integrating condition-based maintenance and statistical process control strategies where the maintenance decisions are made based on the quality information feedback from the control chart. Nevertheless, the interactions between the acceptance sampling plans and maintenance strategies have never received the same attention in the literature. To the best of our knowledge, there is no published study that investigates the usefulness and relevance of information provided by sampling plans such as the observed percentage of accepted/rejected lots, the current inspection mode (sampling or 100% inspection), etc., for process condition monitoring and maintenance decision-making.

To overcome the limitations of existing integrated models, in this paper, we intend to develop a new model integrating production lot sizing, production rate control, inventory control, single

acceptance sampling plan and PM strategy. Our focus on the acceptance sampling plan techniques in the context of integrated operations management is motivated by three considerations. Firstly, acceptance sampling plans have specific statistical properties (Schilling and Neubauer, 2009) that should be deeply analyzed in order to extract relevant information for process condition monitoring and to make the appropriate maintenance decisions accordingly. Secondly, compared with the 100% inspection policy which is extensively used in the integrated models in the literature, sampling plans are usually more economical, and they significantly reduce the unnecessary inspection essentially during periods when the process is in the 'in-control' state (Montgomery, 2008a). Thirdly, it is expected that an economic design of acceptance sampling plans in such a context, instead of using traditional sampling inspection standards such as ANSI/ASQC Z1.4 and ISO 2859, could lead to significant economic savings (Nikolaidis and Nenes, 2009). In fact, those standards are purely based on quality considerations, and completely neglect the economic aspect and the interactions with production, inventory and maintenance in the design of sampling plans.

In this study, we present a stochastic dynamic model considering non-negligible delays and costs of setup, quality control and maintenance operations. Both the product quality and machine reliability deteriorations depend on the production equipment usage. We consider that the production setup includes an imperfect PM activity. An overhaul is also required to perfectly restore the performance of the production process. Our objective is to jointly design and optimize the production, quality control and maintenance policies. The optimal integrated solution should minimize the total incurred cost while meeting a predefined restriction on the average outgoing quality limit (AOQL). We use a simulation-based optimization approach to solve this complex and stochastic problem. Moreover, we present a thorough analysis of the performance and benefits of the proposed integrated model.

The paper is organized as follows. Section 5.2 presents the notations used and the description of the problem under study. The system dynamic modelling and the optimization problem are formulated in Section 5.3. In Section 5.4, we present the simulation-based optimization approach. Illustrative numerical examples, and sensitivity and comparative analyses are given in Section 5.5. Section 5.6 discusses some managerial implications for the proposed integrated

control policy. Finally, Section 5.7 concludes the paper and provides some directions for future research.

5.2 Notations and problem description

5.2.1 Notations

The notations used in this paper are defined as follows:

Decision variables:

Q	Production lot size
S	Surplus inventory threshold
n	Sample size
c	Acceptance number
r	Overhaul threshold (ratio)

Model parameters:

u_{max}	Maximum production rate
d	Demand rate
$AOQL_{max}$	Maximum accepted level of the Average Outgoing Quality Limit
τ_{cm}	Random variable denoting the corrective maintenance duration
τ_{ovr}	Random variable denoting the overhaul duration ($\bar{\tau}_{ovr} >> \bar{\tau}_{cm}$)
τ_{ins}	Unit inspection duration
τ_{set}	Setup duration for each production run
C_h	Unit inventory holding cost per unit time
C_b	Unit backlog cost per unit time ($C_b >> C_h$)
C_{set}	Setup cost (including the cost of the imperfect PM)
C_{cm}	Corrective maintenance cost
C_{ovr}	Overhaul maintenance cost ($C_{ovr} >> C_{cm}$)
C_{ins}	Unit inspection cost
C_{rej}	Unit rejection cost of a defective item
C_{def}	Unit cost of selling a non-inspected defective item

Other notations will be used to model the system deterioration and the inventories dynamics.

5.2.2 Problem description and assumptions

The manufacturing system under study consists of a single-product batch-processing production unit supplying a downstream serviceable stock, as illustrated in Figure 5.1. This stock is used to fulfill a continuous and constant market demand d. The production rate $u(.)$ is flexible and can be set at any time at a value between 0 and a maximum level u_{max}. The production unit is subject to a continuous operation-dependent degradation which leads to an increasing failure probability and an increasing proportion of defectives produced. Therefore, maintenance interventions are required to maintain and restore the performances of the production unit. In response to each failure event, a corrective maintenance (minimal repair) is undertaken, which returns the production unit to the 'as-bad-as-old' condition. To preventively cope with the system degradation, an imperfect PM is carried out as a part of the setup activity at the beginning of each production run. We consider that the efficiency of this imperfect PM decreases continuously as the production unit ages. Thus, we assume that the setup reduces the effective age $a(.)$ of the production unit by a certain amount $\phi(.)$ called the *improvement factor*, which is a decreasing function of the real age $A(.)$ (Wang and Pham, 2006). In addition, a major perfect maintenance (overhaul) is conducted as soon as the rate of defective items produced reaches or exceeds a given threshold r. This feedback overhaul policy is used for two reasons. First, the PM during setups is insufficient to perfectly improve the production unit performance as its perfectness deteriorates with process usage. Second, because the product quality depends intimately on the production unit condition, the rate of defectives produced provides a relevant indication of the overall deterioration state, and it could therefore be useful as a control parameter for the overhaul scheduling.

In order to ensure that the delivered products meet the outgoing quality requirement, a quality control of lots produced is performed before they reach the final serviceable stock. There, a single acceptance sampling plan by attributes is used to guarantee an acceptable outgoing quality level. A sample of size n is drawn randomly from each lot produced and inspected item by item. If the number of defectives does not exceed the acceptance number c, then the lot is accepted. Otherwise, the lot is rejected, and a 100% inspection is performed in order to sort all the defective items. We assume that the defective items are not rectifiable. Hence, all the defectives, found either in sampling or in 100% inspection, are rejected with no replacement.

Depending on the proportion of defective items found in each lot rejected compared to the threshold value *r*, the decision maker can decide whether or not to immediately initiate the overhaul.

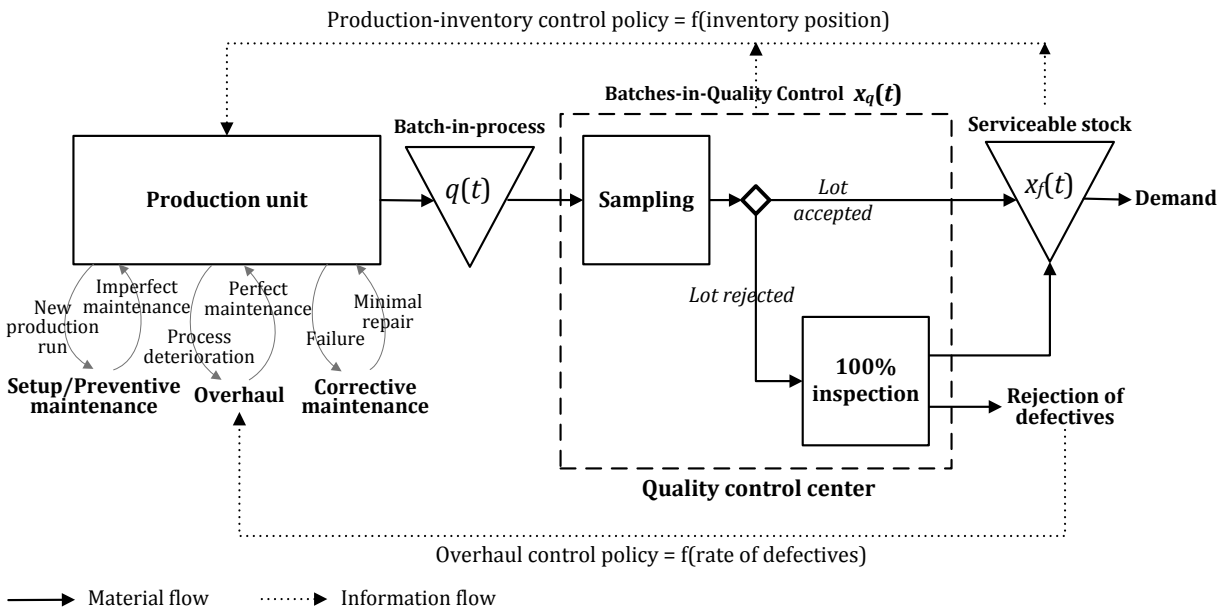


Figure 5-1: A deteriorating production system with quality control, PM and overhaul.

The duration of the setup (including the imperfect PM) is constant. However, the durations of the corrective maintenance (CM) and the overhaul are stochastic, following general probability distributions. Under these assumptions, and because the quality control delay of each lot produced is unpredictable and variable depending on the acceptance/rejection decision, shortages may occur. A make-to-stock production strategy is used in order to provide protection to the serviceable stock against uncertainties in production and quality control. Hence, the production rate is controlled over time by a feedback base-stock control policy derived from the well-known hedging point policy (Akella and Kumar, 1986). Our choice of the hedging point method for the production-inventory control is motivated by its optimality, simplicity and ease of implementation features (Hu et al., 1994; Gershwin, 2000; Sarimveis et al., 2008). Finally, we consider that the production of the interrupted lots is always resumed following maintenance interventions.

Our objective is to find jointly the optimal production lot size *Q*, the optimal inventory surplus *S*, the optimal sampling parameters *n* and *c*, and the optimal overhaul threshold *r* that minimize

the total incurred cost. This includes the inventory and backlog costs, quality control costs and maintenance (setup, overhaul and CM) costs. The optimal solution must satisfy a number of constraints related to the system dynamic and the customer-perceived quality.

5.3 Problem formulation

5.3.1 Deterioration model

The state of the production unit can be characterized at each instant t by five continuous-time components, including:

- A discrete-state stochastic process $\{\alpha(t), t \geq 0\}$ which describes the status of the production unit at each time t, and takes values $\{0,1,2,3\}$ such that: $\alpha(t) = 0$, if the production unit is under CM; $\alpha(t) = 1$, if it is available for production; $\alpha(t) = 2$, if it is under setup, and $\alpha(t) = 3$, if it is under overhaul.
- A piecewise continuous variable, $A(t)$, which represents the cumulative number of items produced since the last overhaul until time t. We call this variable the real age, and it is calculated using the following formula:

$$\frac{\partial A(t)}{\partial t} = u\left(t, \alpha(t)\right), \forall\, t \geq T, A(T) = 0 \tag{1}$$

  where T is the completion time of the last overhaul.
- A piecewise continuous variable, $a(t)$, which represents the reduced age of the production unit at time t. This variable measures the cumulative effects of the setups on the real age of the production unit, and is called the virtual age (also called effective age). It is calculated using these equations:

$$\frac{\partial a(t)}{\partial t} = u\left(t, \alpha(t)\right), \forall t \in \left[\theta_k, \theta_{k+1}\right[, k = 0,1,..,\infty, a(T) = 0 \tag{2}$$

$$a(\theta_k^+) = a(\theta_k^-) - \phi\left(A(\theta_k)\right) \cdot a(\theta_k^-), k = 1,..,\infty \tag{3}$$

  where θ_k is, simultaneously, the end time of the kth setup activity and the start time of the kth production run.
- The improvement factor, $\phi(.)$, which is a decreasing continuous function of the real age $A(.)$, and is described by the following equation:

$$\phi\left(A(t)\right) = \exp\left(-\lambda_{set}\, A(t)^{\gamma_{set}}\right) \tag{4}$$

where λ_{set} and γ_{set} are given positive constants.

- The probability of failure, $F(.)$, which depends instantly on the current virtual age $a(.)$, following a Weibull distribution:

$$F\left(a(t)\right) = 1 - \exp\left(-\lambda_r\, a(t)^{\gamma_r}\right) \tag{5}$$

where λ_r and γ_r are given positive constants.

- The proportion of defective items produced at time t, $p(t)$, which also depends on the current virtual age $a(.)$ as follows:

$$p\left(a(t)\right) = p_0 + \eta\left(1 - \exp\left(-\lambda_q\, a(t)^{\gamma_q}\right)\right) \tag{6}$$

where p_0 is a very small proportion of defectives produced at the initial condition (i.e., 'as-good-as-new' state), λ_q and γ_q are given positive constants, and η is the boundary considered in the quality deterioration.

From Eqs. (4), (5) and (6), the deterioration functions of the improvement factor $\phi(.)$, the probability of failure $F(.)$ and the rate of defectives $p(.)$ belong to the two-parameter exponential family of distributions (Ferguson, 1962). The parameters of these functions can be determined from historical information using estimation methods such as the maximum likelihood and the least squares methods (Hossain and Zimmer, 2003).

5.3.2 Integrated control policy of production, quality and maintenance

5.3.2.1 Quality Control Policy

The decision on the acceptance/rejection of each lot produced is based on the number of defective items found in the random sample n, which itself depends on the number of defective items in the entire lot. Let X_k be the variable denoting the number of defectives in the kth lot produced, $k = 1,2,..,\infty$. X_k can be determined by solving these equations:

$$\frac{\partial X_k(t)}{\partial t} = p\left(a(t)\right)\cdot u\left(t,\alpha(t)\right), \forall t \in \left]\theta_k, \delta_k\right],\ X_k\left(\theta_k\right) = 0 \tag{7}$$

where δ_k is the end time of the kth production run (i.e., time when the kth lot is completely processed).

Let Y_k be the variable indicating the number of defective items in the sample n of the kth lot. The probability of finding j defective items, $0 \leq j \leq n$, in the sample n of the kth lot, k = 1,2,..,∞, can be calculated using the binomial distribution as follows:

$$\Pr\left(Y_k = j\right) = \binom{n}{j}\left(\frac{X_k}{Q}\right)^j\left(1-\frac{X_k}{Q}\right)^{n-j} \tag{8}$$

Then, the probability of acceptance of the kth lot produced $P_a^k(.)$, k = 1,2,..,∞, is calculated as follows:

$$P_a^k\left(n,c,Q,X_k(.)\right) = \Pr\left(Y_k \leq c\right) = \sum_{j=0}^{c}\Pr\left(Y_k = j\right) \tag{9}$$

As the accepted lots do not undergo a 100% screening inspection, the defective items existing in these lots will be transmitted to the final serviceable stock, and will therefore be sold to customers. The average proportion of defective items transmitted to the serviceable stock through each kth lot produced, also called the Average Outgoing Quality (AOQ_k), k = 1,2,..,∞, is given by:

$$AOQ_k\left(n,c,Q,X_k(.)\right) = \frac{\sum_{j=0}^{c}\Pr(Y_k = j)\left(X_k - j\right)}{\sum_{j=0}^{c}\Pr(Y_k = j)\left(Q - Y_k\right) + \sum_{j=c+1}^{n}\Pr(Y_k = j)\left(Q - X_k\right)} \tag{10}$$

The maximum level of AOQ_k, k = 1,2,..,∞, over all possible values of X_k, is called the Average Outgoing Quality Limit ($AOQL$), which can be calculated as follows (Schilling and Neubauer, 2009):

$$AOQL\left(n,c,Q\right) = \max_{0 \leq X_k \leq Q}\left\{AOQ_k\left(.\right)\right\} = y(c)\left(\frac{1}{n} - \frac{1}{Q}\right) \tag{11}$$

where $y(c)$ is equal to

$$y(c) = \frac{e^{-n\,p_M}\,(n\,p_M)^{c+2}}{c!} \tag{12}$$

and p_M is the value of the ratio X_k/Q at which the $AOQL$ occurs. Tables containing the closed approximated values of $y(c)$ for each given c independently of the sample size n can be found in Schilling and Neubauer (2009).

The manufacturer must select the combination of production lot size Q and sampling plan parameters n and c such that the $AOQL(.)$ does not exceed a maximum limit imposed by the customers, denoted $AOQL_{max}$. Thus, from Eq. (11), we obtain this inequality

$$y(c)\left(\frac{1}{n}-\frac{1}{Q}\right)\leq AOQL_{\max} \tag{13}$$

5.3.2.2 Production-Inventory Control Policy

The finished products can be held in three storage locations before being delivered to customers as schematized in Figure 5.1:

- A downstream production area to cumulate the produced parts of the ongoing batch-in-process until the end of the current production run. This inventory is measured instantly by a piecewise continuous variable denoted $q(.)$, where $0\leq q(t)\leq Q$, $\forall\ t$. The dynamic of the inventory $q(.)$ can be described by the following equations:

$$\frac{\partial q(t)}{\partial t}=u\left(t,\alpha(t)\right),\ q\left(\theta_1\right)=0,\forall t\in\left]\theta_k,\delta_k\right[,\forall k=1,..,\infty \tag{14}$$

$$q\left(\delta_k^+\right)=q\left(\delta_k^-\right)-Q,\forall k=1,..,\infty \tag{15}$$

  where δ_k^- and δ_k^+ denote the left and right boundaries of the kth production run end time δ_k, respectively. We should recall that each kth production run, k=1,..,∞, can be interrupted many times by the CM and overhaul interventions. As mentioned earlier, the durations of these interventions are stochastic. In the case where the production rate $u(.)$ remains unchanged during the production run, δ_k can be estimated as follows:

$$\delta_k=\theta_k+Q/u+\sum_{i\in\Lambda(k)}\tilde{\tau}_{cm}^i+\sum_{j\in\Delta(k)}\tilde{\tau}_{ovr}^j \tag{16}$$

  where $\tilde{\tau}_{cm}^i$ is the duration of the ith CM, i=1,..,∞, and $\tilde{\tau}_{ovr}^j$ is the duration of the jth overhaul, j=1,..,∞. $\Lambda(k)$ and $\Delta(k)$ are respectively the sets of CM and overhauls performed during the kth production run.

- A storage area where each lot produced is temporarily held for quality control. This Work-In-Progress (WIP) inventory is measured by the continuous-time variable $x_q(.)$. Its dynamic is given by

$$x_q\left(\delta_k^+\right)=x_q\left(\delta_k^-\right)+Q,\ \forall k=1,..,\infty \tag{17}$$

$$x_q\left(\xi_k^+\right) = x_q\left(\xi_k^-\right) - Q,\ \forall k = 1,..,\infty \tag{18}$$

where ξ_k^- and ξ_k^+ denote the left and right boundaries of the completion time of quality control, ξ_k, of the *k*th lot produced. ξ_k depends on the lot acceptance/rejection decision as follows:

$$\xi_k = \begin{cases} \delta_k + n\,\tau_{ins} & \text{if } Y_k \le c \text{ (lot accpeted)} \\ \delta_k + Q\,\tau_{ins} & \text{if } Y_k > c \text{ (lot rejected)} \end{cases} \tag{19}$$

Note that ξ_k also indicates the arrival time of the *k*th lot at the serviceable stock.

- The final serviceable stock which is used to meet the market demand. This stock (inventory if positive and backlog if negative) is measured by a piecewise continuous variable denoted $x_f(.)$. The dynamic of the serviceable stock is described by these equations

$$\frac{\partial x_f(t)}{\partial t} = -d,\ x_f(0) = x_f,\ \forall t \in \left]\xi_k, \xi_{k+1}\right[,\ \forall k = 1,..,\infty \tag{20}$$

$$x_f\left(\xi_k^+\right) = x_f\left(\xi_k^-\right) + Ind\left\{Y_k \le c\right\}\left(Q - Y_k\right) + Ind\left\{Y_k > c\right\}\left(Q - X_k\right),\ \forall k = 1,..,\infty \tag{21}$$

where, $Ind\{.\}$ is an indicator function defined as follows: $Ind\{\Theta(.)\}=1$ if $\Theta(.)$ is true, and $Ind\{\Theta(.)\}=0$ if $\Theta(.)$ is false. Thus, this function is used in Eq. (21) to indicate whether the *k*th lot has been accepted (i.e., $Y_k \le c$) or not (i.e., $Y_k > c$).

From Eqs. (16), (19) and (21), one can see that the final serviceable stock is affected by two sources of disruption: the uncertainty in the duration of production runs due to the stochastic maintenance interventions, and the variability in the duration of quality control activities due to the uncertain decision on acceptance/rejection of lots produced. A surplus inventory S is used to protect the serviceable stock against stochastic variability and to mitigate the risk of shortage. According to the classical hedging point policy (HPP), the production rate u(.) should be set at its maximum level during the build-up of the buffer stock S, which shall be maintained by setting u(.) at the same level of the demand rate. In our context, some considerations should be included in the production-inventory control policy. First, the control of the surplus inventory should take into account the total amount of on-hand lots, including those under sampling and 100% inspection. Second, as the setup is a regular activity with a non-negligible delay, the loss in production during each setup should be systemically recovered in the subsequent production run. Otherwise, the surplus inventory S will be prematurely

depleted. Third, for practical purposes, we consider some restrictions on the variation of the production rate during each production run. In fact, the classical HPP assumes that there is an infinite surplus of raw material that allows the instantaneous augmentation of the production rate. In the case of unreliable supply systems, the production controllers are more concerned with the availability of the raw material (Hajji et al., 2011b). In order to reduce the effects of the speed variation of operations on the upstream supply chain, we assume that the production rate setting is determined only at the beginning of each production run $[\theta_k, \delta_k[$, k= 1,2,..,∞.

Thus, by dividing the production-planning horizon into consecutive periods $\{[\theta_k, \theta_{k+1}[, k= 1,2,..,\infty\}$, we suggest the following production-inventory control policy:

$$u\left(t \in \left[\theta_k, \theta_{k+1}\right[, x, \alpha\right) = \begin{cases} u_{\max} & \text{if } \left\{x(\theta_k) < S \text{ or } \Gamma^k(t) = 1\right\} \text{and} \left\{\alpha(t) = 1\right\} \text{and} \left\{t \in \left[\theta_k, \delta_k\right]\right\} \\ \dfrac{d}{1 - \tau_{set} \cdot d/Q} & \text{if } \left\{x(\theta_k) = S\right\} \text{and} \left\{\alpha(t) = 1\right\} \text{and} \left\{t \in \left[\theta_k, \delta_k\right]\right\} \\ 0 & \text{if } \left\{\alpha(t) \in \{0,2,3\}\right\} \text{or } \left\{t \in \left]\delta_k, \theta_{k+1}\right[\right\} \end{cases} \quad (22)$$
$$k=1,2,..,\infty$$

where $x(.)$ is called the inventory position, and is calculated instantly as follows:

$$x(t) = x_q(t) + x_f(t), \forall t \geq 0 \quad (23)$$

and, $\Gamma^k(t)$ is a binary function with 1 if a maintenance (CM or overhaul) occurs in $[\theta_k, t[$, and 0 if not. In fact, if the inventory position $x(.)$ at the beginning of each new kth production run is strictly below the threshold S, then the corresponding kth lot is manufactured at the maximum production rate u_{max}. Otherwise, if the inventory position $x(.)$ is exactly equal to the threshold S, then the production rate of the kth lot is set to an adjusted-demand rate $d/(1- \tau_{set} \cdot d/Q)$. This adjustment is required to compensate for the loss in production during setups and to therefore maintain the surplus S. The production rate setting, either u_{max} or $d/(1- \tau_{set} \cdot d/Q)$, is preserved until the end of the production run. However, if a maintenance occurs during the production run, the production is immediately stopped (i.e., $u(.)=0$) and, once it is completed ($\Gamma^k(t) = 1$), the production is resumed at the maximum production rate u_{max}. Finally, the production rate is reset to 0 once the production run is completed and during setups (i.e., $\delta_k < t < \theta_{k+1}$).

5.3.2.3 Maintenance Policy

Once the surplus inventory S is built by setting the production rate at the maximum level u_{max}, it must be maintained through two mechanisms. First, the production rate has to be set at the

adjusted-demand rate $d/(1- \tau_{set} \cdot d/Q)$ as previously explained. Second, the setup activities should be controlled such that the inventory position is equal to the threshold S before starting a new production run. This means that the setup should be started before the inventory position is depleted to $S+\tau_{set} \cdot d$, where $\tau_{set} \cdot d$ is the amount of inventory consumed during the setup. Let $\Pi_k(t,x,\alpha)$ denote a binary function with 1 if the kth setup (including the PM) has to be carried out at time t, and 0 if not. Thus, the setup control policy is given by:

$$\Pi_k\left(t, x(t), \alpha(t)\right) = \begin{cases} 1 & \text{if } \left\{x(t) \le S + \tau_{set} \cdot d\right\} \text{and} \left\{t \ge \delta_{k-1}\right\} \text{and} \left\{\alpha(t) = 1\right\} \\ 0 & \text{Otherwise} \end{cases}, \; k = 1,..,\infty \tag{24}$$

From Eq. (24), a new kth setup is executed only when the following three conditions are satisfied: the inventory position is equal to or less than $S+\tau_{set} \cdot d$, the previous production run is finished (i.e., $t \ge \delta_{k-1}$), and the production unit is available (i.e., $\alpha(t)=1$).

On the other hand, the overhaul is carried out when the 100% inspection of a kth lot is rejected (i.e., $Y_k>c$) results in a rejection rate equal to or greater than the threshold r. Let $\Omega_k(.)$ denote a binary function with 1 if an overhaul has to be performed based on the proportion of defectives in the kth lot produced, and 0 if not. Then, the overhaul control policy is represented by the following equation:

$$\Omega_k\left(n, c, Q, X_k(.)\right) = \begin{cases} 1 & \text{if } \left\{Y_k > c\right\} \text{and} \left\{\dfrac{X_k}{Q} \ge r\right\} \\ 0 & \text{Otherwise} \end{cases}, \; k = 1,..,\infty \tag{25}$$

Although the overhaul decision is made based only on the quality of rejected lots, the relevance of this policy in recognizing the real state of the production process quality and whether to react accordingly by undertaking (or not undertaking) the overhaul lies in the fact that the frequency of rejection of lots produced in itself reflects the degree of quality deterioration. Indeed, one of the intrinsic characteristic of sampling plans is that the probability of rejection $1-P_a^k$, k=1,2,..,∞, increases systematically as the quality deteriorates.

Figure 5.2 depicts the deterioration of process quality with respect to the effective age $a(.)$, and its impacts on the quality of lots produced and the probability of rejection, as described by Eqs. (6), (7) and (9). In practice, regardless of the values of the sampling parameters n and c, the quality deterioration generates an increasing number of lots rejected, which improves the

availability of information about the rate of defectives, and therefore increases the visibility on the process condition.

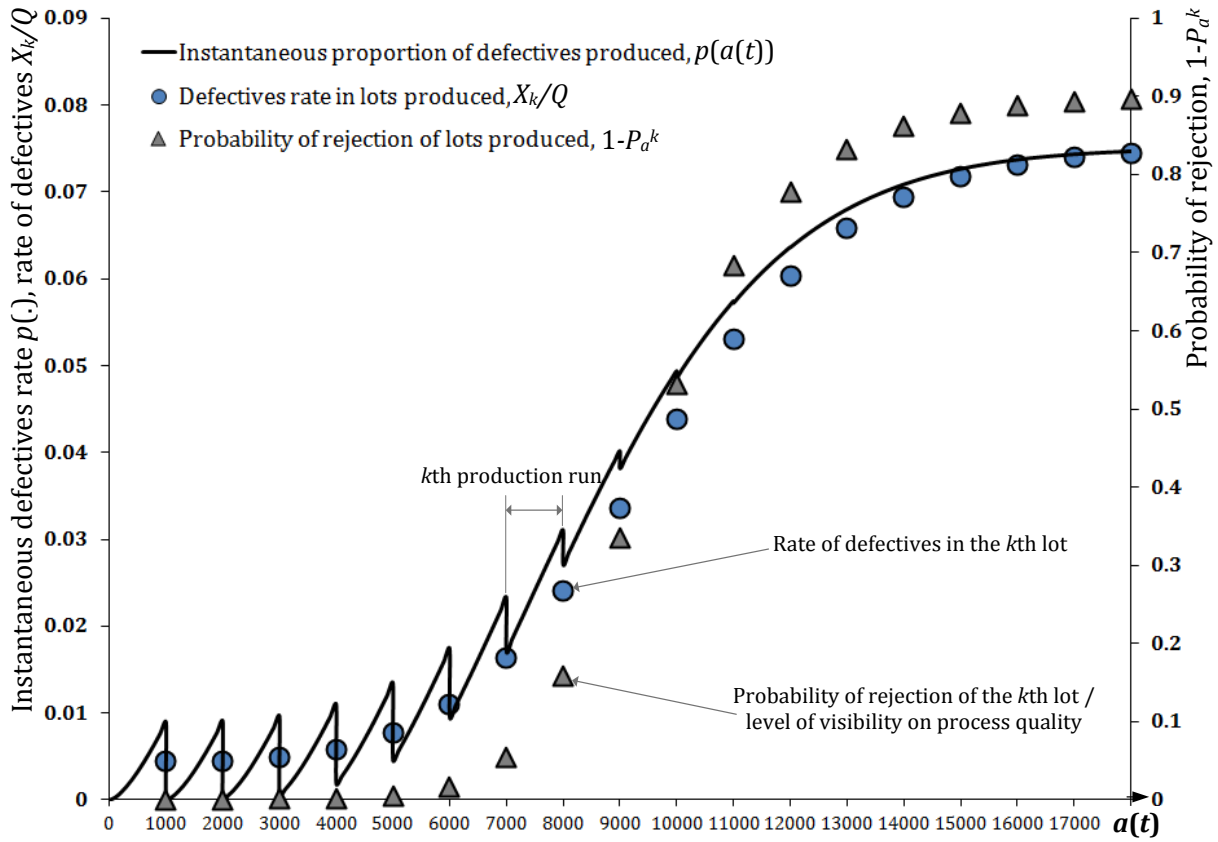


Figure 5-2: Impacts of process usage-deterioration on the quality of lots produced and on the probability of rejection.

5.3.3 Optimization problem

From the above mathematical formulation, many complex interactions between production, inventory, quality and maintenance have been highlighted. For example, the quality deterioration is influenced by the production run length and the production rate, which depend respectively on the production lot size Q and the surplus threshold S, as shown in Eqs. (2), (6), (16), (7) and (22). The production lot size Q also impacts the frequency of the PM, which partially improves the process performance, as in Eq. (3). The overhaul decisions are affected by the design of the sampling plan (n, c), as explained in Section 5.3.2.3. The outgoing quality depends on the production lot size Q, on the quality deterioration state and on the sampling plan (n, c), as shown in Eq. (10). Hence, a trade-off solution resulting from a joint optimization

approach can take into consideration all these interactions, and accordingly increases the overall performance of the manufacturing system. Indeed, our aim is to jointly determine the optimal values of the production lot size Q, the inventory threshold S, the sampling plan parameters c and n and the overhaul threshold r, which minimize the expected total cost per unit time, $ETC(.)$ and at the same time satisfy the $AOQL$ constraint (i.e., Inequality (13)). The ETC consists of the sum of the inventory holding and backlog costs, the costs related to quality, the setup cost, and the maintenance costs.

Let $G(t)$ denote the total cost of inventory holding and backlog in the period $[0,t]$. $G(t)$ is given at any time t by

$$G(t) = \int_0^t \left(C_h \left(q(z) + x_q(z) + x_f^+(z) \right) + C_b x_f^-(z) \right) \cdot dz \tag{26}$$

where $x_f^+(t) = \max\left(x(t), 0\right)$ and $x_f^-(t) = \max\left(-x(t), 0\right)$.

The expected quality cost $Q(t)$ in the period $[0,t]$ includes the sampling cost, the 100% inspection cost of rejected lots, the cost of rejected items and the cost of accepting/selling the non-inspected defective items as follows:

$$\begin{aligned} Q(t) = {} & C_{ins}\, n N(t) && \text{(sampling cost)} \\ & + C_{ins} \sum_{k=1}^{N(t)} \left(1 - P_a^k\right)\left(Q - n\right) && \text{(100\% inspection cost)} \\ & + C_{rej} \sum_{k=1}^{N(t)} \left(1 - P_a^k\right) X_k && \text{(cost of rejected items)} \\ & + C_{def} \sum_{k=1}^{N(t)} \sum_{j=0}^{c} \Pr(Y_k = j)\left(X_k - j\right) && \text{(cost of accepting/selling defective items)} \end{aligned} \tag{27}$$

where $N(t)$ is the total number of lots produced in the period $[0,t]$. $N(t)$ can be calculated as follows: $N(t) = \dfrac{d \cdot t + x(t)}{Q}$ (28)

The expected maintenance cost $M(t)$ during the same period $[0,t]$ includes the costs for setup, CM and overhaul activities. It is given by

$$M(t) = C_{set}\, N(t) + C_{cm}\, f(t) + C_{ovr}\; m(t) \tag{29}$$

where $f(t)$ and $m(t)$ are respectively the expected numbers of CM and overhaul interventions in the period $[0, t]$. Thus, the $ETC(.)$ is obtained

$$ETC\left(Q,S,c,n,r\right)=\lim_{t\to+\infty}\frac{1}{t}\left(G(t)+Q(t)+M(t)\right) \tag{30}$$

The optimization problem is to solve the following mixed-integer, non-linear and stochastic model:

$$\begin{cases} \text{Minimize} \quad ETC\left(Q,S,c,n,r\right) \\ \text{Subject to} \quad y(c)\left(\dfrac{1}{n}-\dfrac{1}{Q}\right)\le AOQL_{\max}, & (AOQL \text{ constraint}) \\ \qquad \text{Eqs. (1)-(9)}, & (\text{dynamics of quality and reliability deteriorations}) \\ \qquad \text{Eqs. (14)-(21)}, & (\text{dynamics of inventories}) \\ \qquad \text{Eqs. (22)-(25)}, & (\text{production, setup and overhaul control policies}) \\ \qquad c<n<Q, \\ \qquad 0<r<1, \\ \qquad Q,\ S,\ c,\ n,\ r\ge 0; \quad Q,\ S,\ c,\ n: \text{integers} \end{cases}$$

Since it is extremely difficult to solve this problem either analytically or numerically, because of the complexity of the dynamic constraints (i.e., continuous-state equations with impulsive ‘jumps’, such as in Eqs. (1)-(3), (7), (15) and (17)-(21)), and given the difficulty of computing the inventory/backlog cost as in Eq. (26), and some probabilistic elements such as the quality and maintenance costs, as in Eqs. (27) and (29) respectively, the simulation-based optimization approaches are more suitable here for finding the optimal solution (Fu, 1994). Hence, using simulation as a powerful tool to imitate the dynamic and stochastic aspects of complex systems, it is possible to run the continuous-time variables instantly, to accurately calculate the expected levels of inventories and backlog, the amount of defectives produced, the number of lots rejected, and the number of overhaul and CM interventions, and to accordingly compute the *ETC*(.).

5.4 Resolution approach

5.4.1 Simulation-based optimization approach

Simulation-based optimization approaches consist in combining computer simulation with optimization techniques such as evolutionary algorithms, the Response Surface Methodology

and stochastic approximation algorithms to heuristically solve problems which are analytically and numerically intractable (Gosavi, 2003; Tekin and Sabuncuoglu, 2004). Computer simulation has been successfully and widely applied to various real-world manufacturing problems in order to provide practical and implementable solutions (Jahangirian et al., 2010). However, most of the existing simulation models in the literature are limited to discrete-event simulation (Jahangirian et al., 2010). In our study, we use a combined discrete-continuous simulation to model both discrete events and continuous variables, and to therefore solve the optimization problem formulated above (Berthaut et al., 2011; Assid et al., 2015a). We suggest the following optimization approach (Figure 5.3):

a. *Mathematical model*: Analytically formulate the problem as shown in Section 5.3. This provides an accurate modeling of the system dynamic as a function of its state, and the formulation of the optimization problem.

b. *Simulation model*: Transform the mathematical model into a discrete-continuous simulation model according to the following logic: the continuous-time equations (i.e., Eqs. (1), (2), (4)-(7), (14), (20) and (23)) are modelled and calculated instantly with C++ subroutines, and the difference equations which can also be called discrete-time equations (i.e., Eqs. (3), (8), (9), (15), (17)-(19), (21), (22), (24) and (25)), are transformed into discrete events using the SIMAN simulation language. Hence, for given values of the decision variables *Q*, *S*, *c*, *n* and *r*, the system performance and the costs incurred are obtained from simulation.

c. *Optimization*: Use an optimization algorithm to conduct experiments and to find the optimal values of the decision variables *Q*, *S*, *c*, *n* and *r* which minimize the *ETC* under the *AOQL* constraint (see Section 5.4.3).

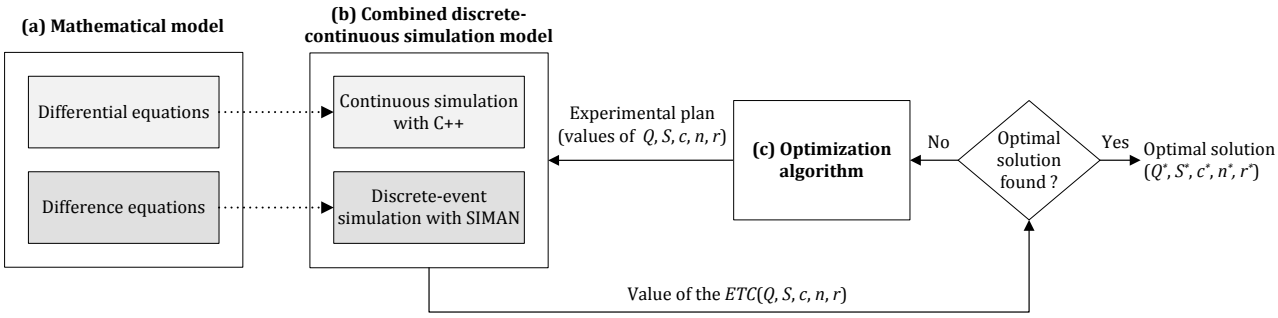


Figure 5-3: Simulation-based optimization procedure.

5.4.2 Simulation model

A combined discrete-continuous simulation model has been developed and executed through the *Arena Simulation* software. The discrete model imitates both the material flow and the logic of the integrated production, quality control and maintenance policy as described in Section 5.3. The differential equations, i.e. Eqs. (1), (2), (7), (14) and (20), are integrated continuously using the Runge–Kutta–Fehlberg method (Pegden et al., 1995; Cheney & Kincaid, 2013), while the remaining continuous-time equations are calculated instantly using the C++ mathematical functions and operators. Both discrete and continuous parts of the simulation model work synchronously to calculate the variations in the real age $A(.)$, the virtual age $a(.)$, the number of defectives X_k in each kth lot produced and the inventories $q(.)$, $x_q(.)$ and $x_f(.)$. Accordingly, the improvement factor $\phi(.)$, the probability of failure $F(.)$ and the proportion of defectives $p(.)$ are instantly updated in the C++ subroutines using Eqs. (4), (5) and (6), respectively. The surplus $x_f^+(.)$ and the backlog $x_f^-(.)$ are also instantly derived from the instantaneous level of the final inventory $x_f(.)$. The duration of simulation runs, t_∞, is set such as to ensure that the steady-state is reached. At the end of each simulation run, the total inventory/backlog cost $G(t_\infty)$, the quality cost $Q(t_\infty)$ and the maintenance cost $M(t_\infty)$ are calculated respectively using Eqs. (26), (27) and (29). The stochastic durations of the CM and overhaul are randomly generated following predefined probability distributions.

To check the accuracy of the simulation model, we used a set of verification and validation techniques such as tracing the model's operation, testing for reasonableness, model structure and data, and using the animation and debug features of *Arena Simulation* (Pegden et al., 1995; Law, 2008). For example, Figure 5.4 shows that the integrated production, quality control and maintenance policy operates properly as intended: Figures 5.4.(a), 5.4.(b) and 5.4.(c) confirm that the setup and production decisions are adequately controlled with respect to the inventory position $x(.)$ and the production unit state $\alpha(.)$, such as in Eqs. (22) and (24). Figures 5.4.(d), 5.4.(e) and 5.4.(f) depict, respectively, the impact of the production equipment usage on the deterioration of reliability, quality of lots produced and PM efficiency, as described in Eqs. (4)-(7). These Figures also show the effects of the overhaul interventions on the restoration of the production process to the initial conditions.

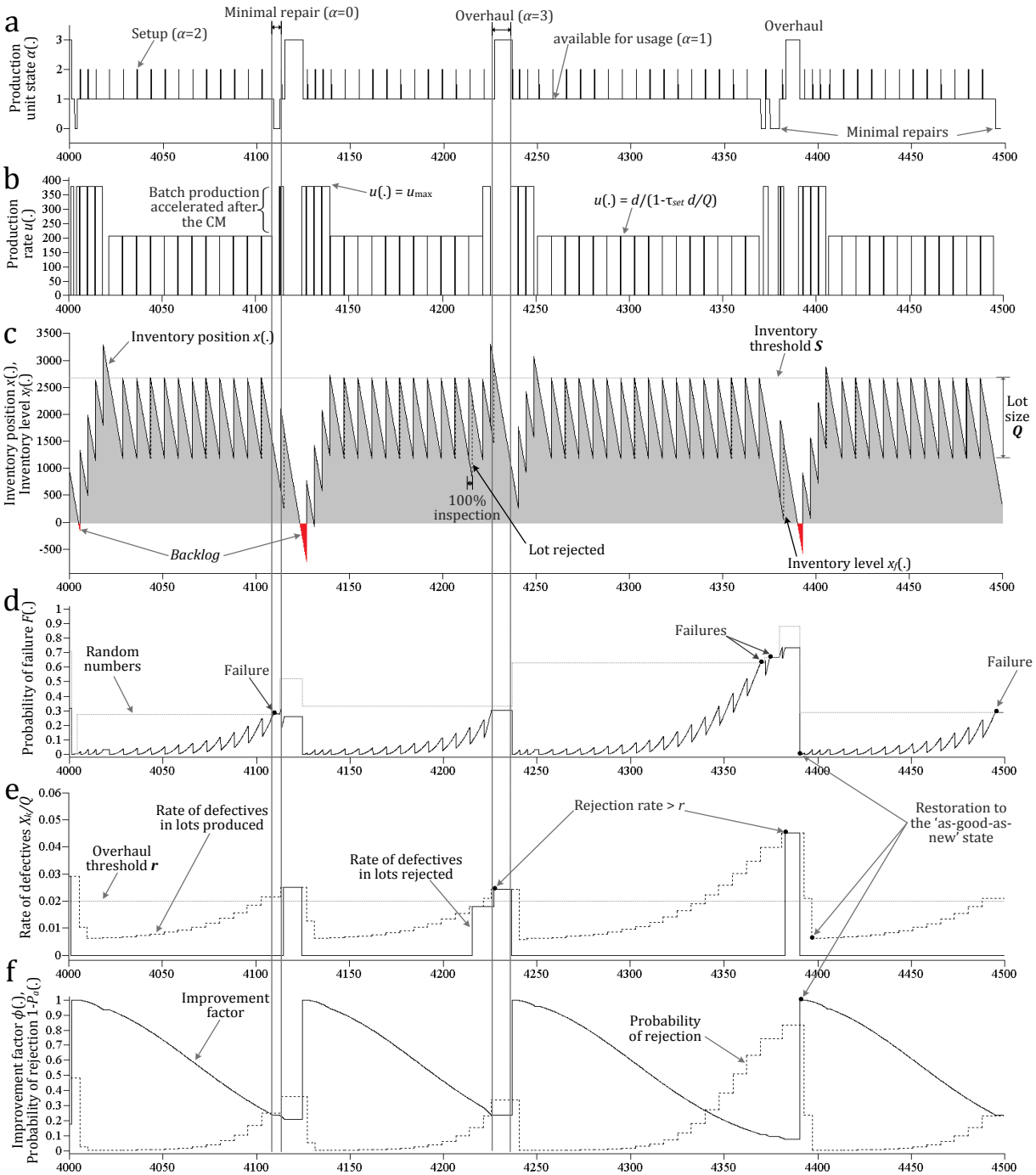


Figure 5-4: Evolution of production, inventory and operations performance during the simulation run.

Figure 5.4.(e) shows that the rate of defectives in lots produced, X_k/Q, k=1,..,∞, increases as the production progresses, and can exceed the threshold r. However, according to the overhaul control policy (i.e., Eq. (25)), if it is found that the defective rate in a rejected lot exceeds the

threshold r, then an overhaul is immediately undertaken as shown in Figure 4.4.(a). The quality deterioration implies an increase in the probability of rejection of lots produced, $1-P_a^k$, k=1,2,..,∞, as shown in Figure 5.4.(f). The impact of the 100% inspection of rejected lots on the inventory is clearly shown on the time lag between the inventory position x(.) and the serviceable inventory level x_f(.), as seen in Figure 5.4.(c).

5.4.3 Optimization algorithm

The optimization algorithm consists of a combination of an enumeration procedure with respect to the acceptance number c, a design of experiments (DOE), a statistical analysis and the Response Surface Methodology (RSM) to find a solution close to the global optimum. This algorithm can be summarized in the following steps:

Step 0. Set $c=0$.

Step 1. For a fixed acceptance number c, determine $\psi_c(.)$ a quadratic approximation function of the expected total cost $ETC_c(Q,S,n,r)$ using a combination of DOE, regression analysis and RSM (Myers et al., 2009). $\psi_c(.)$ is called the response surface and should take the following equation:

$$\begin{aligned}\psi_c(Q,S,n,r) = {} & \beta_0+\beta_1 Q+\beta_2 S+\beta_3 n+\beta_4 r+\beta_{12} QS+\beta_{13} Qn+\beta_{14} Qr+\beta_{23} Sn+\beta_{24} Sr+\beta_{34} nr \\ & +\beta_{11} Q^2+\beta_{22} S^2+\beta_{33} n^2+\beta_{44} r^2+\varepsilon\end{aligned} \tag{31}$$

where β_0, β_i, β_{ii} and β_{ij}, $(i, j) \in \{1,2,3,4\}$, are unknown parameters to be estimated from the collected simulation data, and ε is a random error.

Step 2. Find Q_c^*, S_c^*, n_c^* and r_c^* the optimal solution of the following non-linear constrained problem

$$\begin{cases} \text{Minimize} & \psi_c(Q,S,n,r) \\ \text{Subject to} & y(c)\left(\dfrac{1}{n}-\dfrac{1}{Q}\right) \le AOQL_{\max}, \\ & c<n<Q, \\ & 0<r<1,\ S\ge 0 \end{cases}$$

and calculate $\psi_c\left(Q_c^*, S_c^*, n_c^*, r_c^*\right)$. If $c=0$, then set $c=1$ and go to Step 1.

Step 3. If $\psi_c\left(Q_c^*, S_c^*, n_c^*, r_c^*\right) \le \psi_{c-1}\left(Q_{c-1}^*, S_{c-1}^*, n_{c-1}^*, r_{c-1}^*\right)$, then set $c = c+1$ and go to Step 1. Otherwise, find the optimal acceptance number c^* such that

$$\psi_{c-1}\left(Q_{c-1}^*, S_{c-1}^*, n_{c-1}^*, r_{c-1}^*\right) \ge \psi_c\left(Q_c^*, S_c^*, n_c^*, r_c^*\right) \le \psi_{c+1}\left(Q_{c+1}^*, S_{c+1}^*, n_{c+1}^*, r_{c+1}^*\right).$$

Thus, the optimal values of the production lot size, the surplus inventory, the sample size and the overhaul threshold are respectively Q_{c*}^*, S_{c*}^*, n_{c*}^* and r_{c*}^*.

The enumeration procedure is used since the acceptance number c is usually a very small discrete number which cannot be approximated by a continuous variable. In step 1, we check the fitness of the second-order regression model $\psi_c(.)$ in the local region of the optimal solution using three ways, such as in Myers et al. (2009). First, the model's overall performance is evaluated. This is referred to as the coefficient of multiple determination R-squared and the adjusted R-squared which represent the proportion of total variation explained by the regression model. The values of these two coefficients should be close to 1. Second, a complete residual analysis should be done to check the normality assumption and the homogeneity of residuals. Third, once the optimization is performed, the optimal solution is cross-checked to ensure the validity. In step 2, the minimization problem can be solved using non-linear constrained optimization techniques such as the penalty and barrier methods (Luenberger and Ye, 2008). It can also be solved using the MS-Excel Solver. In step 3, for practical implementation, the optimal values Q_{c*}^*, S_{c*}^* and n_{c*}^* should be rounded to the nearest integers.

5.5 Experimentation and analysis of results

5.5.1 Numerical example

A hypothetical example of the proposed model is provided for illustration. Let us consider the following parameters in the appropriate units: u_{max}=380, d=200, C_h=0.1, C_b=5, C_{set}=2500, C_{ovr}=30000, C_{cm}=7500, C_{ins}=2.5, C_{rej}=20, C_{def}=35, τ_{ins}=5×10^{-4}, τ_{set}=0.15, τ_{cm}~Log-Normal(3,1), τ_{ovr}~Gamma(1,9), λ_{set}= 5×10^{-10}, γ_{set}=2.55 , λ_r=8×10^{-10}, γ_r=2.4, λ_q=4×10^{-6}, γ_q=1.4, p_0=0.3%, η= 0.075 and $AOQL_{\max}$= 2.0%.

For each fixed acceptance number *c*, simulation runs are conducted according to a four-factor Box-Behnken experimental plan (27 runs) for each combination of factors *Q*, *S*, *n* and *r*. This type of design is suitable because of its rotatable feature and its efficiency in terms of number of required runs (Montgomery, 2008b). To adequately select the levels of the experimental design plan factors, we repeat the DOE, simulation and RSM, narrowing the domain of (*Q*, *S*, *n*, *r*) until it is centered about the optimum design point. Through this sequential procedure, the admissible experimentation region is fully explored, and therefore the solution obtained will be a global optimum. In order to ensure that the steady-state is reached, the duration of each simulation run t_∞ is set to 500,000 units of time (it takes on average of 2.5 seconds on a computer with a 2.80 GHz CPU).

Table 5.1: Optimum solutions with respect to the acceptance number *c*.

c	R^2-adj	n_c^*	Q_c^*	S_c^*	r_c^*	$\psi_c^*(.)$	$y(c)$	$AOQL$	$AOQ(\infty)$	$P_a(\infty)$	$\bar{f}(\infty)$	$\bar{m}(\infty)$	$Av(\infty)$
0	0.9701	57	1324	2933	2.990%	1 890.6 $	0.3679	0.62%	0.24%	0.375	0.0359	0.0217	0.807
1	0.9710	84	1341	2632	2.838%	1 839.2 $	0.84	0.94%	0.44%	0.645	0.0330	0.0213	0.814
2	0.9740	129	1411	2549	2.526%	1 791.4 $	1.371	0.97%	0.50%	0.712	0.0251	0.0229	0.818
3	0.9713	150	1474	2636	2.199%	1 723.2 $	1.942	1.16%	0.60%	0.758	0.0312	0.0224	0.811
4	**0.9740**	**157**	**1484**	**2631**	**1.996%**	**1 681.5 $**	**2.544**	**1.45%**	**0.74%**	**0.829**	**0.0333**	**0.0227**	**0.808**
5	0.9749	168	1451	2762	1.864%	1 696.1 $	3.168	1.67%	0.89%	0.842	0.0388	0.0219	0.797

Table 5.2: The ANOVA table for the total expected cost (c = 4).

Factor	SS	d.f.	MS	F-Ratio	P-value	Significant
Q (Linear + quadratic)	1094586	2	547292.9	12273.34	0.000000	Yes
S (Linear + quadratic)	1033646	2	516822.9	11590.04	0.000000	Yes
n (Linear + quadratic)	84681	2	42340.4	949.51	0.000000	Yes
r (Linear + quadratic)	31655	2	15827.4	354.94	0.000000	Yes
Q . S	297388	1	297387.6	6669.08	0.000000	Yes
Q . n	105329	1	105328.5	2362.05	0.000000	Yes
Q . r	379	1	379.3	8.51	0.014027	Yes
S . n	80598	1	80597.9	1807.45	0.000000	Yes
S . r	14366	1	14366.1	322.17	0.000000	Yes
n . r	1187	1	1186.9	26.62	0.000314	Yes
Error	73869	21	7337.8			
Total SS	2835513	35				R^2-Adjusted=0.97395

Table 5.1 presents the results obtained from the step-by-step application of the resolution approach procedure to the present numerical example. The adjusted R-squared for all acceptance numbers is greater than 97%. This means that about 97% of the observed variability in the $ETC_c(.)$ is explained by the second-order models $\psi_c(.)$. It should be mentioned here that the ANOVA of fitting models for all acceptance numbers showed that the linear and quadratic effects of the factors *Q*, *S*, *n* and *r* and their interactions are significant for the response variable at a 5% level of significance. For example, Table 5.2 shows the ANOVA of standardized effects for the Box-Behnken design when the acceptance number *c* is equal to 4.

For each combination of *c*, Q_c^*, S_c^*, n_c^* and r_c^* in Table 5.1, we used the simulation to calculate some performance measures, such as the long-term proportion of acceptance of lots produced denoted by $P_a(\infty)$, the long-term average outgoing quality denoted by $AOQ(\infty)$, the long-term frequency of overhauls denoted by $\bar{m}(\infty)$, the long-term frequency of CM denoted by $\bar{f}(\infty)$ and the long-term system availability denoted by $Av(\infty)$, using the formula in Appendix A. Thus, we see that the variation of the acceptance number *c*, which systematically affects the severity of the sampling plan (i.e., measured by $P_a(\infty)$), has very significant impacts on the remaining decision variables (i.e., optimal values of *Q*, *S*, *n* and *r*), on the optimal expected cost $\psi_c^*(.)$, on the frequency of failures $\bar{f}(\infty)$ and obviously on the outgoing quality $AOQ(\infty)$. This highlights the relevance of the acceptance number optimization in an integrated production, quality control and maintenance context. The optimal acceptance number c^* is 4 because it corresponds to the minimum expected total cost, which is \$1681.5. Using the statistical software STATISTICA the related second order cost function $\psi_4(.)$ is given by:

$$\begin{aligned}\psi_4(Q,S,n,r) = {} & 4908.37 - 277.62\times10^{-3}Q - 784.92\times10^{-3}S - 24.55\,n - 6.27\times10^{-3}r \\ & - 252.35\times10^{-6}QS - 6.59\times10^{-3}Qn + 3.99\times10^{-6}Qr + 3.92\times10^{-3}Sn - 1.14\times10^{-6}Sr \\ & - 8.83\times10^{-6}nr + 638.67\times10^{-6}Q^2 + 107.76\times10^{-6}S^2 + 77.11\times10^{-3}n^2 + 11.9\times10^{-8}r^2\end{aligned} \tag{32}$$

Figure 5.5 presents the projection of the cost response surface $\psi_4(.)$ on two-dimensional spaces. The region with gray-shaded contours in the (*n*, *Q*) two-dimensional space represents the set of the infeasible solutions, where the *AOQL* constraint is not satisfied. The minimum expected total cost, \$1681.5, is located at Q^* = 1484, S^* = 2631, n^* = 157 and r^* = 1.996%.

These values represent the best approximation of the optimal solution of the integrated (Q, S, c, n, r) policy which should be applied to jointly control the setup operations, the production rate, the outgoing quality and the overhaul interventions.

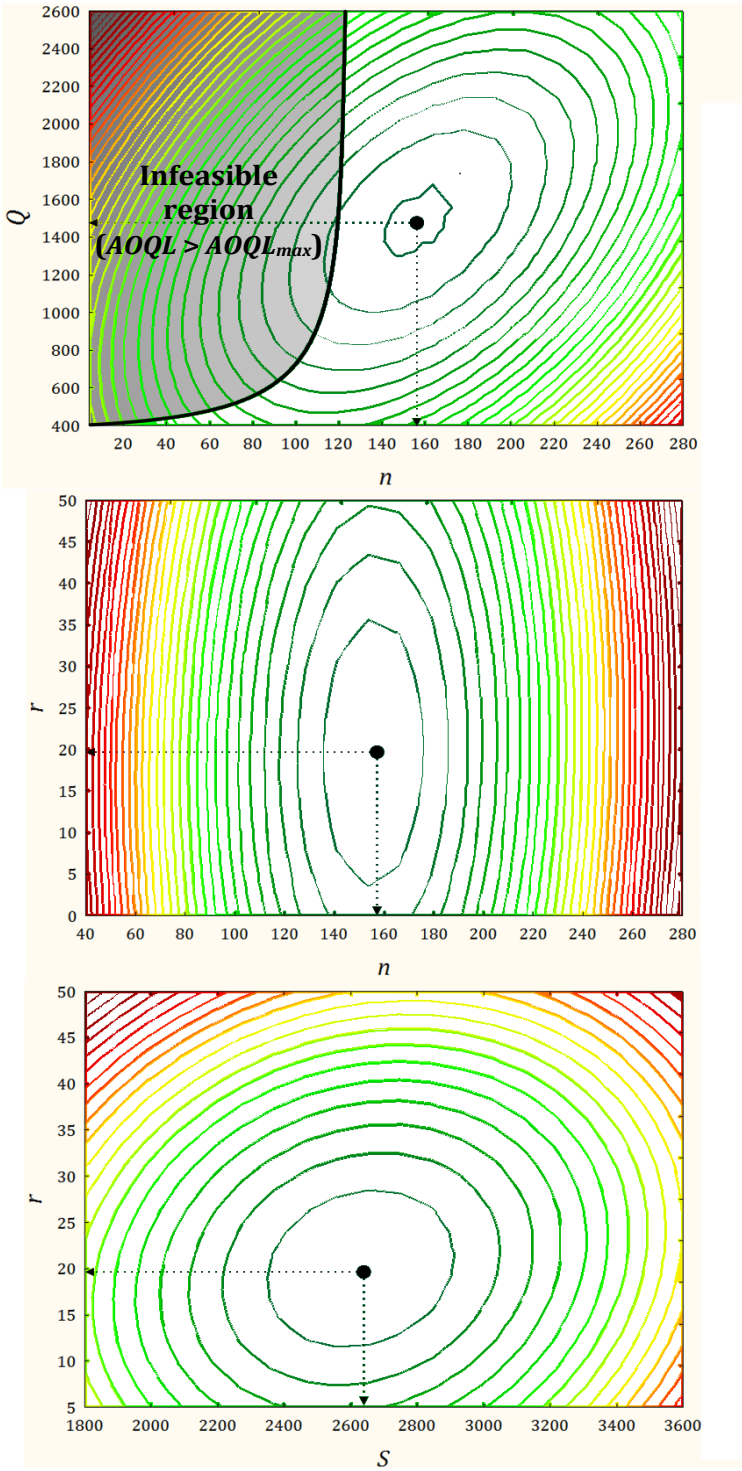


Figure 5-5: Contour plots of the estimated expected total cost $\psi_4(.)$.

From 20 replications of the simulation, we validated the solution by verifying that the estimated optimal cost $\psi_4^*(.) = \$1681.5$ is within the 95% Confidence Interval [$1675.7, $1682.4].

Also, from Table 5.1, we observe a high correlation (about -95%) between the optimal threshold r_c^* and the severity of the corresponding sampling plan measured by $P_a(\infty)$: the optimal overhaul threshold r_c^* decreases as the optimal sampling plan (c, n_c^*) becomes more and more reduced (i.e., $P_a(\infty)$ increases), and vice-versa. In fact, because a reduced inspection narrows the visibility on the process condition increasingly, and implies an increasing outgoing quality, r_c^* decreases gradually in order to maintain the frequency of the overhauls at an optimal level (about an average frequency of 0.0221). Such an observation illustrates how the overhaul control policy and sampling plan technique interact together to monitor the process deterioration (as discussed in Section 5.3.2.3).

5.5.2 Sensitivity analysis

Another set of experiments has been conducted to measure and analyse the sensitivity of the proposed integrated policy with respect to ranges of system parameters. The purpose of this analysis was to validate the simulation results and to study the reaction of the optimal solution in response to changes of model parameters (inputs). Table 5.3 presents twenty four configurations of system parameters derived from the basic case by significantly varying their values above and below one at a time. The results obtained make sense as expected and can be explained as follows:

• *Variation of the holding cost*: When the holding cost C_h increases (case 1), the optimal hedging threshold S^* decreases in order to reduce the global inventory cost. The optimal lot size Q^* decreases in order to reduce the WIP inventory in production and quality control centers. Because the 100% inspection delay decreases proportionally to the decrease in the lot size Q^*, the optimal sampling plan becomes tighter (as n^* increases and $P_a(\infty)$ decreases). However, a tightened plan involves an increasing cost of rejected items. For that reason, the optimal threshold r^* decreases in order to perform the overhaul interventions more frequently (i.e., $\bar{m}(\infty)$ increases). Note that the decrease in the inventory cost produces the opposite effects on the control variables (case 2).

• *Variation of the backlog cost*: When the backlog cost C_b increases (case 3), the optimal inventory surplus S^* increases in order to enhance the protection to the serviceable stock against shortages. Moreover, the optimal lot size Q^* decreases in order to reduce the production delay and therefore ensure a better supply to the final stock. In addition, the optimal sampling plan becomes slightly reduced (as n^* decreases) in order to reduce the quality control delay. The optimal threshold r^* decreases to maintain the outgoing quality at an acceptable level. Note that the decrease in the backlog cost has the opposite effects (case 4).

• *Variation of the setup cost*: When the setup cost C_{set} increases (case 5), the optimal lot size Q^* increases in order to reduce the total number of setup operations. As the production cycle and the 100% inspection both become longer proportionally to the increase in the lot size Q^*, the optimal inventory surplus S^* increases in order to provide better protection to the serviceable stock. Note that a bigger lot size reduces the effects of PM during setups, increases the quality deterioration rate, and therefore, contains more defective items. Thus, the optimal sampling plan becomes tighter (i.e., $P_a(\infty)$ decreases). In addition, the optimal threshold r^* decreases (so $\overline{m}(\infty)$ increases) to improve both the reliability and quality of the production process. Note that the decrease in the setup cost has the opposite effects (case 6).

• *Variation of the CM cost*: When the corrective maintenance cost C_{cm} increases (case 7), the optimal lot size Q^* and the optimal inventory threshold S^* both decrease in order to reduce the reliability deterioration rate. In fact, setting the inventory surplus S^* at a lower level restrains the usage of the production unit during the period of the surplus build-up, and therefore slows down the reliability detrioration. In addition, the optimal overhaul threshold r^* decreases in order to restore the production unit to the 'as-good-as-new' state more frequently, and accordingly reduces the probability of failure. Note that a decrease in the CM cost has the opposite effects (case 8).

• *Variation of the overhaul cost*: When the overhaul cost C_{ovr} increases (case 9), the optimal threshold r^* increases in order to reduce the number, and therefore the total cost, of the overhauls. The optimal sampling plan is reduced (as $P_a(\infty)$ increases) in order to lower the number of overhaul interventions based on the quality of rejected lots. As the reduction of the overhaul maintenance leads to motr frequent system breakdowns, the optimal inventory surplus S^* increases in order to improve the protection of the serviceable stock against shortages during

the CM operations. Note that the decrease in the overhaul cost produces the opposite effects (case 10).

• *Variation of the inspection cost*: When the inspection cost C_{insp} increases (case 11), the optimal sampling is reduced (as $P_a(\infty)$ increases) in order to minimize the cost of 100% inspection of lots rejected. In order to mitigate the risk of accepting a higher number of poor quality lots, more overhaul operations are required to improve the process quality, which explains the decrease in the optimal threshold r^*. The optimal inventory surplus S^* increases in order to meet the increasing shortage risk as the overhaul maintenance becomes more frequent. Note that a lower inspection cost produces the opposite effects (case 12).

• *Variation of the rejection cost*: When the rejection cost C_{rej} increases (case 13), the optimal overhaul threshold r^*decreases in order to improve the process quality and to accordingly reduce the number and the cost of rejected items. As the total rejection cost represents only a small portion of the total operating cost, the optimal lot size Q^* and the optimal inventory surplus S^* decrease slightly in order to reduce the quality deterioration rate. Moreover, the optimal sampling plan is further reduced (i.e., $P_a(\infty)$ increases) in order to diminish the number of rejected lots. Because a reduced inspection narrows the visibility on the process quality, the optimal threshold r^* decreases to maintain the frequency of overhaul maintenances at the same level. Note that the decrease in the rejection cost produces the opposite effects (case 14).

• *Variation of the cost of selling a defective item*: When the cost of selling a defective item C_{def} increases (case 15), the severity of the optimal sampling plan increases slightly (as $P_a(\infty)$ decreases) in order to improve the quality of lots produced. Accordingly, the optimal overhaul threshold r^* increases as the visibility on the process condition increases. The optimal inventory surplus S^* decreases slightly in order to reduce the quality deterioration rate. Note that a lower cost of a defective item sold has the opposite effects (case 16).

• *Variation of the inspection delay*: When the unit inspection delay τ_{insp} increases (case 17), the optimal inventory surplus S^* increases in order to provide additional protection to the serviceable stock against the increasing quality control delay. The optimal lot size Q^* decreases in order to reduce the 100% inspection delay. Although the optimal sampling plan becomes tightened, the long-term proportion of acceptance $P_a(\infty)$ increases due to the significant decrease in the optimal overhaul threshold r^*. In fact, the mechanism (c^*, n^*, r^*) reacts by

improving the process quality and reduces the full inspection operations of rejected lots accordingly. Note that a lower unit inspection delay leads to the opposite effects (case 18).

• *Variation of the quality deterioration rate*: When the quality deterioration rate increases (case 19), the optimal lot size Q^* decreases in order to perform the setup operations more frequently (i.e., imperfect PM). Moreover, the optimal sampling plan (c^*, n^*) and the optimal overhaul threshold r^* vary such that more lots produced are effectively rejected (i.e., $P_a(\infty)$ decreases significantly) in order to increase the full inspection activities and to improve the outgoing quality. The optimal inventory surplus S^* decreases in order reduce the usage-deterioration of the production unit during periods of buffer stock build-up. Note that the decrease in the quality deterioration rate produces the opposite effects (case 20).

• *Variation of the reliability deterioration rate*: When the reliability deterioration increases (case 21), the optimal threshold r^* decreases in order to carry out the overhauls more frequently. In addition, the optimal lot size Q^* decreases in order to increase the setup activities and to reduce the degradation rate between setups. The increase in the maintenance activities improves the process quality, which explains the increase in the long-term proportion of acceptance $P_a(\infty)$, whereas these activities reduce the production unit availability $Av(\infty)$. As a result, the optimal inventory surplus S^* increases in order to mitigate the high risk of shortage during periods of system unavailability. Note that a lower reliability deterioration rate has the opposite effects (case 22).

• *Variation of the PM efficiency*: The decrease in the improvement factor $\phi(.)$ intensifies both the process quality and reliability deteriorations (case 23). The optimal lot size Q^* decreases in order to reduce the production unit aging between setups, which also implies an increase in the number of the setups to therefore slow down deterioration of the efficiency of the PM. The optimal settings of the sampling plan and the overhaul threshold lead to an increase in the 100% inspection operations (i.e., the long-term proportion of acceptance $P_a(\infty)$ decreases), in order to cope with the increasing number of defectives produced. As the increasing number of failures reduces the production unit availability $Av(\infty)$, the optimal inventory surplus increases in order to ensure better protection to the serviceable stock against shortages. Note that the increase in the PM efficiency produces the opposite effects (case 24).

Table 5.3: Sensitivity analysis for model parameters.

Case Number	Parameter	Variation	Policy I (with acceptance sampling plan)												Policy II (with 100% inspection)				Δ-Cost
			c^*	n^*	Q^*	S^*	r^*	$\psi^*_{c^*}(.)$	$AOQL$	$AOQ(\infty)$	$P_a(\infty)$	$\bar{f}(\infty)$	$\bar{m}(\infty)$	$Av(\infty)$	Q^*	S^*	r^*	$\psi^*_{100\%}(.)$	
basic	**-**	**-**	**4**	**157**	**1485**	**2631**	**1.996%**	**1 681.5 $**	**1.45%**	**0.74%**	**0.829**	**0.0333**	**0.0227**	**0.808**	**1573**	**3374**	**2.022%**	**2 116.7 $**	**-20.6%**
1	C_h	+50%	4	168	1451	2161	1.828%	1 798.9 $	1.34%	0.69%	0.821	0.0291	0.0234	0.809	1523	2870	1.766%	2 262.5 $	-20.5%
2		-50%	4	147	1518	3085	2.143%	1 551.3 $	1.56%	0.79%	0.834	0.0377	0.0223	0.803	1625	3897	2.268%	1 946.2 $	-20.3%
3	C_b	+50%	4	153	1418	2812	1.967%	1 768.3 $	1.48%	0.75%	0.831	0.0346	0.0219	0.809	1563	3595	1.937%	2 189.3 $	-19.2%
4		-50%	4	162	1561	2155	2.085%	1 608.0 $	1.41%	0.73%	0.813	0.0333	0.0227	0.805	1589	2776	2.140%	2 051.5 $	-21.6%
5	C_{set}	+50%	4	160	1605	2706	1.833%	1 825.9 $	1.43%	0.74%	0.802	0.0362	0.0228	0.802	1677	3453	1.980%	2 252.4 $	-18.9%
6		-50%	5	156	1004	2286	2.752%	1 498.9 $	1.72%	0.80%	0.880	0.0329	0.0204	0.818	1231	3114	2.144%	1 953.9 $	-23.3%
7	C_{cm}	+50%	4	159	1449	2565	1.859%	1 777.9 $	1.42%	0.73%	0.822	0.0318	0.0229	0.809	1548	3155	1.390%	2 188.3 $	-18.8%
8		-50%	5	151	1522	2963	2.043%	1 629.9 $	1.89%	0.93%	0.859	0.0464	0.0212	0.794	1622	3770	2.970%	2 027.4 $	-19.6%
9	C_{ovr}	+50%	5	165	1472	2983	2.631%	2 072.8 $	1.71%	0.84%	0.847	0.0433	0.0210	0.801	1530	3670	2.957%	2 483.4 $	-16.5%
10		-50%	3	164	1546	2380	0.805%	1 277.2 $	1.06%	0.58%	0.784	0.0227	0.0263	0.802	1652	2716	0.505%	1 631.8 $	-21.7%
11	C_{insp}	+50%	5	154	1451	2822	1.618%	1 777.4 $	1.84%	0.90%	0.868	0.0441	0.0253	0.798	1572	3368	2.006%	2 370.0 $	-25.0%
12		-50%	4	162	1503	2554	2.255%	1 589.1 $	1.40%	0.71%	0.792	0.0323	0.0218	0.808	1574	3381	2.037%	1 863.4 $	-14.7%
13	C_{rej}	+50%	4	155	1471	2613	1.897%	1 699.0 $	1.46%	0.75%	0.834	0.0333	0.0227	0.806	1565	3325	1.899%	2 142.7 $	-20.7%
14		-50%	4	159	1498	2648	2.106%	1 663.5 $	1.44%	0.73%	0.820	0.0334	0.0226	0.807	1581	3424	2.144%	2 089.8 $	-20.4%
15	C_{def}	+50%	4	158	1482	2614	2.031%	1 706.9 $	1.44%	0.74%	0.821	0.0325	0.0227	0.807	1573	3374	2.022%	2 116.7 $	-19.4%
16		-50%	4	155	1486	2651	1.963%	1 656.0 $	1.47%	0.75%	0.834	0.0332	0.0226	0.806	1573	3374	2.022%	2 116.7 $	-21.8%
17	τ_{insp}	+50%	3	166	1444	2859	1.497%	1 730.3 $	1.04%	0.70%	0.841	0.0235	0.0246	0.805	1475	3488	2.182%	2 193.7 $	-21.1%
18		-50%	4	151	1508	2488	2.062%	1 664.3 $	1.52%	0.67%	0.725	0.0351	0.0224	0.800	1632	3319	1.930%	2 023.3 $	-17.7%
19	γ_q	+15%	4	138	1325	2144	4.329%	1 813.0 $	1.65%	0.76%	0.703	0.0083	0.0294	0.809	1549	2790	1.201%	2 275.7 $	-20.3%
20		-15%	3	126	1640	3946	0.411%	1 572.8 $	1.42%	0.61%	0.969	0.0747	0.0176	0.747	1659	4779	3.319%	2 053.0 $	-23.4%
21	γ_r	+15%	2	134	651	3453	1.004%	2 659.2 $	0.81%	1.55%	0.924	0.0915	0.0318	0.625	900	4052	1.516%	3 065.4 $	-13.3%
22		-15%	7	198	1718	2258	2.628%	1 228.2 $	2.00%	0.59%	0.800	0.0015	0.0192	0.882	1801	2842	2.222%	1 799.6 $	-31.7%
23	γ_{set}	+15%	3	118	1277	3418	2.242%	2 243.1 $	1.49%	0.79%	0.773	0.0486	0.0327	0.719	1419	5670	2.931%	2 438.9 $	-8.0%
24		-15%	2	127	1629	2537	1.678%	1 162.1 $	1.00%	0.62%	0.841	0.0040	0.0093	0.937	1687	3293	1.723%	1 547.0 $	-24.9%

5.5.3 Influence of the AOQL constraint

Table 5.4 presents the optimal solutions of the integrated policy for different levels of the $AOQL_{max}$. For values of $AOQL_{max}$ from 0.1% to 1.45%, the *AOQL* constraint is active (i.e., $AOQL = AOQL_{max}$). However, for all values of $AOQL_{max} > 1.45\%$, the *AOQL* constraint is inactive as the optimal solution obtained at $AOQL_{max} = 1.45\%$ realizes the minimum possible cost (i.e., 1681.5 $) among all solutions obtained for all given acceptance numbers and $AOQL_{max}$ values. Thus, we see that the total expected cost increases as the $AOQL_{max}$ decreases (with $AOQL_{max} < 1.45\%$), while it remains the same for $AOQL_{max} > 1.45\%$. Moreover, faced with a decrease in the $AOQL_{max}$ level, the optimal solutions (Q^*,S^*,c^*,n^*,r^*) lead to an increase in the severity of the optimal sampling plan (i.e., as shown by the decreasing values of $P_a(\infty)$) and to an increase in the frequency of the overhauls (i.e., as shown by the increasing values of $\bar{m}(\infty)$) in order to improve the quality of lots produced (i.e., as also shown by the decreasing values of $AOQ(\infty)$) and to accordingly satisfy the *AOQL* constraint. When the optimal acceptance number c^* remains unchanged (e.g., cases when $AOQL_{max}$ takes values from 0.1% to 0.5%, and values greater than 1.25%), we notice that as the $AOQL_{max}$ decreases, the optimal sample size n^* increases to tighten the quality control, the optimal threshold r^* decreases in order to perform the overhauls more frequently, the optimal inventory threshold S^* decreases in order to reduce the usage of the production unit during periods of inventory surplus build-up and to consequently slow down the process quality deterioration, and finally the optimal lot size Q^* increases in order to reduce the setup activities as the overhauls, which are more efficient than the setups, become more frequent.

Table 5.4: Sensitivity analysis for the *AOQL* constraint.

$AOQL_{max}$	c^*	n^*	Q^*	S^*	r^*	$\psi^*_{c^*}(.)$	$AOQL$	$AOQ(\infty)$	$P_a(\infty)$	$\bar{f}(\infty)$	$\bar{m}(\infty)$	$Av(\infty)$	Δ-Cost
0.10%	0	294	1485	2024	1.945%	2 103.8 $	0.10%	0.01%	0.089	0.0108	0.0273	0.826	-0.6%
0.25%	0	134	1458	2481	2.303%	1 946.5 $	0.25%	0.06%	0.246	0.0212	0.0243	0.821	-8.0%
0.50%	0	70	1394	2841	2.610%	1 898.9 $	0.50%	0.19%	0.450	0.0215	0.0238	0.820	-10.3%
0.75%	2	162	1431	2117	2.425%	1 801.4 $	0.75%	0.38%	0.635	0.0227	0.0232	0.819	-14.9%
1.00%	3	172	1485	2246	2.182%	1 734.4 $	1.00%	0.52%	0.719	0.0276	0.0230	0.813	-18.1%
1.25%	4	179	1508	2262	1.852%	1 701.3 $	1.25%	0.66%	0.806	0.0280	0.0228	0.809	-19.6%
≥1.45%	4	157	1484	2631	1.996%	1 681.5 $	1.45%	0.74%	0.829	0.0333	0.0226	0.808	-20.6%

In addition, Table 5.4 shows that, for a highly restricted *AOQL* constraint (i.e., $AOQL_{max} \leq 0.5\%$), the zero-acceptance number sampling plans are more economical than the non-zero acceptance sampling plans, as the former provides a higher discriminatory power (Schilling and Neubauer, 2009). However, for a higher acceptable level of *AOQL* (e.g., $AOQL_{max} \geq 0.75\%$), non-zero acceptance number plans are more economical as they reduce the extra 100% inspection cost. For example, for an $AOQL_{max}$ = 2.0% (basic case), we observe in Table 5.1 that the optimal zero-acceptance number sampling plan (c=0, n_c^*=57) provides the best quality protection for the customer (i.e., with the lowest values of *AOQL* and $AOQ(\infty)$) but it is too costly for the manufacturer (i.e., 11.38% more costly than the optimal sampling plan (c^*=4, n_c^*=157)). These results are in line with previous findings in the literature, showing that the total inspection cost of zero acceptance sampling plans are generally significantly higher than non-zero acceptance sampling plans (Baker, 1988).

5.5.4 Comparative study

In this section, we compare the performance of the integrated (Q, S, c, n, r) policy, called Policy-I, with a similar integrated model proposed in the literature by Radhoui et al. (2009, 2010) and others, where the quality control consists of a 100% inspection of all lots produced instead of using the acceptance sampling plan techniques. In reality, the 100% inspection policy can be viewed as a special case of sampling inspection, where each lot produced is fully inspected during the sampling step (i.e., n=Q) and the acceptance number is set to zero. Thus, a simplified version of the optimization approach described in Section 5.4 can be used to find the optimal values of the lot size Q, the inventory surplus S and the overhaul threshold r for fixed parameters c=0 and n=Q (called Policy-II). Therefore, we used a combination of a three-factor Box-Behnken experimental plan for each combination of Q, S and r, a regression analysis and RSM to fit the total expected cost by a quadratic model denoted by $\psi_{100\%}(.)$. Using the same basic case data, the ANOVA of this model leads to an adjusted R-squared equal to 0.9766. In addition, the three design factors (including the linear and the quadratic effects) and their interactions are significant (P-value < 0.05). Thus, we get the following quadratic function:

$$\begin{aligned}\psi_{100\%}(Q,S,r) &= 3346.87 - 109.57\times10^{-2}Q - 16.25\times10^{-2}S - 93.06\times10^{-4}r - 11.45\times10^{-5}QS \\ &+589.65\times10^{-8}Qr - 452.01\times10^{-8}Sr + 433.23\times10^{-6}Q^2 + 64.32\times10^{-6}S^2 + 37.795\times10^{-8}r^2\end{aligned} \quad (33)$$

Minimizing the $\psi_{100\%}(.)$ function provides the following optimal solution: Q^* = 1573, S^* = 3374 and r^* = 2.022% and the corresponding expected total cost is $2116.7. Herein, Policy-I (with an acceptance sampling plan) is 20.6% more economical than Policy-II (with 100% inspection). Table 5.5 presents complementary performance measures obtained by simulation with the optimal solutions of both Policies I and II for the basic case. According to Policy-I, only 17.1% (i.e., 1-$P_a(\infty)$) of lots produced are fully inspected to economically meet the output quality requirement and to provide sufficient visibility on the process quality for the overhaul control system. Under this policy, the long-term average outgoing quality of all lots produced is 0.74%, while one lot could contain, on average, a maximum outgoing quality of 1.45%. On the other hand, Policy-II always ensures the delivery of defect-free products to customers through the 100% inspection of all lots produced (i.e., $AOQ(\infty)$=0). The significant gap between the costs of both policies is due to two factors. First, Policy-II generates extra quality control costs especially during periods when the process quality is perfect. Second, the 100% inspection operations (Policy-II) lead to extra holding costs due to the increase in the WIP in the Quality Control center, and the increase in the optimal inventory surplus S^* in the serviceable stock as the total quality control delay increases. From Table 5.5, the WIP inventory $E[x_q]$ under Policy-II is 4 times greater than the $E[x_q]$ under Policy-I. Similarly, the average positive inventory $E[x_f^+]$ in the serviceable stock under Policy-II is 1.5 times greater than the $E[x_f^+]$ under Policy-I. However, the average negative inventory $E[x_f^-]$ under Policy-I is much higher than the $E[x_f^-]$ under Policy-II. This is due to the increasing degree of uncertainty in Policy-I caused by the effects of the probabilistic acceptance/rejection decision of lots produced. Also from Table 5.5, we notice that the optimal lot size Q^* under Policy-I is smaller than that under Policy-II. In fact, smaller lots reduce the number of defectives transmitted to the serviceable stock and improve the visibility on the process quality as, discussed in Section 5.5.2.

Table 5.5: Comparison of the optimal control policies.

Policy	Optimal solution						Quality control			Inventory		
	c^*	n^*	Q^*	S^*	r^*	ETC^*	$AOQL$	$AOQ(\infty)$	$P_a(\infty)$	$E[x_q]$	$E[x_f^+]$	$E[x_f^-]$
Policy-I	4	157	1485	2631	1.996%	1 681.5 $	1.45%	0.74%	82.9%	39.0	1642.9	27.5
Policy-II	-	-	1573	3374	2.022%	2 116.7 $	0.0%	0.0%	0.0%	159.3	2482.9	0.6

Additional comparisons are also provided in Tables 5.3 and 5.4. For each configuration of the system parameters in those tables, we calculated the cost savings resulting from using the acceptance sampling plan rather than 100% inspection as follows:

$$\Delta\text{-}Cost(\%) = \frac{\psi^*_{c*}(.) - \psi^*_{100\%}(.)}{\psi^*_{100\%}(.)} \times 100 \tag{34}$$

For all configurations of model parameters presented in both Tables 5.3 and 5.4, Policy-I is always more economical than Policy-II. However, the level of savings *Δ-Cost* achieved under Policy-I depends on the system parameters settings. For example, the savings are much more significant for high inspection cost, as well as the process quality is improved by decelerating the quality deterioration such as increasing the efficiency and frequency of maintenance activities (setups and overhauls). The savings are negligible in situations where the maximum allowed *AOQL* is very low (e.g., $AOQL_{max} \leq 0.1\%$). In addition, all the results obtained in both Tables 5.3 and 5.4 confirm the observations mentioned above: the optimal inventory threshold S^* and the optimal lot size Q^* under Policy-I are always smaller than those under Policy-II.

5.6 Managerial implications

The integrated production, quality control and maintenance policy proposed in this paper can be implemented in batch processing manufacturing systems where both acceptance sampling techniques and dynamic production-inventory control are effective. For example, in the pharmaceutical industry, single acceptance sampling plans are used to reduce the delivery lead time of drugs which are safe and unique in the market and can improve the survival of some vulnerable patients. The cost of 100% inspections of a lot of such a drug is far greater than that for accepting a bad lot. This is because delayed treatment could result in a patient's death while in accepting the bad lot, the drug could still have some beneficial placebo effect on the patient (Yang and Carlin, 2001). Likewise, dynamic production-inventory control based on the concept of the Hedging Point Policy has various applications in the pharmaceutical industry, as reported in Assid et al. (2015). Other potential applications of the integrated control policy also include the military, electronic, semiconductor, paper pulp and food industries (Pearn and Wu, 2007; Anthony, 2004; Gonzalez and Palomo, 2003; Gershwin, 2000).

In order to facilitate the implementation of the proposed integrated control policy in practice, an implementation logic chart is presented in Figure 5.6 for the basic case (Section 5.5.1). It shows how the integrated decisions on setup, production rate setting, lots acceptance/rejection and overhaul should be made. Managerial implications for business practice relating to the integrated policy require full information about the state of the production unit and the inventory position. The manager should monitor the production quality by observing the defectives rate of batches rejected in sampling inspection and predictably make the decision on the overhaul intervention based on the quality of the latest batch rejected. In addition, the maintenance team should utilize the setup times as opportunities to perform PM actions. This should help industrials eliminate production stoppages for PM and overcome system scheduling complexity (Xia et al., 2015).

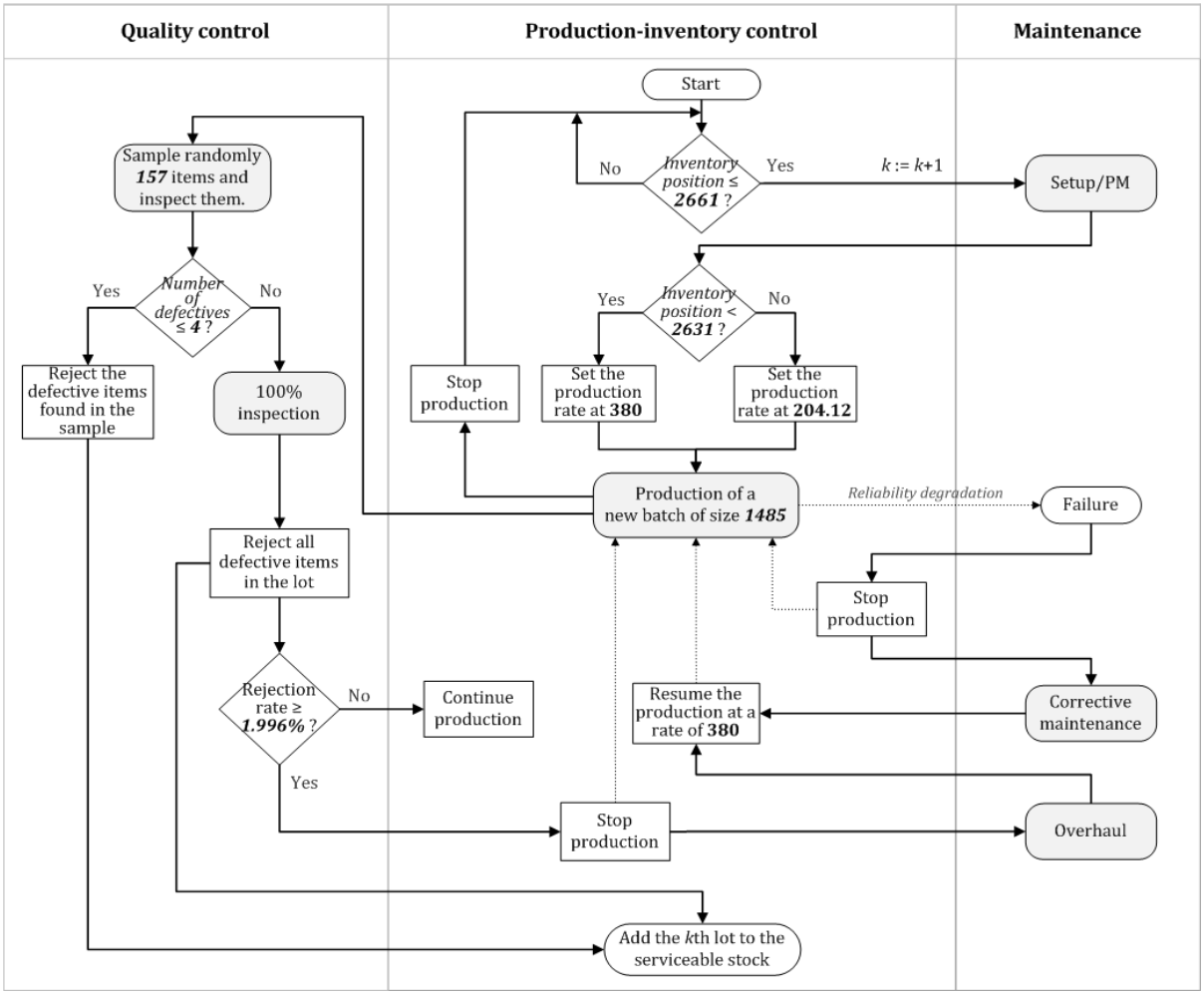


Figure 5-6: Implementation logic chart of the integrated control policy of production, quality and maintenance.

5.7 Conclusion

The joint design and optimization of production, PM and quality control using acceptance sampling plans have never been studied before in the literature. In this paper, we have proposed a new holistic approach to the joint optimization of the production lot size, the safety stock, the acceptance sampling plan and the overhaul scheduling, considering an outgoing quality constraint for degrading production systems. The suggested approach contributes to the research on integrated production, maintenance and quality control in three ways. First, in the context of correlated quality and reliability deteriorations, we investigated the intrinsic statistical characteristics of the single acceptance sampling plan in order to show the relevance of quality information resulting from such a quality control technique to support maintenance decision-making. Second, we provided a new modelling framework combining stochastic mathematical formulation and discrete-continuous simulation in order to model complex interactions between degradation phenomena, operations planning and settings, product quality and process reliability. Thus, this modelling framework can be employed to relax many unrealistic assumptions used in the literature, to overcome the limitations of classical resolution approaches and to solve such difficult optimization problems in manufacturing systems. Third, due to the fact that acceptance sampling plans adapt systemically the level of quality inspection with the degree of process deterioration, we showed experimentally that significant cost savings could be realized by using these plans rather than 100% inspection. At the practical level, operations managers should figure out from this study the strong and deep links that exist between production, maintenance and quality control (acceptance sampling plans). Practitioners should recognize that the capacity of satisfying the demand without back orders and the level of quality perceived by the final customers (i.e., outgoing quality) are the results of the complete operations settings of production, PM and quality control, and are not determined by only one of these three functions.

One limitation of our model is that we assume a single quality attribute deteriorating with age. Modern products are complex, with numerous quality attributes that can deteriorate at different rates. In such a situation, various quality control tests could be required. Moreover, separate AOQL could be defined for each test. Future research could be conducted to investigate the optimal sampling inspection and preventive maintenance settings for multi-attribute products. In addition, our study should stimulate further research on the interpretation and usefulness of

quality information feedback from acceptance sampling plans in integrated operations management and control. In fact, other sampling techniques such as multiple sampling plans and sampling plans by variables have specific inspection procedures and more particular statistical characteristics that should be extensively explored in order to integrate additional quality measures in managerial decision-making. Further research could be carried out to integrate the production, inventory and process reliability aspects in the design of acceptance sampling schemes. Sampling schemes are widely used in industry to adapt the inspection severity to variations of quality of lots produced. The switching rules procedures as described in MIL-STD-105E and ISO 2859-1 can be improved by including quality history, process reliability and inventory state in order to enhance responsiveness and adaptive control to deal with production process deterioration.

Appendix A - Formulas used to calculate the quality and availability performances

The long-term proportion of acceptance of lots produced, $P_a(\infty)$, is given by

$$P_a(\infty) = \frac{\sum_{k=1}^{N(t_\infty)} Ind\left\{Y_k \le c\right\}}{N(t_\infty)} \tag{A.1}$$

The calculation of the long-term average outgoing quality, $AOQ(\infty)$, is derived from Eq. (10) as follows

$$AOQ(\infty) = \frac{\sum_{k=1}^{N(t_\infty)} Ind\left\{Y_k \le c\right\}\cdot\left(X_k - Y_k\right)}{\sum_{k=1}^{N(t_\infty)} Ind\left\{Y_k \le c\right\}\cdot\left(Q - Y_k\right) + \sum_{k=1}^{N(t_\infty)} Ind\left\{Y_k > c\right\}\cdot\left(Q - X_k\right)} \tag{A.2}$$

The long-term frequencies of overhauls and CM, denoted respectively by $\bar{m}(\infty)$ and $\bar{f}(\infty)$, are determined as follows

$$\bar{m}(\infty) = \frac{1}{t_\infty}\cdot m(t_\infty) = \frac{1}{t_\infty}\cdot\sum_{k=1}^{N(t)} Ind\left\{Y_k > c\right\}\cdot Ind\left\{\frac{X_k}{Q} \ge r\right\} \tag{A.3}$$

$$\bar{f}(\infty) = \frac{1}{t_\infty}\cdot f(t_\infty) = \frac{1}{t_\infty}\cdot\sum Ind\left\{\alpha(t+\delta t) = 0 \mid \alpha(t) = 1\right\} \tag{A.4}$$

The long-term system availability $Av(\infty)$ is given by

$$Av(\infty) = 1 - \frac{N(t_\infty)\,\tau_{set} + \sum_{i=1}^{f(t_\infty)} \tilde{\tau}_{cm}^{i} + \sum_{j=1}^{m(t_\infty)} \tilde{\tau}_{ovr}^{j}}{t_\infty} \tag{A.5}$$

CHAPITRE 6 ARTICLE 3: JOINT ECONOMIC DESIGN OF PRODUCTION, CONTINUOUS SAMPLING INSPECTION AND PREVENTIVE MAINTENANCE OF A DETERIORATING PRODUCTION SYSTEM

Soumis pour publication dans

International Journal of Production Economics

Date de soumission : 10 Juin 2015

Date de réception des commentaires du comité de lecture : 6 Août 2015

Date de soumission de la version révisée: 2 Octobre 2015

Rédigé par:

Bassem BOUSLAH
Department of Mathematics and Industrial Engineering,
École Polytechnique de Montréal
{*bassem.bouslah@polymtl.ca*}

Ali GHARBI
Automated Production Engineering Department,
École de Technologie Supérieure
{*ali.gharbi@etsmtl.ca*}

Robert PELLERIN
Department of Mathematics and Industrial Engineering,
École Polytechnique de Montréal
{*robert.pellerin@polymtl.ca*}

Abstract

Standard continuous sampling procedures and tables are conventionally applicable only to continuous production processes that are statistically 'in-control'. Consequently, these standards cannot be used to control quality in deteriorating production processes. Moreover, existing continuous sampling models do not consider interactions with production, inventory and maintenance aspects. In this paper, we attempt to fill these gaps in the literature. We investigate the joint design and optimization of a type-1 continuous sampling plan (CSP-1), make-to-stock production and preventive maintenance of a stochastic production system subject to both quality and reliability deteriorations. Two models of CSP-1 are considered and compared: the classical CSP-1 as in the standard procedures, and a CSP-1 plan with a stopping rule that is combined with condition-based maintenance. For both models, the optimization problem is to minimize the total incurred cost under a constraint on the outgoing quality. A combination of mathematical formulation, simulation and optimization techniques is used to solve such stochastic and constrained problems. Numerical examples are given to illustrate the resolution approach and to highlight some interesting aspects in the interactions between production, inventory, quality, maintenance and reliability. The results obtained demonstrate that sampling inspection plans realize significant cost savings compared to the 100% inspection which is commonly used in the literature of integrated models, and that using the CSP-1 with an inspection stopping rule for deteriorating processes is more cost-effective than the classical CSP-1.

Keywords - Deteriorating process, production/inventory control, continuous sampling plan, inspection stopping rule, preventive maintenance, simulation optimization.

6.1 Introduction

The integration of production, maintenance and quality control has attracted much attention in the past three decades. Many integrated models have been proposed in the literature to study various interactions and intersections between the three fundamental functions. Examples of such models include the integration of production and preventive maintenance (PM) planning (see for example the literature review by Budai et al., 2008), the integration of production and quality control policies (see the literature review by Inman et al., 2013) and the combination of PM and Statistical Process Control (SPC) techniques (e.g., Ben-Daya and Rahim, 2000; Yeung et al.,

2007; Panagiotidou and Tagaras, 2010; Xiang, 2013; Yin et al., 2015). However, despite production, maintenance and quality control being strongly interrelated, the simultaneous integration of the three functions has received relatively very little attention in the literature (Hadidi et al., 2012).

Moreover, the quality control policies used in the existing integrated models are either 100% inspection of all items produced or control charts. Nevertheless, sampling inspection techniques have not yet been integrated simultaneously with production and PM policies. Acceptance sampling plans have been widely used in the industry for a long time to reduce the cost and time of quality inspection and to statistically control the outgoing quality (Montgomery, 2008a). In recent years, some authors have investigated the integration of acceptance sampling plans with production policies. For example, Bouslah et al. (2013, 2015) studied the interactions between the design of the lot-by-lot single sampling plan and the production-inventory settings for batch processing manufacturing systems. Also, Cao and Subramanian (2013) proposed an integrated quantity and quality model for performance analysis of manufacturing systems with continuous sampling plans.

Continuous sampling plans, which consist of alternating sequences of sampling inspection and 100% inspection, were initially introduced by Dodge (1943) to control the outgoing quality for *continuous production* systems. A continuous production system is a system that is dedicated to the production of a very narrow range of standardized products with high-volume sales (Blackstone, 2010). Thus, the setups are seldom changed, contrary to the batch production systems where setups are frequent (for these systems, lot-by-lot acceptance sampling plans are more suitable for quality control rather than the continuous sampling plans). To achieve standardization and low cost, the productive equipments use automation and complex technologies and they are organized and sequenced according to the routing of the jobs, which makes the material flow *continuous* during the production process as in transfer and assembly lines (Kim and Lee, 1993; Blackstone, 2010). In practice, continuous sampling plans have been popularly employed in various industrial sectors where continuous production systems are used such as in electronics, automobile, military and food industries (see Anthony, 2004; Antila et al., 2008; Oprime and Ganga, 2013). The design of the first generation of continuous sampling plans as in Dodge (1943) and in the military standard MIL-STD-1235 series are purely based on

quality criteria such as the Average Outgoing Quality Limit (AOQL), and completely neglect the economic impact of such designs.

The economic design of the type-I continuous sampling plan (CSP-1), which is the most popular continuous sampling plan used in industry, has attracted many researchers over the past two decades. Vander Wiel and Vardeman (1994) and Cassady et al. (2000) have formulated CSP-1 cost models to prove that, for a steady production process with a constant defective rate, the optimal inspection policy is either no inspection or 100% inspection. Haji and Haji (2004) have shown that the economic CSP-1 generally leads to either 100% inspection or random partial inspection depending on the quality costs and the fraction of defectives produced. Those models are merely based on economic considerations. Chen and Chou (2002, 2003) and Eleftheriou and Farmakis (2011) suggested various extensions of Cassady et al.'s model considering an Average Outgoing Quality Limit (AOQL) constraint. In the presence of the AOQL constraint, it is found that the CSP-1 is economically optimal.

All aforementioned CSP-1 design models are commonly based on the assumption of an 'in-control' production process which is capable to yield a stable product quality. This assumption is absolutely unrealistic for a wide range of manufacturing systems where the production process is subject to quality deterioration (Rivera-Gomez et al., 2013a). In addition, while several studies have shown the strong interdependencies between quality, maintenance and productivity (Ben-Daya and Duffuaa, 1995; Lee et al., 2007; Colledani and Tolio, 2009; Rotab Khan and Darrab, 2010), almost all of the existing CSP-1 models do not consider any interactions with production, inventory and maintenance aspects. An exception is Cao and Subramanian (2013), who provided an analytical framework to evaluate the effects of the CSP-1 design parameters on the Work-In-Progress (WIP) inventory and manufacturing throughput.

Furthermore, the continuous sampling plans provide a lot of useful quality information that could be exploited for process condition monitoring and maintenance-decision making. For example, according to the CSP-1 procedure, one can easily recognize that an excessive long sequence of 100% inspection exhibits a significant increase in the proportion of defectives produced (Schilling and Neubauer, 2009). Surprisingly, an interesting study related to this topic has not attracted much attention so far: Murphy (1959) suggested some criteria based on quality inspection data to determine when the manufacturing process must be stopped to correct the

process condition. These criteria have been called the inspection stopping rules for CSP-1 plans. In the literature, much effort has been devoted in recent years to integrating quality information from either 100% inspection or control chart techniques in the PM policies (e.g., Radhoui et al., 2010; Panagiotidou and Tagaras, 2010; Pan et al., 2012; Zhang et al., 2015). Nevertheless, unlike 100% inspection and control charts, the integration of the CSP-1 stopping rules in maintenance decision-making has not yet been studied in the literature.

This paper has four main objectives. The first is to develop a new joint economic design approach of production, continuous sampling inspection and PM policies for *continuous-flow* production systems subject to both quality and reliability deteriorations. This aims to jointly optimize the control parameters of those interrelated policies, in such a way to minimize the total operating cost while satisfying a predefined restriction on the AOQL. The second objective is to investigate how the proposed approach can properly extend the use of the continuous sampling plans to control quality of unstable and even deteriorating production processes (as the application of those plans are currently limited to stable processes). The third objective is to show how using CSP-1 plans rather than the 100% inspection policy, which is usually used in the literature to deal with deteriorating processes, can generate significant economic savings. Finally, the fourth objective is to demonstrate how additional cost savings can be achieved by using the CSP-1 with inspection stopping rules for deteriorating processes rather than the classical CSP-1. Advanced simulation techniques have been used to model, simulate, optimize and compare three integrated models associated with the three aforementioned inspection policies: 100% inspection, classical CSP-1 and CSP-1 with stopping rules. An extensive sensitivity analysis is also conducted to explore the effects of the system parameters on the optimal solutions and to illustrate the effectiveness of the proposed models.

This paper is organized as follows. Section 6.2 presents the notations used and the description of the problem being studied. In Section 6.3, we formulate the three integrated models. In Section 6.4, we present the resolution approach used to solve the three optimization problems. An illustrative numerical example is provided in Section 6.5. Sensitivity and comparative analyses are given in Section 6.6. Finally, Section 6.7 concludes the paper.

6.2 Problem statement

6.2.1 Notations

The notations used in this paper are defined as follows:

Decision variables:

s	Surplus inventory
m	PM period
i	Clearance number
f	Fraction of sampling
r	Inspection stopping threshold

Model parameters:

u_{max}	Maximum production rate
d	Demand rate
AOQL	Average Outgoing Quality Limit
τ_{pm}	Random variable denoting the preventive maintenance duration
τ_{cm}	Random variable denoting the corrective maintenance duration
τ_{insp}	Unit inspection duration
τ_{rect}	Unit rectification duration
C_h	Unit inventory holding cost per unit time
C_b	Unit backlog cost per unit time ($C_b >> C_h$)
C_{pm}	Preventive maintenance cost
C_{cm}	Corrective maintenance cost
C_{insp}	Unit inspection cost
C_{rect}	Unit rectification cost of a defective item
C_{def}	Unit cost of accepting/selling a defective item
$p(.)$	Proportion of defective items (function of cumulative production)
$F(.)$	Probability distribution of failure (function of cumulative production)

Other notations will be introduced where they are needed.

6.2.2 Problem description and assumptions

We consider a single-unit, *continuous-flow* production system subject to aging which leads to an increasing failure rate and an increasing proportion of defectives produced. Both reliability and quality deteriorations are operation-dependent. Failures are instantaneously detected and they are removed by corrective maintenance (CM) interventions with a random duration τ_{cm}. The productive unit is preventively maintained through time-based preventive maintenance (TBPM) actions of random duration τ_{pm}. Both stochastic durations τ_{cm} and τ_{pm} follow general distributions. The cost and duration of the PM activities are smaller than those of the CM, i.e., $C_{pm} < C_{cm}$ and $E[\tau_{pm}] < E[\tau_{cm}]$. We assume that both CM and PM restore the production unit to an 'as good as new' state. This assumption is reasonable in real-life for situations where maintenance interventions may include the replacement of key, failed and deteriorating components in the production unit.

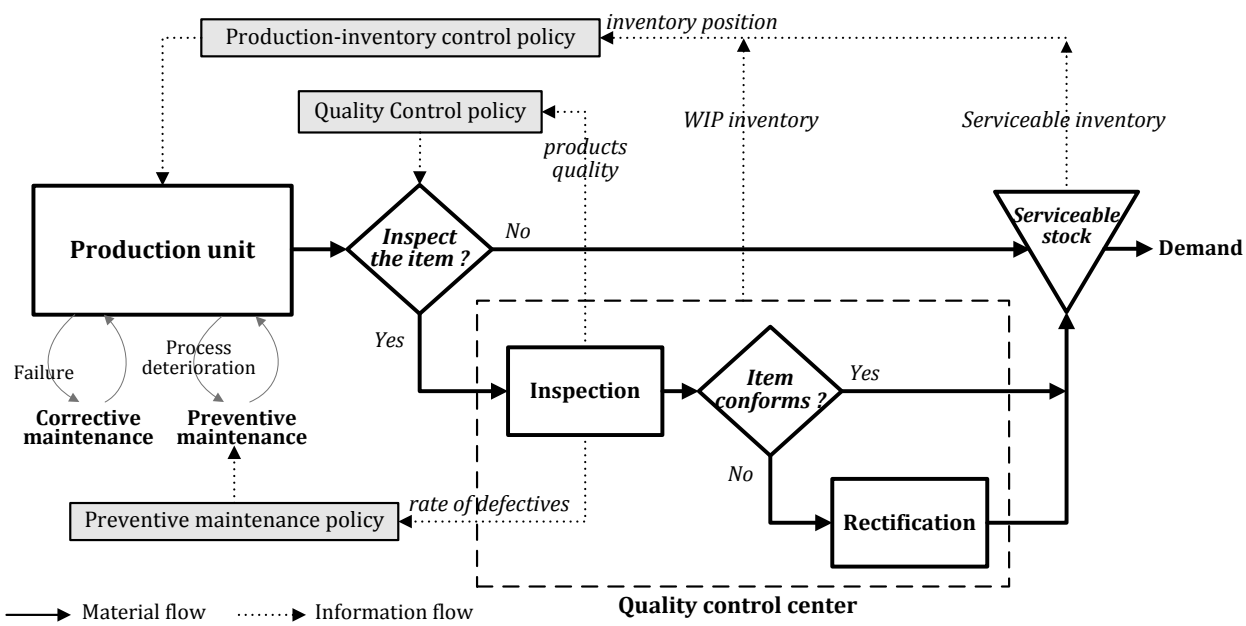


Figure 6-1. Manufacturing system under study.

The production unit supplies a serviceable downstream stock to meet a continuous and constant market demand *d*, as shown in Figure 6.1. As the quality of delivered products is a key factor in sustaining the market share, a quality inspection of the final products is necessary to meet the Average Outgoing Quality Limit (AOQL) requirement. Depending on the quality control policy used (100% inspection or sampling), an item produced may or may not be subject to quality inspection by attributes before being added to the serviceable stock. The defective items sorted

during quality inspection are perfectly rectified before they are transmitted to the final stock. We consider that the inspection and rectification delays are not negligible. Hence, the serviceable stock is affected by two sources of uncertainties: the stochastic maintenance durations, and the variability of quality control delay which mainly depends on the variation of the inspection frequency (in the case of continuous sampling plans).

The production rate $u(.)$ is flexible and can be set at any time at a value between 0 and a maximum level u_{max} ($u_{max} > d$). A make-to-stock production policy is used in order to avoid shortages during maintenance actions and to mitigate uncertainties in quality control. Herein, the well-known hedging point policy (HPP) is employed to control the production rate over time (Berthaut et al., 2010). The HPP consists in building a safety stock s after each production interruption by setting the production rate $u(.)$ at its maximum level u_{max}. Once built, the safety stock s shall be maintained by setting $u(.)$ at the level of the demand rate. Our choice of the hedging point method for production-inventory control is motivated by its optimality, simplicity and ease of implementation (Sarimveis et al., 2008).

Several models integrating the HPP and PM policies have been proposed in the literature. For example, Berthaut et al. (2010) studied the joint optimization of the HPP and periodic TBPM. Radhoui et al. (2009, 2010) integrated HPP with a PM policy that is based on the proportion of defectives found in lots produced. Rivera-Gomez et al. (2013a, 2013b) developed models integrating the HPP and age-based preventive maintenance for deteriorating production systems. In this study, the periodic TBPM policy is adopted because its ease of implementation in practice as it does not require keeping records on unit usage and age (Wang, 2002).

As a matter of fact, production, inventory, quality, maintenance and reliability closely interact and interrelate with each other, which influence the overall operational performance. Thus, these interactions and interdependencies should be taken into consideration when designing integrated models. For example, the acceleration of production during periods of safety stock build-up, which depends on the level of the safety stock setting, increases both quality and reliability deteriorations. Consequently, maintenance and quality inspection activities are increasingly required to cope with the effects of the production speed-up. However, excessive maintenance actions could have negative effects on the availability of the productive unit. A condition-based predictive maintenance (CBPM) strategy could be more appropriate for deteriorating processes to

enhance the planning and efficiency of the PM activities (Mann et al., 1995; Jardine et al., 2006). In a context of integrated operations management, a closed-loop maintenance policy can be employed based on the feedback of quality information such as monitoring the observable proportion of defectives captured in quality inspection (Colledani and Tolio, 2012). In the literature, maintenance based on feedback quality information is generally coupled with 100% inspection policy, as in Hsu and Kuo (1995) and Radhoui et al. (2009, 2010). Excessive quality control, such as the 100% inspection, increases the WIP inventory and the manufacturing lead time. In continuous-flow production systems, continuous sampling inspection plans represent an alternative quality control strategy to the 100% inspection. Continuous sampling plans can be used to significantly reduce the quality inspection efforts while satisfying the outgoing quality requirement. In order to study those complex interactions, and to compare the derived scenarios of integrated production, maintenance and quality control policies, we consider the following integrated models:

- Model A, integrating the 100% inspection plan, the HPP and a periodic TBPM policy;
- Model B, integrating the classical CSP-1 plan, the HPP and the TBPM policy used in Model A;
- Model C, integrating the CSP-1 plan with a stopping rule, the HPP and a combined TBPM and CBPM.

In this research, we aim to develop an optimization approach to find the optimal solution for each of the three integrated models, to appraise the performance of those models when optimal solutions are applied and to conduct a comparative analysis. The first purpose of the comparative analysis is to show how the sampling inspection policy could significantly improve the performance of the manufacturing system (i.e., models B and C versus Model A). The second purpose consists of investigating how the CSP-1 stopping rules can be used for condition monitoring of deteriorating processes in order to improve the overall operational performance (i.e., Model C versus Model B).

6.3 Problem formulation

The state of the production unit can be described at each instant t by two continuous-time components, including:

- A discrete-state stochastic process $\{\alpha(t), t\geq 0\}$ taking values $\{0,1,2\}$ such that: $\alpha(t) = 0$, if the production unit is under CM at time t; $\alpha(t) = 1$, if it is available for production, and $\alpha(t) = 2$, if it is under PM.
- A piecewise continuous variable $a(t)$ which represents the age of the productive unit at time t. This age is measured by the cumulative number of items produced at time t since the last maintenance (CM or PM, whichever occurs last). It is calculated using the following differential equation:

$$\frac{\partial a(t)}{\partial t} = u\left(t, \alpha(t)\right), \forall\ t \geq T,\ a(T) = 0 \qquad (1)$$

where $u(t,\alpha(t))$ is the production rate at time t, also denoted $u(t)$. T is the completion time of the last maintenance.

We consider that both the probability of failure $F(.)$ and the proportion of defectives produced $p(.)$ are continuous increasing functions of the age $a(.)$. In practice, these functions can be determined from real data using mathematical, numerical and statistical techniques, as shown by Meeker and Escobar (1998) and Lai and Xie (2006).

6.3.1 Model A (integrated 100% inspection, HPP and TBPM)

Quality Control Policy

Quality control consists of 100% inspection of all items produced, so that all defective items are sorted and rectified before being transmitted to the serviceable stock. This policy is widely used in the literature of integrated models for simplicity, as there is no quality control variable to be optimized herein. The 100% inspection policy ensures the delivery of defect-free products to consumers. However, it increases the WIP inventory and the costs of quality inspection and rectification.

Preventive Maintenance Policy

The productive unit is preventively maintained at fixed time intervals with a period m, irrespective of the unit's age.

Production-Inventory Control Policy

The so-called hedging point policy is used to instantly control the production rate $u(.)$ as follows:

$$u\left(t,\alpha(t)\right)=\begin{cases} u_{\max} & \text{if } \left\{x(t)<s\right\} \text{and} \left\{\alpha(t)=1\right\} \\ d & \text{if } \left\{x(t)=s\right\} \text{and} \left\{\alpha(t)=1\right\} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where, s is the safety stock, also called the hedging level, and $x(t)$ is the instantaneous inventory position, which is the sum of the serviceable inventory level $x_s(t)$ (inventory stock if positive and backlog if negative) and the WIP inventory in the quality center $x_q(t)$ (sum of items under inspection and rectification, see Figure 6.1). Under this production control policy, the dynamics of the inventories $x_s(t)$ and $x_q(t)$ can be described by the following equations:

$$\frac{\partial x_s(t)}{\partial t}=u\left(t\right)-\frac{\partial x_q(t)}{\partial t}-d \tag{3}$$

$$\frac{\partial x_q(t)}{\partial t}=u\left(t\right)-u\left(t-\tau_{insp}\right)\cdot\left(1-p\left(a\left(t-\tau_{insp}\right)\right)\right)-u\left(t-\tau_{insp}-\tau_{rect}\right)\cdot p\left(a\left(t-\tau_{insp}-\tau_{rect}\right)\right) \tag{4}$$

where, $u(t)\cdot\left(1-p\left(a(t)\right)\right)$ represents the effective production rate at time t, i.e., the number of conforming items produced in the time unit, and $u(t)\cdot p\left(a(t)\right)$ represents the defective production rate at time t, i.e., number of defective items produced in the time unit. Thus, $x_q(t)$ is the difference between the cumulative production and the cumulative quantities of products fully inspected and rectified up to time t. From Eq. (4), one can see the impact of quality control delays on inventory dynamic.

Optimization Problem

The optimization problem of Model A consists of finding the optimal values of the TBPM period m and the hedging level s, which minimize the expected total incurred cost per unit time (ETC). This cost includes the total quality cost, the inventory holding/backlog cost and the total maintenance cost.

The average quality cost per unit time $Q(t)$ during the interval [0, t] includes the costs of 100% inspection and rectification of defectives produced. It is given by:

$$Q(t)=\frac{1}{t}\cdot\left(C_{insp}\int_0^t u\left(z\right).dz+C_{rect}\int_0^t p\left(a(z)\right)\cdot u\left(z\right).dz\right) \tag{5}$$

The average cost per unit time of inventory holding and backlog $G(t)$ during [0, t] is given by:

$$G(t)=\frac{1}{t}\cdot\int_0^t\left(C_h\left(x_q(z)+x_s^+(z)\right)+C_b x_s^-(z)\right)\cdot dz \tag{6}$$

where $x_s^+(t)=\max\left(x_s(t),0\right)$ and $x_s^-(t)=\max\left(-x_s(t),0\right)$.

The average maintenance cost per unit time $M(t)$ during [0, t] includes the costs of both CM and PM actions as follows:

$$M(t)=\frac{C_{cm}\ N_{cm}(t)+C_{pm}\ N_{pm}(t)}{t} \tag{7}$$

where $N_{cm}(t)$ and $N_{pm}(t)$ are respectively the numbers of CM and PM during [0, t].

Therefore, the optimization problem is to solve the following non-linear and stochastic model:

$$\begin{cases} \text{Minimize} \quad ETC\left(s,m\right)=\lim\limits_{t\to\infty}\left(Q(t)+G(t)+M(t)\right) \\ \text{Subject to} \quad \text{Eqs. (1)-(4)} \\ \qquad\qquad\quad s,\ m>0 \end{cases}$$

6.3.2 Model B (integrated CSP-1, HPP, and TBPM)

Quality Control Policy

A CSP-1 plan is used for quality control rather than the 100% inspection policy. The procedure of the CSP-1 plan is as follows (Dodge, 1943):

Step 1: Inspect 100% of the items consecutively as produced and continue such inspection until i items in succession are found clear of defects. i is called the clearance number or clearing interval.

Step 2: When i successive items are found clear of defects, discontinue 100% inspection, and randomly inspect a fraction f of the products ($0 \le f \le 1$).

Step 3: If a sample item is found defective, revert immediately to the 100% inspection (Step 1).

All defective items found are rectified before they are added to the serviceable stock. However, the defectives that have been accepted during sampling inspection will be transmitted to consumers. The Average Outgoing Quality (AOQ) for given CSP-1 parameters i and f, and a

given proportion of defectives produced p can be estimated as follows (Schilling and Neubauer, 2009):

$$AOQ(i, f, p) = p\frac{(1-f)(1-p)^i}{f+(1-f)(1-p)^i} \tag{8}$$

The AOQL is the maximum level of AOQ over all possible values of p. Using Dodge's (1943) results, the AOQL is given by:

$$AOQL = \frac{(i+1)\,p_M - 1}{i} \tag{9}$$

where p_M is the proportion of defectives at which the AOQL occurs.

The manufacturer must select the clearance number i and the sampling fraction f such that the long-run AOQ, denoted AOQ_∞, does not exceed a specified AOQL. Then, from Eqs. (8) and (9), for given values of i and AOQL, the sampling fraction f must be greater than or equal to a minimum fraction f_{min} calculated as follows:

$$f_{\min}(i, AOQL) = \frac{\left(1-\frac{1+i\cdot AOQL}{i+1}\right)^{i+1}}{i\cdot AOQL+\left(1-\frac{1+i\cdot AOQL}{i+1}\right)^{i+1}} \tag{10}$$

Preventive Maintenance Policy

The PM policy is the same as in Policy A.

Production-Inventory Control Policy

The production-inventory control policy is the same as in Policy A. Consequently, the dynamic of the serviceable inventory x_s is also described by Eq. (3). However, the dynamic of the WIP inventory x_q is affected by the alternation of sampling and 100% inspection as follows:

$$\begin{aligned}\frac{\partial x_q(t)}{\partial t} = &\left(ind\{\Gamma(t)=1\}\cdot f + ind\{\Gamma(t)=2\}\right)\cdot u(t)\\ &-u\left(t-\tau_{insp}\right)\left(1-Y(t)\right)-u\left(t-\tau_{insp}-\tau_{rect}\right)\cdot Y\left(t-\tau_{rect}\right)\end{aligned} \tag{11}$$

where $\Gamma(t)$ describes the actual CSP-1 inspection mode at time t, as follows: $\Gamma(t)=1$, if the CSP-1 is in the sampling inspection mode, and $\Gamma(t)=2$, if the CSP-1 is in the 100% inspection

mode. *Ind*{.} is an indicator function defined as follows: *Ind*{Θ(.)}=1 if Θ(.) is true, and *Ind*{Θ(.)}=0 if Θ(.) is false. Thus, this function is used in Eq. (11) to indicate whether the CSP-1 is in the sampling inspection mode (i.e., $\Gamma(t)=1$) or not (i.e, $\Gamma(t)=2$). *Y*(*t*) is the proportion of defectives found in quality inspection (random sample of fraction *f* or 100% inspection) at time *t*. If $\Gamma\left(t-\tau_{insp}\right)=1$, then *Y*(*t*) is a random number described by the conditional distribution $P\left\{Y(t)\mid p\left(a\left(t-\tau_{insp}\right)\right)\right\}$ with an expected mean equal to $f\cdot p\left(a\left(t-\tau_{insp}\right)\right)$. Otherwise, if $\Gamma\left(t-\tau_{insp}\right)=2$, *Y*(*t*) is exactly equal to $p\left(a\left(t-\tau_{insp}\right)\right)$ as in Eq. (4).

Optimization Problem

The decision variables of Model B are the CSP-1 parameters *i* and *f*, the hedging level *s* and the TBPM period *m*. The objective is to minimize the excepted total incurred cost while meeting the AOQL requirement. The average inventory holding/backlog cost *G*(*t*) and the average total maintenance cost *M*(*t*) during [0, *t*] are calculated respectively using Eqs. (6) and (7) as in Model A. Herein, the average quality cost *Q*(*t*) in the period [0, *t*] includes the cost of 100% inspection, the cost of rectification and the cost of accepting/selling defective items. *Q*(*t*) is given by:

$$Q(t)=\frac{1}{t}\cdot\left(\begin{array}{l} C_{insp}\int_0^t\left(ind\left\{\Gamma(z)=1\right\}\cdot f+ind\left\{\Gamma(z)=2\right\}\right)\cdot u(z).dz+ \\ C_{rect}\int_0^t Y\left(z+\tau_{insp}\right)\cdot u(z).dz+C_{def}\int_0^t\left(p\left(a(z)\right)-Y\left(z+\tau_{insp}\right)\right)\cdot u(z).dz \end{array}\right) \tag{12}$$

Hence, the optimization problem is to solve the following mixed-integer, non-linear and stochastic model:

$$\begin{cases} \text{Minimize} & ETC(s,m,i,f)=\lim_{t\to\infty}\left(Q(t)+G(t)+M(t)\right) \\ \text{Subject to} & \text{Eqs. (1)-(3), (11)} \\ & f_{\min}\left(i,AOQL\right)\le f\le 1 \\ & s,\ m,\ i\ \ge 0\ ;\quad i:\text{integer} \end{cases}$$

6.3.3 Model C (integrated CSP-1 with a stopping rule, HPP and combined TBPM/CBPM)

Quality Control Policy

A CSP-1 plan is basically employed for quality control as in Model B. However, a stopping rule is incorporated into the CSP-1 procedure in order to avoid wasted labour and resources in situations of excessive, long 100% inspection sequences. This involves shutting down production in order to restore the process condition, as soon as the proportion of defectives in any one 100% inspection sequence reaches or exceeds a given threshold r ($0 < r < 1$). Note that the problem of long 100% inspection sequences is often observed in deteriorating processes, overmuch occurs than in stable processes. This is because the probability that the CSP-1 will shift again from 100% inspection to the sampling inspection decreases as quality deteriorates with production unit usage.

Preventive Maintenance Policy

The feedback information from the quality inspection that has been incorporated into the CSP-1 plan as an inspection stopping rule should be also integrated in the PM strategy. Thus, we suggest combining the periodic TBPM with a CBPM as follows: the productive unit is preventively maintained after a period m of time since the last PM, or when the proportion of defectives sorted during the 100% inspection, $\beta(.)$, reaches or exceeds a given threshold r, whichever occurs first. Let $\Omega_k(t)$ denote a binary function with 1 if a kth PM has to be performed at time t, and 0 if not. Then, the PM control policy can be described by the following equation:

$$\Omega_{k+1}(t) = \begin{cases} 1 & \text{if } \beta(t) \geq r \text{ or } t - T_k \geq m \\ 0 & \text{otherwise} \end{cases}, \; k=1,..,\infty \qquad (13)$$

where T_k is the completion time of the last kth PM.

The relevance of the proportion of defectives sorted during the 100% inspection sequences on recognizing the real condition of the production process, even this information is partially observable (i.e., not available during sampling sequences), lies in the fact that the dynamic of the CSP-1 over time reflects in itself the degree of quality deterioration. Indeed, while the CSP-1 remains in the sampling inspection mode, the process quality can expect to be considered acceptable as no defective item is found in the random samples. In such situations, the length of

the sampling sequence is in itself an inference on the healthiness of the production process, so that there is no need to investigate the proportion of defectives produced. However, the fact that the CSP-1 shifts to the 100% inspection mode indicates that the process quality has moved above the acceptable level. Starting from this point (i.e., switching from sampling inspection to 100% inspection), the CSP-1 provides a complete information about the defective items produced. Based on a continuous monitoring of the observed production quality during the 100% inspection periods, a CBPM is performed as soon as the proportion of defectives surpasses the threshold r. The TBPM is more useful in situations where the random sampling inspection fails to capture any defective product while the process deterioration condition is already critical.

Production-Inventory Control Policy

The production-inventory control policy is the same as in Policies A and B. The dynamics of the final inventory x_s and the WIP inventory x_q are, respectively, described by Eqs. (3) and (11).

Optimization Problem

The decision variables of Model C are the clearance number i, the sampling inspection f, the stopping inspection rule r, the TBPM period m, and the hedging level s. The objective is to minimize the excepted total incurred cost while meeting the AOQL constraint. The average inventory holding/backlog cost $G(t)$ and the average quality cost $Q(t)$ during a period [0, t] are calculated, respectively, using Eqs. (6) and (12). Also, the average maintenance cost $M(t)$ during [0, t] is calculated using the general Eq. (7), given that $N_{pm}(t)$ is the total number of both TBPM and CBPM actions during [0, t]. Hence, the optimization problem is to solve the following mixed-integer, non-linear and stochastic model:

$$\begin{cases} \text{Minimize} & ETC(s,m,i,f,r) = \lim_{t\to\infty}\left(Q(t)+G(t)+M(t)\right) \\ \text{Subject to} & \text{Eqs. (1)-(3), (11), (13)} \\ & f_{\min}\left(i, AOQL\right) \le f \le 1 \\ & 0 < r < 1 \\ & s,\ m,\ i\ \ge 0\ ; \quad i: \text{integer} \end{cases}$$

6.4 Resolution approach

The three above-formulated optimization problems are non-linear, constrained and highly stochastic. The stochastic events are mainly the random occurrence of failures, the CM and PM actions which are following general distributions and the uncertainty in the dynamic of the CSP-1 which is based on the products quality and random samples. In addition, models B and C are mixed-integer problems because the discreteness constraint on the clearance number *i*. An explicit analytical expression of the average maintenance cost for models A and B can be derived from Eq. (7) based on previous findings in the literature as in Barlow and Proschan (1965). However, deriving a closed-form expression of the average maintenance cost for Model C is challenging as the CBPM intimately depends on the dynamic of the CSP-1 with a stopping rule. Moreover, computation of the total inventory/backlog and quality costs either analytically or numerically is very challenging too. This is because the complexity of the inventories' dynamics as in Eqs. (3), (4) and (11), the stochastic behaviour of maintenance actions and the complexity dynamic of the CSP-1. Thus, classical mathematical programming methods cannot be used to solve the three complex stochastic models under study, as there is no way to derive the closed-form analytical expressions for the objective functions. Rather, we used a combination of simulation, statistical and optimization techniques to estimate the objective function and to find the optimal solution for each integrated model.

6.4.1 Simulation-optimization approach

Simulation-optimization approaches consist in combining computer simulation with optimization techniques to heuristically solve problems that are analytically and numerically intractable (Gosavi, 2014). Discrete-event simulation has been increasingly used in the literature to imitate stochastic and complex manufacturing systems and to solve a wide range of operations management problems (see the review by Negahban and Smith, 2014). In this study, we use a combined discrete-continuous simulation to accurately model both discrete events and continuous variables. Thus, the resolution approach consists of the following step-by-step simulation-optimization methodology (Figure 6.2):

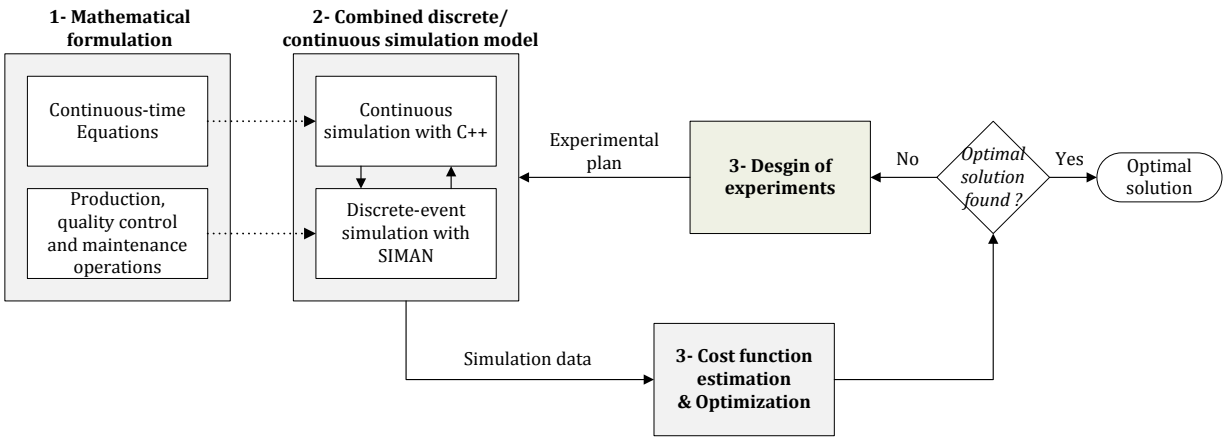


Figure 6-2. Simulation-optimization approach.

- *Step* 1 - *Mathematical model*: Analytically formulate each optimization problem, as shown in Section 6.3. This provides a rigorous modelling of the system dynamic as a function of its state, the definition of the decision variables, the objective function to be minimized and the problem constraints.
- *Step* 2 - *Simulation model*: Transform each mathematical model into a discrete-continuous simulation model according to the following logic: the continuous-time equations (e.g., unit age $a(.)$, probability of failure $F(.)$, proportion of defectives produced $p(.)$ and inventory-consumption rate d) are modelled and calculated instantly with C++ subroutines, while the discrete events (e.g., failures occurrence, CM and PM actions, production rate change, CSP-1 inspection mode change, etc.) are modelled with the SIMAN language in *Arena Simulation* environment. Hence, for each model, the expected total incurred cost for given values of the decision variables is obtained from simulation.
- *Step* 3 - *Cost function estimation and Optimization*: Use Design of Experiments (DOE) and Response Surface Methodology (RSM) to fit the total incurred costs calculated from experimental data by second-order regression models (Myers et al., 2009). The regression model for each integrated control policy must include the main effects and interactions between its decision variables. Those interaction effects play an important role to obtain an optimal trade-off solution for each integrated production, quality and maintenance control policy. Then, each optimization problem can be solved using non-linear constrained optimization techniques such as the relaxation and penalty algorithms (Floudas, 1995). The optimal solution is determined within the feasible region defined by the problem constraints and the region of the DOE. This sequential procedure is iteratively repeated in order to fully

explore the admissible experimentation region and to therefore bring out a global optimal solution.

6.4.2 Simulation models

A simulation model has been developed for each integrated model A, B and C, and executed with *Arena Simulation* software. The differential equation (1) is continuously integrated in C++ using the Runge–Kutta–Fehlberg method (Pegden et al., 1995). The given functions describing the probability of failure $F(.)$ and the proportion of defectives $p(.)$ are calculated instantly using the C++ mathematical functions and operators. Discrete events are used to model the discrete-material-flow as shown on Figure 6.1. Thus, the dynamic of the serviceable stock $x_s(.)$ is modeled by combining discrete events (inflow of finished products) and continuous modeling of the demand as in Eq. (3). Then, the surplus inventory $x_s^+(.)$ and the backlog $x_s^-(.)$ are instantly derived in C++ from calculation of the final inventory $x_s(.)$. Additional discrete events have also been used to model the production control policy as in Eq. (2), the CSP-1 procedure, the planned PM actions, the stochastic occurrence of breakdowns and the restoration of the production unit to the 'as-good-as-new' state after of each maintenance action. The stochastic durations of CM and PM actions are randomly generated following predefined probability distributions. The duration of simulation runs t_∞ is set in such a way to ensure that the steady-state is reached. Both discrete and continuous parts of the simulation model work synchronously to calculate the performances of the three integrated models (see Bouslah et al., 2013). At the end of each simulation run, the average total inventory/backlog cost $G(t_\infty)$, the average maintenance cost $M(t_\infty)$ and the average quality cost $Q(t_\infty)$ are calculated using the corresponding formulas as in Section 6.3.

To check the accuracy of the simulation models, we used a set of verification and validation techniques such as tracing the models' operation, testing for reasonableness, testing the models' structure and data and using the animation and debug features of *Arena* software (Pegden et al., 1995). For example, Figure 6.3 represents a simulation sample of the dynamics of operations of Model C over time. Figures 6.3.(a), 6.3.(b) and 6.3.(c) show that the production-inventory control policy performs correctly with respect to the inventory position $x(.)$ and the production unit state $\alpha(.)$ as in Eq. (2). They also show the effects of the CM and PM interventions on depleting the serviceable stock, resulting sometimes in shortage situations. Figures 6.3.(d) and 6.3.(e) depict, respectively, the impact of the production unit usage on the reliability and quality deteriorations.

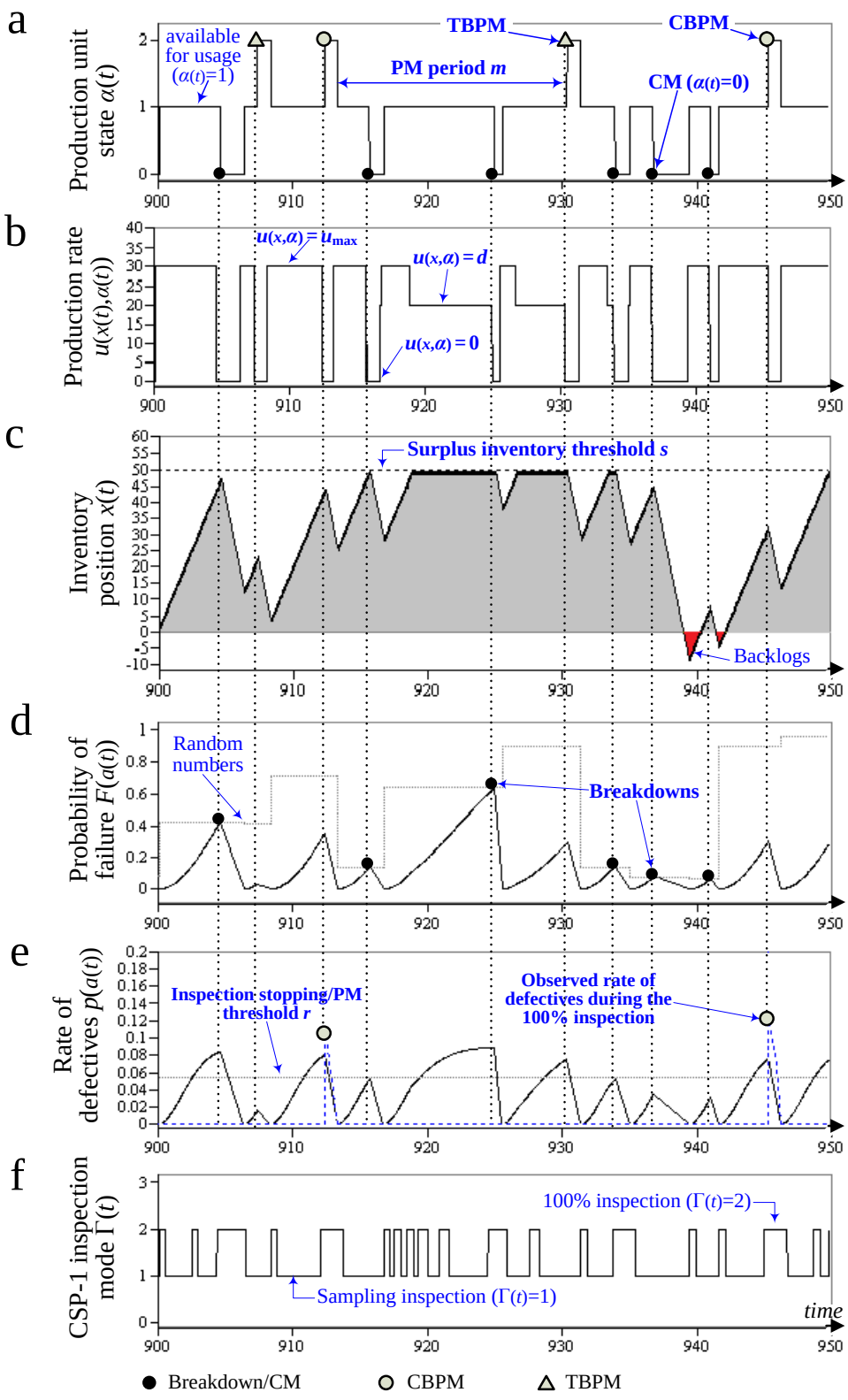


Figure 6-3. Dynamics of operations during the simulation run.

These Figures also show the effects of maintenance actions on the restoration of the process quality and the production system reliability to the initial conditions. Figure 6.3.(f) shows the dynamic of the CSP-1 plan (i.e., alternation between sampling and 100% inspection sequences). Finally, from Figures 6.3.(a) and 6.3.(e), we verify that the PM control policy operates properly as in Eq.(13): a PM action is triggered either when the observable rate of defectives exceeds the inspection stopping threshold *r* or after a period of *m* since the last PM.

6.5 Numerical example

A basic hypothetical example is used to illustrate the resolution approach and to compare the models presented. We consider that the probability of failure *F*(.) follows a two-parameter Weibull distribution given by:

$$F\left(a(t)\right) = 1 - \exp\left(-\lambda_f \, a(t)^{\gamma_f}\right) \tag{14}$$

where λ_f and γ_f are given positive constants. Similarly, the proportion of defective items produced *p*(.) increases with age *a*(.) as follows:

$$p\left(a(t)\right) = p_0 + \eta\left(1 - \exp\left(-\lambda_q \, a(t)^{\gamma_q}\right)\right) \tag{15}$$

where p_0 is a very small proportion of defectives produced at the initial condition, λ_q and γ_q are given positive constants and η is the boundary considered in the quality deterioration. The parameters of Eqs.(14) and (15) can be derived from historical data records using techniques such as the maximum likelihood estimation and the median-rank regression methods (Soliman et al., 2006; Olteanu and Freeman, 2010).

We consider the following values of parameters in the appropriate units for the illustrative example: u_{max}=30, d=20, C_h=1.2, C_b=18, C_{pm}=700, C_{cm}=1800, C_{ins}=6, C_{rect}=35, C_{def}=50, τ_{ins}=5×10^{-3}, τ_{rect}=15×10^{-3}, τ_{pm}~Log-Normal(1,0.1), τ_{cm}~Gamma(0.5,2.5), *AOQL*=2.0%., λ_r=3×10^{-5}, γ_r=2.0, λ_q=4×10^{-4}, γ_q=1.8, p_0=0.01% and η= 0.09.

6.5.1 Experimentation and results

Simulation runs are conducted according to a complete 3^2 design of experiments for Model A (as there are only two independent variables *s* and *m*), while Box-Behnken experimental plans are used for both models B (four independent variables *s*, *m*, *i* and *f*) and C (five independent variables *s*, *m*, *i*, *f* and *r*). The Box-Behnken design is suitable for plans with more than two

factors because of its rotatable feature and its efficiency in terms of number of runs required (Montgomery, 2008b). For each combination of independent factors, simulation is replicated four times. The simulation horizon t_∞ of each replication is set to 500000 units of time to ensure that the steady state is achieved (it takes on average 55 seconds for each replication on a computer with a 2.80 GHz CPU).

For each integrated model, collected simulation data are used to fit the dependent variable (i.e., average total incurred cost) by a continuous, convex, second-order regression function. To check the fitness of the regression models, we used a set of validation techniques (Myers et al., 2009). First, the model's overall performance is evaluated. This is referred to as the coefficient of multiple determination R-squared and the adjusted R-squared, which represent the proportion of total variation explained by the regression model. The values of these two coefficients should be close to 1. Second, a complete residual analysis is conducted to check the homogeneity of variances and the normality assumption of residuals. Third, once the optimization is performed, each optimal solution is cross-checked to ensure the validity.

The simulation results are handled using the statistical software STATISTICA in order to produce the analysis of variance (ANOVA), and to seek and validate the regression models fitting the total incurred costs. ANOVA analyses are carried out as presented in Tables 6.1, 6.2 and 6.3. All factors and quadratic effects and most of interactions are statistically significant for the response variables (P-Value ≤ 5%). Moreover, the three ANOVA tables indicate that the F-ratio test for 'lack of fit' is not significant. The adjusted R-squared values for models A, B and C are, respectively, 0.9818, 0.9777 and 0.9728. This states that the second-order regressions models explain more than 97.0% of the variability observed in the excepted total incurred costs. Let $\psi_A(.)$, $\psi_B(.)$ and $\psi_C(.)$ be, respectively, the regression functions for models A, B and C. From STATISTICA, the corresponding cost functions are given as follows:

$$\psi_A(s,m) = 784.64 - 7.12\, s + 49.02\times10^{-3}\, s^2 - 16.27\, m + 317.74\times10^{-3}\, m^2 + 106.09\times10^{-3}\, s\cdot m \qquad (16)$$

$$\begin{aligned}\psi_B(s,m,i,f) &= 921.67 - 10.37\, s + 77.13\times10^{-3} s^2 - 37.52\, m + 110.21\times10^{-2} m^2 - 505.60\times10^{-3} i \\ &+ 5.57\times10^{-3} i^2 - 57.67\times10^{-3}(1/f) + 545.82\times10^{-6}(1/f)^2 + 197.69\times10^{-3} s\cdot m + 20.97\times10^{-4} s\cdot i \\ &+ 434.85\times10^{-3} s\cdot(1/f) + 18.85\times10^{-3} m\cdot i - 98.19\times10^{-4}\, m\cdot(1/f) - 158.26\times10^{-6} i\cdot(1/f)\end{aligned} \qquad (17)$$

$$\begin{aligned}\psi_C(s,m,i,f,r) &= 753.93 - 8.26\,s + 698.01\times10^{-4}s^2 - 11.87\,m + 245.19\times10^{-3}m^2 + 335.88\times10^{-3}i \\ &+ 47.76\times10^{-4}i^2 - 128.11\times10^{-3}(1/f) + 464.85\times10^{-6}(1/f)^2 - 193.87\times10^{-2}\,r + 20.92\times10^{-3}r^2 \\ &+ 81.51\times10^{-3}s\cdot m + 834.62\times10^{-6}s\cdot i + 127.11\times10^{-6}s\cdot(1/f) - 12.71\times10^{-4}s\cdot r + 11.43\times10^{-4}m\cdot i \\ &- 65.07\times10^{-4}\,m(1/f) - 99.44\times10^{-4}m\cdot r - 16.63\times10^{-4}i(1/f) - 72.83\times10^{-4}i\cdot r + 24.34\times10^{-4}(1/f)r\end{aligned} \tag{18}$$

Figures 6.4.(a), 6.4.(b) and 6.4.(c) present the projection of the cost response surfaces on different two-dimensional spaces. In Figure 6.4.(b), the AOQL constraint described by Eq.(10) separates the space (i,1/f) into two regions: the region with gray-shaded contours represents the infeasible solutions (i.e., the AOQL constraint is not satisfied), while the remaining space represents the region of feasible solutions. The optimal solutions of the three policies are presented in Table 6.4. From 20 replications of simulation, we validated the optimal solutions by verifying that the corresponding estimated optimal costs ψ_A^*=\$455.7, ψ_B^*=\$421.2 and ψ_C^*=\$398.2 fall, respectively, within the confidence intervals [\$455.23, \$457.21], [\$419.43, \$421.62] and [\$396.14, \$399.17].

Table 6.1: ANOVA table for the Model A.

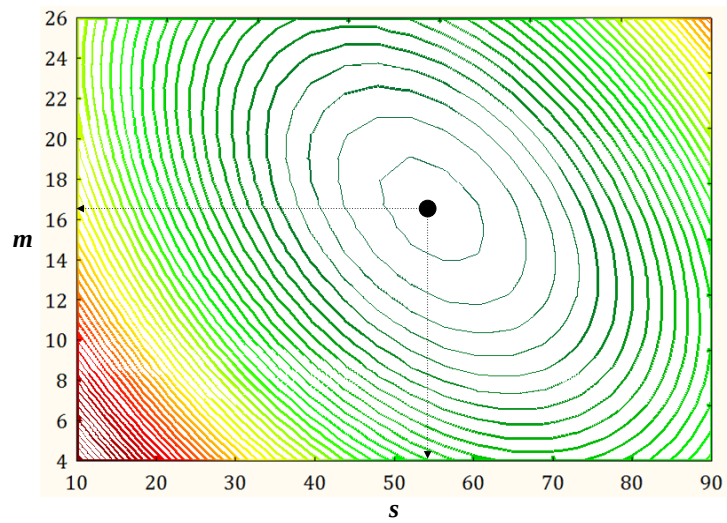
Effect	SS	d.f.	MS	F-ratio	P-Value	Significant
$s + s^2$	8363.54	2	4181.768	321.3969	0.000317	Yes
$m + m^2$	12658.50	2	6329.248	486.4451	0.000170	Yes
$s \cdot m$	1119.90	1	1119.901	86.0719	0.002650	Yes
Lack of Fit	184.69	3	61.562	4.7315	0.117030	No
Pure Error	39.03	3	13.011			
Total SS	23980.40	11		R^2 =0.9901; R^2_Adjusted= 0.9818		

Table 6.2: ANOVA table for the Model B.

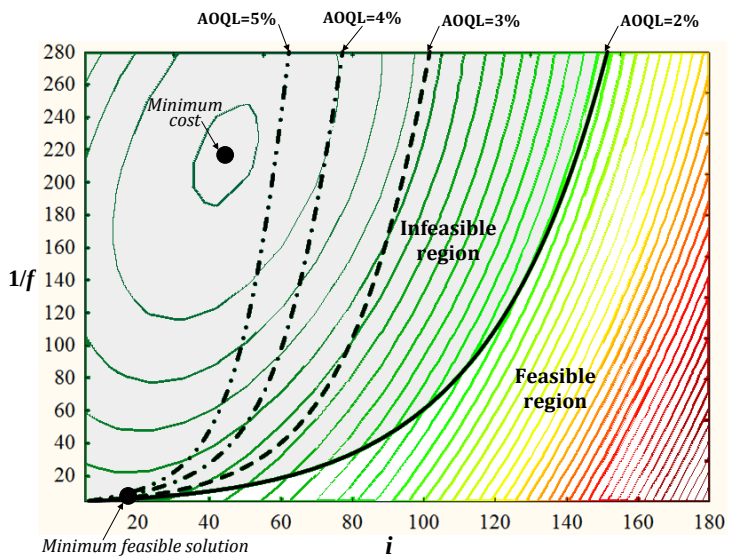
Effect	SS	d.f.	MS	F-ratio	P-Value	Significant
$s + s^2$	41262.92	2	20631.46	3083.527	0.000324	Yes
$m + m^2$	39122.79	2	19561.39	2923.598	0.000342	Yes
$i + i^2$	9401.16	2	4700.58	702.537	0.001421	Yes
$1/f + 1/f^2$	1648.51	2	824.25	123.191	0.008052	Yes
$s \cdot m$	2251.02	1	2251.02	336.432	0.002959	Yes
$s \cdot i$	21.29	1	21.29	3.182	0.216399	No
$s \cdot (1/f)$	3.03	1	3.03	0.452	0.570575	No
$m \cdot i$	154.78	1	154.78	23.133	0.040614	Yes
$m \cdot (1/f)$	138.83	1	138.83	20.749	0.044968	Yes
$i \cdot (1/f)$	303.05	1	303.05	45.293	0.021373	Yes
Lack of Fit	925.03	10	92.5	13.825	0.069295	No
Pure Error	13.38	2	6.69			
Total SS	91326.24	26		R^2 =0.9897; R^2_Adjusted= 0.9777		

Table 6.3: ANOVA table for the Model C.

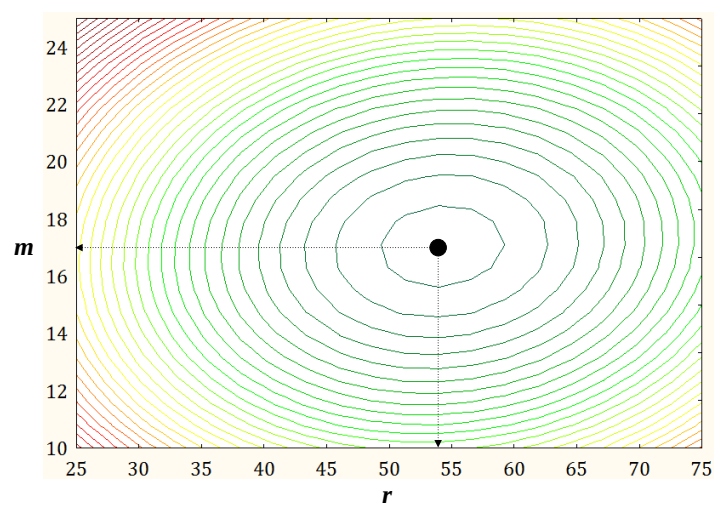
Effect	SS	d.f.	MS	F-ratio	P-Value	Significant
$s + s^2$	33601.66	2	16800.83	1762.547	0.000000	Yes
$m + m^2$	7874.98	2	3937.49	413.075	0.000003	Yes
$i + i^2$	44378.09	2	22189.04	2327.815	0.000000	Yes
$1/f + 1/f^2$	5141.50	2	2570.75	269.693	0.000008	Yes
$r + r^2$	1991.87	2	995.94	104.482	0.000083	Yes
$s \cdot m$	602.04	1	602.04	63.159	0.000508	Yes
$s \cdot i$	3.92	1	3.92	0.411	0.549493	No
$s \cdot (1/f)$	16.38	1	16.38	1.718	0.246911	No
$s \cdot r$	55.59	1	55.59	5.832	0.060497	No
$m \cdot i$	95.20	1	95.20	9.987	0.025088	Yes
$m \cdot (1/f)$	108.14	1	108.14	11.345	0.019928	Yes
$m \cdot r$	9.41	1	9.41	0.987	0.366164	No
$i \cdot (1/f)$	286.23	1	286.23	30.027	0.002759	Yes
$i \cdot r$	673.42	1	673.42	70.648	0.000391	Yes
$(1/f) \cdot r$	84.85	1	84.85	8.901	0.030675	Yes
Lack of Fit	423.51	20	21.18	2.2220	0.191761	No
Pure Error	47.66	5	9.53			
Total SS	91208.75	45		R^2 =0.9849; R^2_Adjusted= 0.9728		



(a). Cost response surface (*s*, *m*) for Model A.



(b). Cost response surface (*i*, 1/*f*) for Model B.



(c). Cost response surface (*r*, *m*) for Model C.

Figure 6-4. Projection of the cost response surfaces on different two-dimensional spaces.

Table 6.4: Comparison of the three optimal solutions.

Model	Optimal solution					Optimal cost		Quality			Reliability/Maintenance			Inventory		
	s^*	m^*	i^*	f^*	r^*	$Cost^*$	Confidence Interval	ADP_∞	AFI_∞	AOQ_∞	FR_∞	FPM_∞	AV_∞	$E[x_q]$	$E[x_s^+]$	$E[x_s^-]$
Model A	54.8	16.46	-	-	-	455.7	[455.23, 457.21]	5.62%	100.0%	0.00%	0.1049	0.0568	0.852	0.23	41.5	1.3
Model B	51.2	12.30	17	0.4222	-	421.2	[419.43, 421.62]	5.45%	62.2%	1.53%	0.0992	0.0744	0.841	0.14	37.0	1.8
Model C	49.6	17.05	14	0.4838	5.421%	398.2	[396.14, 399.17]	4.37%	60.8%	1.45%	0.0662	0.1529	0.823	0.13	35.4	1.5

6.5.2 Comparison of the performances of the three integrated models

Table 6.4 contains complementary performance indices obtained from simulation when the optimal solutions are applied. Quality performance indices include the long-run Average Fraction of Defectives Produced denoted by ADP_∞, the long-run Average Fraction of production Inspected denoted by AFI_∞ and the long-run Average Outgoing Quality denoted by AOQ_∞. The reliability/maintenance indices are the long-run Failure Rate denoted by FR_∞, the long-run Frequency of PM denoted by FPM_∞ and the long-run availability of the production unit denoted by AV_∞. The inventory indices are the average WIP inventory per unit time denoted by $E[x_q]$, the average serviceable inventory per unit time denoted by $E[x_s^+]$ and the average backlog per unit time denoted by $E[x_s^-]$. Note that the WIP inventory $E[x_q]$ intimately depends on the AFI_∞, so that $E[x_q]$ increases as AFI_∞ increases and vice versa. Finally, let Δ-B/A, Δ-C/A and Δ-C/B be the cost differences between the three models calculated as follows:

$$\Delta\text{-i/j}(\%) = \frac{\psi_i^*(.) - \psi_j^*(.)}{\psi_j^*(.)} \times 100,\ (i,j) \in \{(B,A),(C,A),(C,B)\} \tag{19}$$

The incurred cost under models B and C are significantly better than that under Model A, i.e., Δ-B/A = -7.57% and Δ-C/A = -12.62%. These significant economic savings are mainly due to the fact that the sampling inspection considerably reduces the inspection efforts, the total lead time and the WIP inventory. In fact, under policies B and C, only 60.8% to 62.2% of the production should be inspected in the long run to meet the AOQL requirement (AOQ_∞ = 1.53% under Model B and AOQ_∞ = 1.45% under Model C, both less than the predefined $AOQL$ = 2.0%). Moreover, the optimal safety stock s^* dropped from 54.8 under Model A to 51.2 and 49.6 under models B and C, respectively. Consequently, the average WIP inventory per unit time $E[x_q]$ dropped from 0.23 to 0.13-0.14 under models B and C. Similarly, the average serviceable stock $E[x_s^+]$ dropped from 41.5 under Model A to 37.0 and 35.4 under models B and C. This led to, respectively, 10.84% and 14.69% of reductions in the total inventory. However, the average backlog per unit time $E[x_s^-]$ increases from 1.3 under policy A to 1.8 and 1.5 under policies B and C, respectively. The increase of the risk of shortage under the last two policies is due to the increase in the uncertainty in the quality control delay as explained in Section 6.2.2. In addition, we see that, when the CSP-1 plan is used, the PM is further frequent (i.e., FPM_∞ increases from 0.0568 under Model A to 0.0744 and 0.1529 under models B and C) in order to improve the process quality

(i.e., ADP_∞ dropped from 5.62% under Model A to 5.45% and 4.37% under models B and C, respectively). Thus, the reduction of the quality control activities (i.e., using the CSP-1 plan rather the 100% inspection) is compensated with an increase in the PM actions. This is an interesting observation as it shows how the PM and the CSP-1 plan interact with each other to control the level of the outgoing quality. As the FPM_∞ increases, the production unit reliability is improved so that the long-run failure rate FR_∞ dropped from 0.1049 under Model A to 0.0992 and 0.0662 under models B and C, respectively.

Furthermore, from Table 6.4, we find that Model C is more profitable in comparison with Model B, i.e., Δ-C/B = -5.46%. In fact, the incorporation of the predictive maintenance coupled with the CSP-1 dynamic into the PM strategy provides the data required to recognize the actual process condition (as explained in Section 6.3.3). Based on that data, CBPM actions are performed on an as-needed basis. This reduces the occurrence of breakdowns and avoids unnecessary TBPM actions. Table 6.4 illustrates that the optimal TBPM period m^* increased from 12.30 under Model B to 17.05 under Model C, and that the frequency of all PM actions has been concurrently doubled from 0.0744 to 0.1529. These results show that less TBPM are performed compared with Model B and that most of the PM actions are triggered by the CBPM. As a result, both quality and reliability have been significantly improved. Indeed, only 4.37% of defectives are produced in the long-run under Model C compared to 5.45% defective production under Model B. Moreover, the long-run failure rate FR_∞ dropped from 0.0992 under Model B to 0.0662 under Model C. Furthermore, note that the average backlog $E[x_s^-]$ consequently decreases from 1.8 to 1.5 despite the fact that the optimal hedging level s^* decreased from 51.2 to 49.6.

6.6 Sensitivity analysis and comparative study

Another set of experiments was conducted to measure and analyze the sensitivity of the proposed integrated models with respect to the ranges of system parameters. The objective is to study the behaviour of the three integrated models and to compare their incurred costs for different system conditions derived from the basic case.

6.6.1 Impact of cost and deterioration parameters

Table 6.5 presents eighteen configurations of cost and deterioration parameters derived from the basic case by varying their values above and below one at a time by 50%. The variations of the

optimal solutions of the three integrated models compared to the basic case make sense and can be explained as follows:

• *Variation of the holding inventory cost*: When the holding cost C_h increases (case 1), the three integrated models react by decreasing the optimal surplus inventory s^*. In models B and C, the optimal clearance number i^* increases and the optimal sampling fraction f^* decreases in such a way to reduce the fraction of production inspected AFI_∞ and to consequently reduce the WIP inventory. As the decrease of the AFI_∞ deteriorates the outgoing quality (i.e., AOQ_∞ increases), the optimal period m^* decreases in order to more frequently reinstate the process quality to initial conditions through TBPM actions. The optimal CBPM threshold r^* in model C becomes less restricted because the decrease of the PM period m^*. In model A, the PM period m^* increases because the decrease of the surplus inventory s^* which slows down the process deterioration. Note that a lower holding cost produces the opposite effects (case 2).

• *Variation of the backlog cost*: When the backlog cost C_b increases (case 3), the optimal surplus inventory s^* increases in order to provide better protection to the serviceable stock against shortages. The optimal TBPM period m^* decreases in order to improve the reliability of the production equipment and to reduce the effects of failures. Because increasing PM activities also enhances the process quality, the optimal sampling fraction f^* decreases and the clearance number i^* increases such that the severity of the CSP-1 plan is reduced (i.e., AFI_∞ decreases). In model C, the optimal threshold r^* increases (so less CBPM actions are performed) because the decrease of the TBPM period m^*. The decrease of the backlog cost has the opposite effects (case 4).

• *Variation of the corrective maintenance cost*: When the CM cost C_{cm} increases (case 5), the PM should be performed more frequently in order to reduce the occurrence of failures, so that the optimal TBPM period m^* decreases. This also implies improving the process quality, which explains the fact that the optimal CSP-1 plan becomes reduced (i.e., f^* decreases and i^* increases such that the AFI_∞ is reduced). The optimal threshold r^* becomes less restricted because the TBPM actions become more frequent as the optimal period m^* decreases. Note that a decrease in the CM cost produces the opposite effects (case 6).

• *Variation of the preventive maintenance cost*: When the PM cost C_{pm} increases (case 7), the optimal period m^* increases in order to reduce the number and cost of periodic TBPM actions. The optimal surplus inventory s^* decreases to reduce the intensity of process deterioration due to

the production speed-up during periods of safety stock build-up. Moreover, in models B and C, the CSP-1 plan becomes tighter in order to maintain the outgoing quality lower than the allowable AOQL level. So, the optimal sampling fraction f^* increases and the clearance number i^* decreases such that the AFI_∞ increases. In model C, the optimal threshold r^* becomes more restricted in order to increase the frequency of CBPM actions and to compensate for the decrease in TBPM actions. Note that the decrease in the PM cost produces the opposite effects (case 8).

• *Variation of the inspection cost*: In models B and C, when the inspection cost C_{insp} increases (case 9), the optimal sampling fraction f^* decreases to reduce the inspection efforts during sampling inspection periods, while the clearance number i^* increases to satisfy the AOQL requirement. The optimal TBPM period m^* decreases in order to improve the process quality more frequently. In Model C, the optimal CBPM threshold r^* increases due to the decrease of m^*. In Model A, the optimal basic solution remains unchanged as a 100% inspection policy is used. Note that a lower inspection cost produces the opposite effects (case 10).

• *Variation of the rectification cost*: When the rectification cost C_{rect} increases (case 11), the three models react by increasing the frequency of the periodic TBPM (i.e., m^* decreases) in order to improve the process quality. In models B and C, the CSP-1 plan becomes reduced so that more defectives are accepted (i.e., less rectification efforts). Thus, the optimal sampling fraction f^* decreases and the optimal clearance number i^* increases in order to lower the AFI_∞. In model C, the optimal CBPM threshold r^* increases due to the decrease of m^*. Note that the decrease in the rectification cost has the opposite effects (case 12).

• *Variation of the cost of accepting a defective item*: In models B and C, when the cost of selling a defective item C_{def} increases (case 13), the optimal sampling fraction f^* increases and the optimal clearance number i^* decreases so that the CSP-1 plan becomes tighter (as the AFI_∞ increases). This implies that quality inspection should be intensified in order to reduce the AOQ_∞. The frequency of TBPM actions slightly decreases (i.e., m^* increases) because the increase of quality control activities. In Model C, the optimal threshold r^* decreases to carry out the CBPM actions more frequently and to improve the outgoing quality. In Model A, the optimal basic solution remains unchanged as the 100% inspection involves defect-free products. Note that a lower cost of a defective item sold has the opposite effects (case 14).

Table 6.5: Sensitivity analysis for cost and deterioration parameters.

Case Number	Parameter	Variation	Model A			Model B							Model C								Cost differences	
			s^*	m^*	$Cost$	s^*	m^*	i^*	f^*	$Cost^*$	AOQ_∞	AFI_∞	s^*	m^*	i^*	f^*	r^*	$Cost^*$	AOQ_∞	AFI_∞	Δ-B/A	Δ-C/B
basic	**-**	**-**	**54.8**	**16.46**	**455.7**	**51.2**	**12.30**	**17**	**0.4222**	**421.2**	**1.53%**	**62.2%**	**49.6**	**17.05**	**14**	**0.4838**	**5.421%**	**398.2**	**1.45%**	**60.8%**	**-7.57%**	**-5.45%**
1	C_h	+50%	48.1	17.49	479.2	47.3	11.99	20	0.3699	442.4	1.59%	60.1%	45.4	16.63	19	0.3864	5.818%	411.6	1.73%	55.5%	-7.67%	-6.96%
2		-50%	61.6	15.57	429.4	55.2	12.63	14	0.4838	397.3	1.45%	64.7%	54.0	17.77	11	0.5566	4.854%	373.8	1.26%	65.2%	-7.49%	-5.91%
3	C_b	+50%	59.5	15.62	466.2	54.1	12.03	24	0.3118	429.7	1.67%	58.0%	53.0	16.69	15	0.4621	5.632%	404.0	1.51%	59.5%	-7.84%	-5.97%
4		-50%	40.9	19.29	438.6	43.2	13.13	7	0.6762	408.5	1.11%	74.6%	40.6	18.16	12	0.5309	5.052%	386.8	1.32%	63.6%	-6.86%	-5.30%
5	C_{cm}	+50%	55.8	15.41	502.9	52.1	11.53	18	0.4038	461.9	1.55%	60.2%	50.4	15.46	20	0.3699	5.634%	423.8	1.79%	54.6%	-8.16%	-8.26%
6		-50%	54.3	17.03	409.4	50.6	12.89	15	0.4621	379.8	1.49%	64.8%	49.0	18.18	7	0.6762	5.137%	375.1	0.99%	73.1%	-7.23%	-1.26%
7	C_{pm}	+50%	54.2	17.13	466.3	50.5	12.91	16	0.4416	434.0	1.50%	64.0%	49.0	18.28	10	0.5839	5.214%	424.5	1.19%	66.9%	-6.94%	-2.18%
8		-50%	56.2	15.20	445.5	52.1	11.65	18	0.4038	403.8	1.54%	60.3%	50.6	15.23	18	0.4038	5.594%	370.6	1.68%	56.3%	-9.35%	-8.24%
9	C_{insp}	+50%	54.8	16.46	516.2	51.5	12.00	31	0.2343	445.2	1.84%	55.1%	49.8	16.91	43	0.1481	6.161%	412.0	1.94%	47.9%	-13.75%	-7.46%
10		-50%	54.8	16.46	396.7	50.6	12.70	11	0.5566	386.7	1.34%	68.1%	48.9	17.48	9	0.6128	4.951%	368.6	1.13%	68.7%	-2.54%	-4.67%
11	C_{rect}	+50%	54.9	16.14	473.8	51.3	12.12	19	0.3864	431.1	1.57%	60.8%	49.8	16.88	16	0.4416	5.602%	401.4	1.58%	58.4%	-9.00%	-6.89%
12		-50%	54.7	16.76	439.5	51.0	12.49	15	0.4621	411.5	1.47%	63.7%	49.4	17.25	13	0.5067	5.259%	392.9	1.40%	62.1%	-6.38%	-4.53%
13	C_{def}	+50%	54.8	16.46	455.7	50.8	12.62	14	0.4838	430.9	1.45%	64.7%	49.1	17.59	11	0.5566	5.192%	410.0	1.26%	65.2%	-5.74%	-4.86%
14		-50%	54.8	16.46	455.7	51.6	11.97	21	0.3543	409.8	1.62%	59.4%	50.1	16.55	19	0.3864	5.676%	383.8	1.75%	55.5%	-10.37%	-6.35%
15	γ_r	+50%	66.1	14.51	528.9	63.1	10.18	22	0.3394	502.4	1.56%	55.9%	60.3	15.26	17	0.4222	3.626%	465.1	1.54%	56.4%	-5.01%	-7.44%
16		-50%	45.3	17.32	380.8	42.6	13.21	12	0.5309	348.4	1.51%	68.9%	40.7	22.26	11	0.5566	6.248%	337.7	1.34%	65.8%	-8.51%	-3.08%
17	γ_q	+50%	55.4	15.70	467.7	53.5	11.58	10	0.5839	436.2	1.61%	70.8%	51.7	16.44	8	0.6435	3.449%	421.7	1.48%	71.6%	-6.73%	-3.33%
18		-50%	54.3	17.14	443.4	50.8	12.96	25	0.2990	397.1	1.46%	50.8%	49.3	20.01	19	0.3864	8.025%	367.7	1.41%	52.4%	-10.43%	-7.41%

• *Variation of the reliability deterioration rate*: When the deterioration of the production unit reliability increases (case 15), failure occurrence becomes more frequent. As a result, the three integrated models react by increasing the surplus inventory s^* to mitigate the higher risk of shortage and decreasing the optimal period m^* to perform the TBPM actions more frequently. Because more frequent TBPM improves the production quality, the optimal sampling fraction f^* decreases and the optimal clearance number i^* increases so that the optimal CSP-1 plan in both models B and C becomes reduced (i.e., the AFI_∞ decreases). In Model C, similar to the variation of the TBPM period m^*, the optimal threshold r^* decreases to carry out the CBPM actions more frequently. In addition, since the threshold r^* is basically used as a CSP-1 stooping rule and to assess the process quality, its significant sensitivity to the reliability deterioration shows that it also reflects the reliability of the production unit. This is because both quality and reliability deteriorations are operation-dependent. Finally, note that the decrease in the reliability deterioration rate produces the opposite effects (case 16).

• *Variation of the quality deterioration rate*: When the deterioration of the process quality increases (case 17), the three integrated models react by increasing the optimal sampling fraction f^* and decreasing the optimal clearing number i^* in order to tighten the CSP-1 plan (as the AFI_∞ increases) and to improve the outgoing quality. In addition, the optimal period m^* decreases to perform the TBPM actions more frequently and to enhance the process quality. Likewise, the optimal threshold r^* in Model C decreases to intensify the frequency of CBPM. In the three models, the surplus inventory s^* increases as a result of the increase of PM activities. The decrease in the quality deterioration rate has the opposite effects (case 18).

6.6.2 Influence of the AOQL constraint

Additional experiments have been conducted to analyze the influence of the AOQL constraint on models B and C. We should recall that Model A is insensitive to the AOQL constraint. Table 6.6 presents the optimal solutions of models B and C for different levels of the AOQL. The first observation from Table 6.6 is that, as expected, the optimal costs of both models B and C increase in response to the decrease in the AOQL and vice versa. When the AOQL is restricted (i.e., $AOQL < 2.0\%$), the optimal sampling fraction f^* increases and the clearance number i^* decreases such that the CSP-1 plan becomes tighter (i.e., AFI_∞ increases), and in order to improve the outgoing quality (i.e., AOQ_∞ decreases taking values less than the AOQL). In Model C, the optimal fraction r^* decreases in order to increase the frequency of CBPM actions and to improve

the production quality. For a highly restricted AOQL, the optimal inspection policy of both models B and C leads to a near-100%-inspection policy (e.g., $AFI_{\infty} \geq 97.7\%$ for $AOQL \leq 0.1\%$).

When the AOQL is oppositely varied (i.e., increasing AOQL above 2.0%), the optimal sampling fraction f^* decreases in order to reduce the severity of the CSP-1 plan (i.e., AFI_{∞} decreases). The optimal clearance number i^* firstly increases to compensate for the decrease in the sampling fraction f^* as the AOQL constraint is still active, and then it diminishes as the AOQL constraint becomes less and less restricting. From Table 6.6, the switch in the variation of the optimal clearance number i^* occurs at AOQL = 5.0% in Model B, and at AOQL = 4.5% in Model C. The optimal period m^* is first maintained at the same level while the AOQL constraint is active (m^* =12.3 in Model B, and m^* =17.1 in Model C), and, once the AOQL is less constrained, it climbs to a higher level in order to reduce the frequency of TBPM actions (m^* rises to 13.2 in Model B and to 19.4 in Model C). In Model C, similar to the reaction of i^* when the AOQL increases, the optimal threshold r^* first increases to reduce the CBPM actions while the frequency of the TBPM is maintained at the same level, and then it perversely decreases in order to perform more CBPM actions when the TBPM actions are less frequently performed (r^* rises up to 5.672% and then it starts decreasing to 4.668% for $AOQL \geq 8.0\%$). In both models, the optimal hedging level s^* decreases due to the reduction of the AFI_{∞}.

When the AOQL constraint becomes completely inactive for Model B (i.e., $AOQL \geq 7.0\%$), the optimal quality control policy leads to a near-no-inspection policy (0.46% of production inspected during sampling periods and only 3.1% of products are inspected in the long-run). This result is aligned with previous findings in the literature showing that the optimal CSP-1 plan with no AOQL constraint leads to either no-inspection or 100% inspection (Vander Wiel and Vardeman, 1994; Cassady et al., 2000). However, when the AOQL constraint becomes completely inactive for Model C (i.e., $AOQL \geq 8.0\%$), the CSP-1 plan is still relevant so that 5.0% of production is randomly inspected during sampling periods and more than 10.0% of production is inspected in the long run. This also means than about 10.0% of production should be at least inspected to monitor the products quality and to maintain the visibility of the process condition. In addition, we notice that r^* takes its smallest value 4.668% when the AOQL is greater than 8.0%. This shows the important role of the CBPM in determining the economic level of process quality and in improving the production unit reliability even when the AOQL constraint is inactive. All these results demonstrate the relevance of the strategy combining

continuous sampling plans with stopping rules, CBPM and TBPM to optimally control quality inspection and maintenance activities.

6.6.3 Concluding remarks and comparison of the integrated models

From the preceding analyses (Sections 6.5.2, 6.6.1 and 6.6.2) and the experimental results in Tables 6.5 and 6.6, we can draw the follow conclusions. **Firstly**, using the CSP-1 plan in integrated models is always more-cost effective than the 100% inspection. In fact, by applying models B and C, it is possible to economically determine the optimal level of quality inspection which is a combination of safety stock, PM and CSP-1 settings. This avoids the waste of excessive quality control (in the case of 100% inspection). For example, from Table 6.5, the inspection of product quality (i.e., AFI_{∞}) can be reduced by 25% to 50% while the AOQL is properly satisfied. **Secondly**, the parameters that mostly influence the amount of economic savings when the classical CSP-1 is employed rather the 100% inspection, Δ-B/A, are the AOQL, the PM cost, the quality related costs and the process deterioration functions. The economic savings Δ-B/A significantly increase as the AOQL constraint is less and less restrained (more than 25% of cost savings as in Figures 6.5 and 6.6. Then, Δ-B/A reaches its maximum level once the AOQL constraint becomes completely inactive. **Thirdly**, additional economic savings, Δ-C/B, are achieved by using the CSP-1 with the stopping rule (r) rather the classical CSP-1. In fact, such a rule involves the incorporation of the CBPM into the PM policy, which reduces the waste of unnecessary TBPM actions. For example, from Tables 6.5 and 6.6, the TBPM actions in Model C are on average 30% less frequent than those in Model B. Δ-C/B is mostly impacted by the AOQL and the costs of backlog, CM, PM and quality inspection. Figures 6.5 and 6.6 depict the impact of different combinations of those parameters on Δ-C/B. We observe that significant cost savings (more than 5.0% as in Figures 6.5 and 6.6 and up to 10% as in Figures 6.7 and 6.8) are particularly realized when the AOQL takes intermediate values (i.e., $0.5\% \leq AOQL \leq 4.5\%$). Δ-C/B is less important for highly restricted AOQL (i.e., $AOQL < 0.5\%$) as the CSP-1 leads to a near-100%-inspection plan, and also for reduced AOQL restriction (i.e., $AOQL > 4.5\%$) as the CSP-1 trends to a near-no-inspection policy.

Table 6.6: Sensitivity analysis for the AOQL constraint

AOQL	Model B							Model C								Cost differences	
	*s**	*m**	*i**	*f**	*Cost**	AOQ_∞	AFI_∞	*s**	*m**	*i**	*f**	*r**	*Cost**	AOQ_∞	AFI_∞	Δ-B/A	Δ-C/B
0.1%	51.2	12.3	15	0.9590	454.2	0.08%	97.8%	49.6	17.0	12	0.9667	5.392%	450.7	0.07%	97.7%	-0.20%	-0.79%
0.5%	51.2	12.3	15	0.8142	446.9	0.39%	89.5%	49.6	17.0	12	0.8465	5.396%	439.1	0.35%	89.0%	-1.81%	-1.74%
1.0%	51.2	12.3	16	0.6527	439.3	0.78%	79.5%	49.6	17.0	13	0.7031	5.408%	422.8	0.72%	78.5%	-3.49%	-3.75%
1.5%	51.2	12.3	16	0.5348	428.6	1.16%	70.8%	49.6	17.0	13	0.5952	5.413%	408.5	1.07%	69.8%	-5.84%	-4.69%
2% (basic)	**51.2**	**12.3**	**17**	**0.4222**	**421.0**	**1.53%**	**62.1%**	**49.6**	**17.1**	**14**	**0.4838**	**5.421%**	**398.3**	**1.45%**	**60.8%**	-7.50%	-5.40%
2.5%	51.2	12.3	18	0.3296	412.5	1.90%	53.9%	49.6	17.1	16	0.3671	5.453%	386.6	1.92%	51.1%	-9.38%	-6.27%
3.0%	51.2	12.3	20	0.2399	404.2	2.29%	45.7%	49.6	17.1	17	0.2883	5.466%	377.4	2.34%	43.6%	-11.20%	-6.63%
3.5%	51.1	12.3	22	0.1707	394.0	2.70%	37.8%	49.6	17.1	21	0.2259	5.531%	375.0	2.63%	39.3%	-13.44%	-4.81%
4.0%	50.6	12.3	52	0.0197	371.3	3.98%	14.5%	49.4	17.2	31	0.0964	5.672%	366.2	3.60%	25.9%	-18.42%	-2.29%
4.5%	50.6	12.3	58	0.0092	365.3	4.43%	8.5%	48.0	19.3	33	0.0590	5.001%	357.6	4.25%	15.7%	-19.74%	-2.11%
5.0%	48.6	13.2	71	0.0039	362.7	4.59%	6.1%	48.0	19.3	29	0.0508	4.925%	356.2	4.27%	14.1%	-20.32%	-1.77%
6.0%	48.9	13.2	52	0.0044	358.7	4.69%	3.7%	48.0	19.4	24	0.0506	4.810%	354.1	4.38%	12.2%	-21.19%	-1.29%
7.0%	48.9	13.2	45	0.0046	357.7	4.73%	3.1%	48.1	19.4	21	0.0500	4.729%	353.3	4.38%	11.1%	-21.40%	-1.24%
≥8.0%	48.9	13.2	45	0.0046	357.7	4.73%	3.1%	48.2	19.4	18	0.0500	4.668%	353.9	4.43%	10.2%	-21.40%	-1.08%

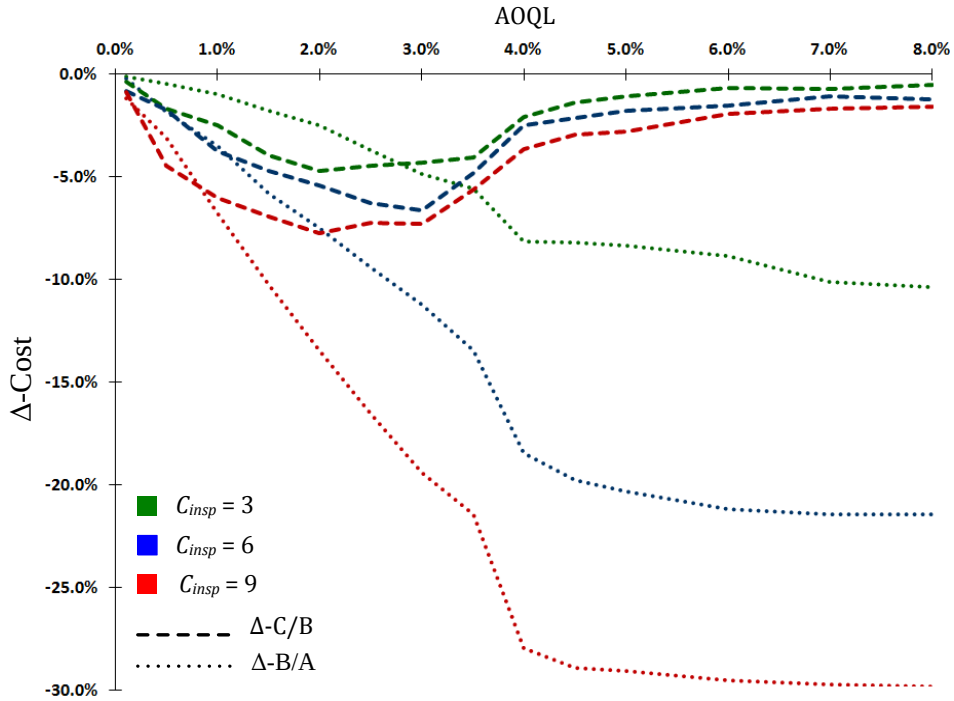


Figure 6-5. Cost comparison with different C_{insp} and AOQL.

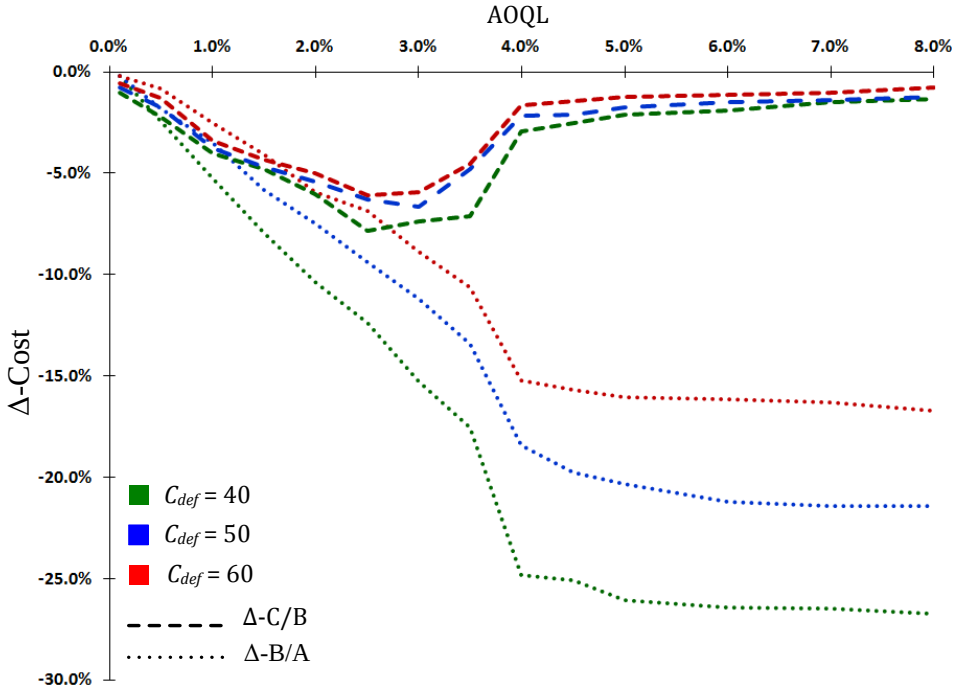


Figure 6-6. Cost comparison with different C_{def} and AOQL.

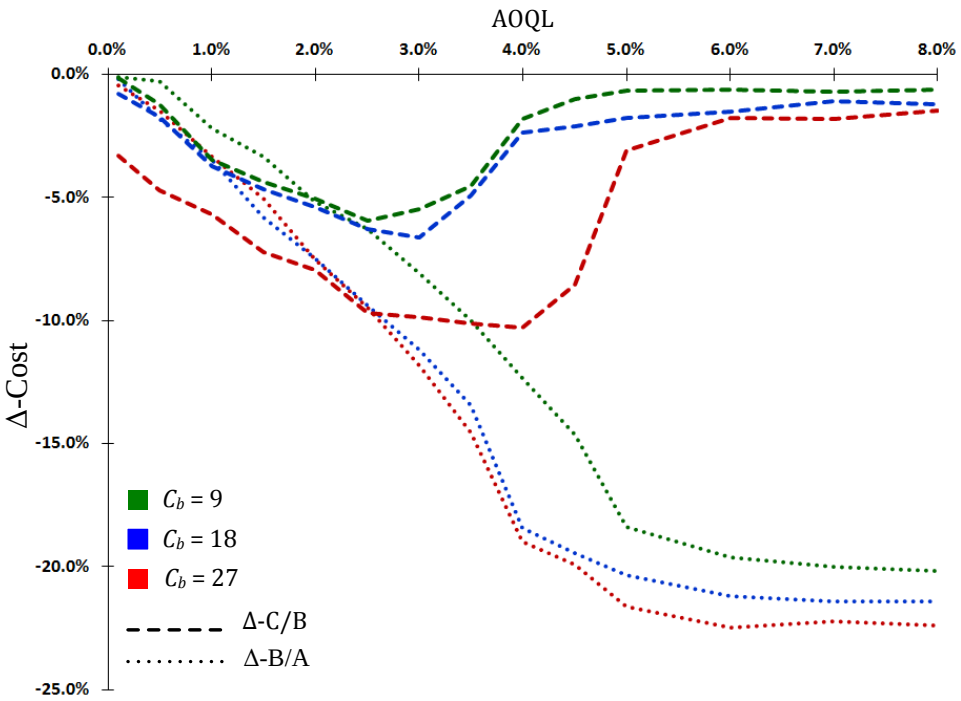


Figure 6-7. Cost comparison with different C_b and AOQL.

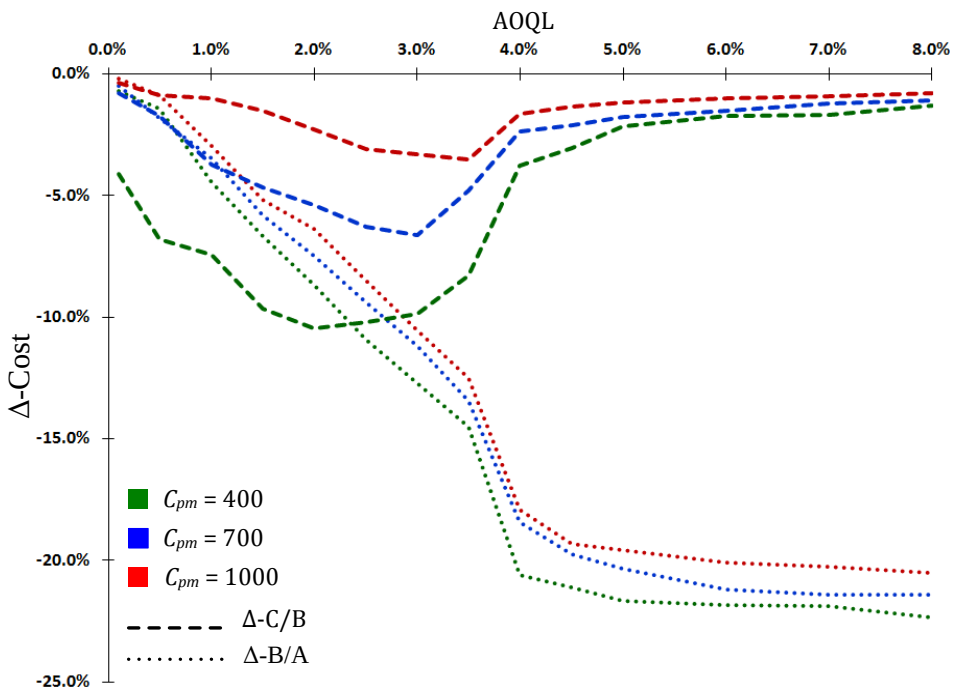


Figure 6-8. Cost comparison with different C_{pm} and AOQL.

6.7 Conclusion

In the literature, the design of continuous sampling plans has considerably evolved over the past three decades from design purely for quality requirements with no economic consideration to the economic design under quality constraints. Nevertheless, the existing continuous sampling plans models do not consider interactions with production, inventory and maintenance aspects. In this paper, we have developed new models to the joint economic design of type-1 continuous sampling plan, production, inventory and preventive maintenance for deteriorating production processes subject to an AOQL constraint. The proposed models contribute to research on integrated production, quality and maintenance in four ways. First, we have shown that continuous sampling plans can be used for deteriorating processes, provided that the interrelations with production, maintenance and process quality are fully considered in the design process of those plans. In practice, this finding should extend the application of continuous sampling plans to new industrial areas, as they are presently limited to stable production processes. Second, we demonstrated through arguments and experiments that using continuous sampling plans rather than the 100% inspection policy increases the overall operational performance and can realize important cost savings. Third, we have found that the CSP-1 with stopping rules is more effective for deteriorating processes, than the classical CSP-1. In fact, when a CSP-1 stopping rule is coupled with the CBPM, unnecessary TBPM actions are avoided and therefore additional cost savings are achievable. One advantage of this strategy lies in the fact that the CBPM based on quality information feedback does not require costly and advanced technology for data acquisition and analysis such as vibration, corrosion and acoustics analysis techniques. Quality information can easily be collected from the CSP-1 and interpreted to assess the process condition. Finally, another important contribution of this study lies in the effectiveness of the proposed modeling and optimization framework to tackle complex and highly stochastic optimization problems in integrated operations management.

The integrated production, CSP-1 and maintenance models proposed in this paper can be applied for continuous production systems subject to reliability and quality deteriorations, whose inspection is only performed at the end of production, and where both closed-loop production-inventory control and sampling plans are effective such as in the electronics and semiconductor industries (see Antila et al., 2008; Cao and Subramaniam, 2013; Mok, 2009). Managerial

implications for implementing those integrated models require a real-time visibility and control of operations, WIP, finished products inventory, products quality and inspection rate. In addition, historical data related to the products quality should be properly recorded to manage the CSP-1 procedure, to monitor the production process and to schedule the CBPM actions. This is can be easily supported by modern computer software such as the Manufacturing Execution Systems (Kletti, 2007).

One limitation of our study is to assume that only finished products are inspected at the end of manufacturing operations. Nevertheless, inspection of intermediate products could reduce the total cost of poor quality and improve the outgoing quality. Possible extensions of this paper could be carried out to develop integrated production, sampling inspection and maintenance models for multistage manufacturing systems. Those models should address important design problems in multistage systems such as optimal inspection location, sampling plan optimization at each inspection point and optimal quality control of complex products with many attributes. Further research could be conducted to study more sophisticated continuous sampling plans such as the Dodge-Torrey's (1951) improvements of the CSP-1 plan (i.e., CSP-2 and CSP-3) and the multilevel continuous sampling plans as suggested by Lieberman and Solomon (1955). The main advantage of those plans is their ability to meet the AOQL requirement with less inspection effort than the CSP-1.

CHAPITRE 7 ARTICLE 4 JOINT PRODUCTION, QUALITY AND MAINTENANCE CONTROL IN A TWO-MACHINE LINE SUBJECT TO OPERATION-DEPENDENT AND QUALITY-DEPENDENT FAILURES

Soumis pour publication dans

OMEGA, The International Journal of Management Science

Date de soumission : 11 Novembre 2015

Rédigé par:

Bassem BOUSLAH
Department of Mathematics and Industrial Engineering,
École Polytechnique de Montréal
{*bassem.bouslah@polymtl.ca*}

Ali GHARBI
Automated Production Engineering Department,
École de Technologie Supérieure
{*ali.gharbi@etsmtl.ca*}

Robert PELLERIN
Department of Mathematics and Industrial Engineering,
École Polytechnique de Montréal
{*robert.pellerin@polymtl.ca*}

Abstract – Correlated failures in multistage manufacturing systems such as failures caused by defective products manufactured in upstream processes have always been overlooked in the literature of integrated production, quality and maintenance control. Ignoring the effect of the incoming product quality in the reliability modeling of those systems may results in a significant overestimation of the overall manufacturing performance. In this paper, we propose a modeling and optimization framework for the joint production, quality and maintenance control of a small production line composed of two machines subject to both quality and reliability degradations. The second machine is also subject to failures induced by the incoming product quality. The main objective of this study is to jointly optimize the production-inventory, quality control and preventive maintenance settings of the production line by minimizing the total cost incurred under a prescribed constraint on the outgoing quality. Numerical examples are given to illustrate the effectiveness of the modeling and resolution approach and to study some important aspects such as the optimal allocation of inspection and maintenance efforts, the effect of incoming product quality on reliability and the interdependence between production, quality and maintenance control settings. The results obtained demonstrate that failure correlation has a significant impact on the optimal control settings, and that maintenance and quality control activities in preceding stages can play an important role in the reliability improvement of the subsequent machines.

Keywords – quality and reliability degradation, quality-dependent failures, production control, quality control, preventive maintenance, simulation-based optimization

7.1 Introduction

Production, quality and maintenance control for multistage manufacturing systems have been extensively studied in the literature. Traditionally, they have been treated by scientists and practitioners as separate problems even though they are strongly interrelated (see the recent comprehensive review by Colledani et al., 2014). In the last decade, there is a growing interest in integrating production, quality and maintenance control for multistage systems. This trend may be motivated by the fact that research in integrated control policies for single-stage production systems resulted in several important findings indicating that integrated models outperform those dealing with only one separate aspect at a time (see the survey papers by Hadidi et al. (2012) and

Inman et al. (2013)). Integrated models essentially aim at analyzing, designing, controlling and optimizing manufacturing systems through a holistic approach, taking into consideration the substantial interrelations and intersections between production, quality and maintenance aspects. Integrated models for multistage systems can be classified into two main categories. The first category consists of evaluating and analyzing the performance of such systems under various configurations of production, quality and maintenance control policies, while, the second category aims for the joint design of the three control policies. We call them integrated analysis and integrated design models, respectively.

Most existing integrated models for multistage systems in the literature belong to the first category. For example, Kim and Gershwin (2005, 2008) introduced analytical models to evaluate and analyze the performance of production lines subject to both operational and quality failures. They have investigated various important issues related to the interactions between production systems design, quality and productivity. Colledani and Tolio (2006, 2009, 2011a) proposed also analytical methods for evaluating the quality and productivity performance of manufacturing lines which are monitored by Statistical Process Control (SPC). Also, Cao et al. (2012) presented an analytical method for the performance evaluation of multistage production systems with rework loops, unreliable machines and finite buffers. Furthermore, Cao and Subramaniam (2013) proposed an integrated quantity and quality model for evaluating the performance of multistage manufacturing systems with continuous sampling plans. Ruifeng et al. (2012) have investigated the effect of Preventive Maintenance (PM) on Kanban controlled assembly lines and developed an analytical model for performance evaluation for such systems. The only existing integrated analysis model that considers simultaneously production, quality and maintenance control is probably the work of Colledani and Tolio (2012) who developed an integrated modeling framework for performance evaluation of multistage asynchronous manufacturing lines with degrading machines controlled by PM and SPC.

Integrated analysis models has numerous practical applications that generally deal with only one specific manufacturing problem such as identification of production/quality bottleneck machines (e.g., Meerkov and Zhang, 2010, 2011; Ju et al., 2015), optimal allocation of inspection stations (e.g., Cao et al., 2012), optimization of quality inspection plans (e.g., Cao and Subramaniam, 2013) and prediction of the production lead time distribution (e.g., Colledani et al., 2015). Nevertheless, on the other hand, there are a very limited number of integrated models in the

literature that address the problem of the joint design of production, quality and maintenance control policies for multistage systems. For instance, Rezg et al. (2004) presented an integrated method for PM and inventory control of an unreliable production line without intermediate buffers. Darwish and Ben-Daya (2007) proposed a joint design of production inventory and imperfect PM model for a two-stage production system with imperfect production processes and inspection errors. Colledani and Tolio (2011b) proposed an analytical method for the joint design of Kanban production control and statistical quality control charts in unreliable multistage lines. Finally, Mhada et al. (2013) addressed the problem of the joint assignment of buffer sizes and inspection stations in unreliable production lines with imperfect machines. The aforementioned models addressed the joint design of only two aspects at a time, among production, quality and maintenance control.

The first objective of this paper is to develop an integrated model for the joint design of production, quality and maintenance control policies for multistage manufacturing systems. To the best of our knowledge, there is no published study in the literature that investigates the simultaneous design of these policies for multistage systems. Specifically, we are interested in continuous-flow manufacturing lines with machines subject to both quality and reliability degradations.

Operations-Dependent Failures (ODF) and Time-Dependent Failures (TDF) are the most failure models used in the literature (Mourani et al., 2007). Basically, these two models can pattern only uncorrelated failures. Uncorrelated failures are those where the failure process of each machine is assumed to be independent of any failure in the rest of the system (Gershwin, 1994). However, in real-life manufacturing systems, machines may be substantially affected by complex failure dynamics such as increased degradation and tool wear caused by defective products generated in upstream processes (Colledani et al., 2014). The effect of incoming product quality on the reliability of the downstream machines has always been overlooked in the literature of integrated models. Neglecting such effect in the system reliability modeling may lead to a significant overestimation of the overall system reliability (Chen et al., 2004; Sun et al., 2009), and ineffective production, inventory and maintenance policies accordingly.

The second objective of this paper is to incorporate failure correlation into the joint design of integrated control policies for production lines with degrading machines. Particularly, this study

will address the problem of operational failures caused by defective products manufactured in the previous stations. We call such kind of failures as Quality-Dependent Failures (QDF). Because the quality of the incoming products is driven by production, quality and maintenance control settings in the upstream machines, this study will additionally investigate the interactions between those settings across the manufacturing stages and their effects on the overall performance of the manufacturing line.

The third objective of this paper is to develop a practical modeling framework for the joint design of integrated control policies for multistage systems subject to degradation and correlated failures. In fact, for mathematical tractability, almost all of the existing integrated models are based on several simplifying assumptions that may make them unrealistic. A common assumption made in those models is that the machines' reliability relies on the Markovian property which implies that failures and repairs are independent and exponentially distributed. In reality, those models cannot be used for manufacturing systems subject to complex failure dynamics such as dependent and correlated failures (Colledani and Gershwin, 2013). Moreover, it has been shown through many industrial studies that the repair time in real-life systems cannot be approximated by the exponential distribution (Buzacott and Hanifin, 1978; Boyd and Radson, 1998). Additionally, it is very challenging to use Markovian models to pattern manufacturing systems composed of machines with dynamic production rates that may change over time, resulting in time-varying degradation rates of quality and reliability. On the other hand, simulation as a powerful modeling tool can effectively imitate complex systems and overcome the limitations of the traditional analytical approaches (Negahban and Smith, 2014). In this study, we will show how practitioners can take advantage of advanced simulation techniques such as the combined discrete/continuous simulation to adequately model the dynamic relationships between operation speed, aging, quality and reliability as observed in real-life. The objective is to develop more effective and practical integrated control policies for complex manufacturing lines.

In this paper, we propose an integrated design model for a small production line composed of two serial processing machines subject to quality and reliability degradations. For both machines, degradation processes are operation-dependent. The second machine is additionally subject to quality-dependent failures. The production line is governed by a base-stock control policy. Moreover, each machine is submitted to an age-based PM policy. The durations of corrective and preventive maintenances are random with general distributions. An inspection station may be

allocated in the downstream of each processing machine. Indeed, the optimal quality control level at each production stage can be either 0%, sampling or 100%. An integrated model is developed for jointly optimizing the production, quality and maintenance control settings, which minimize the total cost incurred under a prescribed constraint on the outgoing quality. A combination of simulation, statistical and optimization techniques is used to solve such constrained stochastic problem. Numerical examples are provided to show the effectiveness of the proposed modeling and optimization methodology. Also, an extensive sensitivity analysis is conducted to study the effects of the system parameters on the optimal control settings and to point out some important aspects of manufacturing lines subject to correlated failures.

The paper is organized as follows. In Section 2, we discuss the industrial context of the study. We particularly provide various real industrial examples where quality-dependent failures could have critical impact on manufacturing performance. Section 3 presents the notations, the description of the problem under study and the assumptions used. The integrated model and the optimization problem are formulated in Section 3. In Section 4, we present the simulation-based optimization approach. A numerical example and a thorough sensitivity analysis are presented in Section 6. Finally, Section 7 concludes the papers.

7.2 Industrial context

The integrated production, quality and maintenance control model presented in this paper has applications in multistage manufacturing systems where quality degradation intimately depends on operations, and machines are subject to operation-dependent and quality-dependent failures. The effect of operations on quality has been observed in many industrial contexts. For example, in robotic assembly lines, robot repeatability and accuracy which are critical for product quality deteriorate with increased operating speed (see Khouja et al., 1995). The effect of the operating speed on product quality has also been demonstrated in machining processes such as metal cutting and surface milling (see Owen and Blumenfeld, 2008).

In general, most machines' failures in manufacturing lines are operation-dependent (Buzacott and Hanifin, 1978). Nevertheless, failures caused by defective products manufactured in upstream processes may have significant impact on the production system reliability. For example, in the automotive industry, the car body assembly line involves a number of serial stations that typically

assemble 150 to 250 sheet metal parts. An assembly station can fail due to catastrophic tooling failures caused by defective products. Indeed, large dimensional errors associated with the locating-holes of one sheet metal part may lead to locating tool failures such as locating pin being broken during the part loading process, a part being stuck at pins, or a part being unable to be correctly positioned by the locators (Chen et al., 2004). In real-life, the locating tool failures induced by the incoming product quality represent more than 40% of all locating tool catastrophic failures (see Chen et al. (2004) and the references therein).

Additionally, the effect of product quality on reliability can be observed in machining industry. For example, in drilling processes, material properties (considered as quality characteristics) of the incoming work-pieces have a significant impact on the wear and breakage rate of the drill (see Chen and Ji, 2005). On the other hand, the quality of the hole drilled (in terms of diameter, depth, straightness, orientation, etc.) is affected by the drill condition. In the subsequent processes (e.g., tapping, boring, milling, etc.), nonconforming drilled holes can induce severe thermal and frictional effects and impact the reliability of the machining tools accordingly (Chen and Ji, 2005; Sun et al., 2009). Those effects show an inherent property of multistage manufacturing systems, which is the propagation of the complex interactions between quality and reliability across the manufacturing stages, called Quality-Reliability chain effect (Chen and Ji, 2005; Shi, 2006).

In the food industry, the impact of product quality on reliability is often observed in the packaging process which is generally the last operation in food manufacturing. This has been experienced for example in biscuit and cake manufacturing as in Akbarov et al. (2008) who conducted a questionnaire survey about the reliability of packaging machines. According to the surveyed experts, quality of the incoming products is a significant cause of failure. Moreover, improving the quality of the incoming products is listed among the prioritized failure prevention methods for the packaging machines.

In some industrial contexts, the effect of machines' failures caused by defective products can lead to costly maintenance operations and important production losses. For example, in automated brick and tile factories, materials essentially flow through four sequential manufacturing processes: mixing clay with water and other additives, molding the mixtures, drying the molded materials and firing the bricks/tiles in a tunnel kiln (Brick Industry Association, 2006). Once dried, the bricks/tiles are loaded in pallets so that the kiln can fire up to 50 tonnes at a time. Poor-

quality products can be partially or fully broken during the firing process and damage the kiln accordingly. The accumulation of broken products within the kiln may result in a complete breakdown of the kiln. This phenomenon often occurs because the lack of homogeneity in mixtures or because products have not been properly dried during the drying process. In brick manufacturing processes, the problem of poor-quality is routinely critical, as about 10% of bricks produced are usually defectives (Okuno and Takahashi, 1997; Hamer and Karius, 2002). Repairing the failed kiln is costly and time-consuming because needed to wait until the kiln which operates at approximately 1000°C is cooled, remove the broken products from the kiln, clean the kiln and repair the failed components. Consequently, the long downtime of the kiln (sometimes up to one week) causes important production losses.

In this study, we attempt to incorporate the dynamic relationships between operations, quality and reliability in the joint design and optimization of integrated control policies for multistage systems. This aims to provide a realistic modeling framework of complex dynamics in manufacturing systems and to develop effective integrated policies for operations management and control.

7.3 Notations and problem description

7.3.1 Notations

The following notations are used throughout the paper.

Decision variables:

s_k Inventory threshold after the kth machine in the production line M_k

m_k Critical PM age of machine M_k

f_k Level of quality control at M_k ($0 \le f_k \le 1$)

Model parameters:

$u_{\max}^k$ Maximum production rate of M_k

d Market demand rate

AOQL Average Outgoing Quality Limit

C_h Unit inventory holding cost per unit time

C_b Unit backlog cost per unit time ($C_b >> C_h$)

C_{cm}^k Corrective Maintenance cost of M_k

C_{pm}^k Preventive Maintenance cost of M_k ($C_{cm}^k > C_{pm}^k$)

C_{insp}^k Unit inspection cost at M_k

C_{rej}^k Unit rejection cost of a defective part at produced by M_k ($C_{rej}^2 > C_{rej}^1$)

C_{def} Unit cost of accepting/selling a defective finished product ($C_{def} > C_{rej}^2$)

$p_k(.)$ Distribution function of the proportion of defective parts produced by M_k

$F_{R,k}(.)$ Cumulative probability distribution function of ODF of M_k

$F_{Q,k}(.)$ Cumulative probability distribution function of QDF of M_k

$R_k(.)$ Reliability function of M_k

τ_{cm}^k Random variable denoting the corrective maintenance time of M_k

τ_{pm}^k Random variable denoting the preventive maintenance time of M_k

τ_{insp}^k Unit inspection time at M_k

Other notations will be introduced where they are needed.

7.3.2 Problem description

We consider a continuous-flow production line composed of two processing machines M_1 and M_2 in series, as shown in Figure 7.1. The two machines are separated by an intermediate buffer. Let $x_1(t)$ denote the level of this buffer at time t, $x_1(t) \geq 0$. The production line supplies a downstream stock of finished products which is used to satisfy a constant market demand with rate d. Let $x_2(t)$ denote the level of this serviceable stock at time t (inventory if positive and backlog if negative).

Each machine is subject to aging which leads to increasing failure rate and decreasing product quality. Aging processes in both machines are operation-dependent. M_2 is additionally subject to quality-dependent failures caused by defective parts produced by M_1. In both machines, failures are removed by Corrective Maintenance (CM) interventions. To preventively cope with quality and reliability degradations, each machine is submitted to an age-based Preventive Maintenance (PM) policy (Savsar, 2006; Berthaut et al., 2011). We assume that both CM and PM actions restore the machines to the ‘as-good-as-new’ condition. This assumption is reasonable in many

industrial situations where maintenance actions may include the replacement of failed and degrading key components such as bearings, gearboxes, crucial electrical and hydraulic parts and machining tools. To make our study more suitable for practical applications, we consider that the durations of CM and PM actions for each machine M_k are random, following general distributions denoted by τ_{cm}^{k} and τ_{pm}^{k}, respectively. This is because, in real-life, both CM and PM times can take various random patterns (Chakraborty et al., 2009; Wee and Widyadana, 2013).

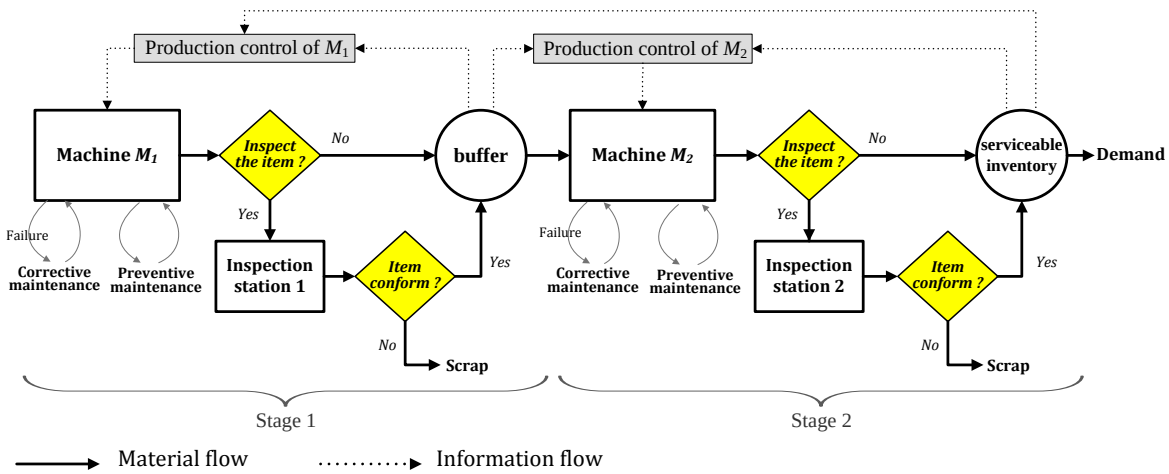


Figure 7-1. Two-machine production line subject to quality and reliability degradations.

The finished product has two key attributes related to the processing operations by M_1 and M_2, respectively. If one attribute does not conform to specifications, the finished product is considered defective. In order to meet quality requirements, a prescribed constraint related to the Average Outgoing Quality Limit (AOQL) is imposed. Basically, each processing machine may be followed by an inspection station according to a ubiquitous inspection strategy. This means that an inspection station at machine M_k can only detect defective features made only by M_k (Kim and Gershwin, 2008). We assume that all defective parts sorted during quality control in both inspection stations are rejected. However, the rejection of a finished product is always more expensive than the rejection of a semi-finished product, i.e., $C_{rej}^{2} > C_{rej}^{1}$. This is because the processing cost and the material added to the semi-finished products in M_2. The inspection cost and time in both stages are considered non-negligible. The quality control problem consists of finding the optimal inspection level at each machine M_k which can be either 0%, sampling or 100%. The first scenario means that no resources will be allocated for quality inspection at M_k. Under no-inspection policy, all defective parts produced by M_k will be transmitted to the

downstream customer (which can be internal or external). On the other hand, under sampling inspection, only defective parts that have not been inspected will be transmitted to customers. Sampling inspection policies are widely used in industry to reduce the cost and time of inspection and to statistically control the outgoing quality (Schilling and Neubauer, 2009). The 100% inspection which is generally a costly and time-consuming inspection process is usually employed in situations where the product quality is extremely critical so that passing any defectives to would result in high economic impact at the next stages (Montgomery, 2008a).

The production rate of each machine M_k, denoted $u_k(.)$, is flexible and can be set at any time to a value between 0 and the maximum production rate $u_{\max}^k$, with $u_{\max}^k > d$. The raw material supply for M_1 is considered infinite, so that M_1 is never starved. However, M_2 is starved if the intermediate buffer is empty. In the literature, several production control policies have been proposed for unreliable production lines such as extended Kanban, CONWIP and two-boundary control policies (Bonvik et al., 1997, Lavoie et al., 2010). In this study, we consider that the production line is controlled by a hierarchical feedback control policy as proposed by Samaratunga et al. (1997). Our choice of this hierarchical control policy is motivated by its simplicity and ease to implement. More importantly, it is a near-optimal control policy that performs as well or better than several complex heuristics in the literature such as extended Kanban controls (see Samaratunga et al., 1997).

As a matter of fact, the overall operational performance of the production line is intimately influenced by the complex relationships between operations, quality and reliability and the interrelations between production, quality and maintenance control settings. For example, the acceleration of production rate during the periods of inventory surplus build-up intensifies both quality and reliability degradations (Owen and Blumenfeld, 2008; Savsar, 2006). Consequently, an optimal surplus inventory level at each manufacturing stage should be set to balance between the need to protect the production against starvation and shortage situations, and the effect of production speed-up on machines' degradation. Moreover, the PM program plays an important role to improve the machines reliability and production quality. However, excessive PM actions may reduce the operational time of machines (Colledani et al., 2014) and increase the total maintenance cost as well. The optimal PM level for each machine should trade-off between these opposite effects. Because defective semi-finished products may break down M_2, the reliability of

this machine should be taken into consideration when setting the control parameters of M_1. Furthermore, because the outgoing quality is influenced by all production, quality and maintenance control settings of both machines, these settings should be jointly fixed to ensure that the AOQL constraint is fully satisfied. Therefore, the main purpose of this work is to jointly optimize the control settings of the production line in order to minimize the total cost incurred taking into considerations the AOQL constraint and all those complex interactions and interrelations.

7.4 Problem formulation

7.4.1 Degradation model

The state of each machine M_k is mainly characterized by two continuous-time components: a discrete-state stochastic process $\{\alpha_k(t)\}$ describing its operational state at time t, and a piecewise continuous variable $A_k(t)$ indicating its age at time t. The stochastic process $\{\alpha_k(t)\}$ takes values $\{0,1,2\}$ such that: $\alpha_k(t) = 0$, if M_k is under CM at time t; $\alpha_k(t) = 1$, if it is operational; and $\alpha_k(t) = 2$, if it is under PM. The age $A_k(t)$ is measured by the cumulative number of parts produced by M_k until the time t since the last maintenance (CM or PM, whichever occurs last). It is calculated using the following differential equation:

$$\frac{\partial A_k(t)}{\partial t} = u_k\left(t, \alpha_k(t)\right), \forall\ t \geq T_k,\ A_k(T_k) = 0 \qquad (1)$$

where $u_k(t,\alpha_k(t))$ is the production rate of M_k at time t, also denoted $u_k(t)$. T_k is the completion time of the last maintenance on M_k.

We consider that quality and reliability degradations for both machines follow two-parameter Weibull distributions. The Weibull distribution is a typical versatile statistical model that can fit numerous non-linear degradation patterns by fixing the adequate values of its parameters (Rinne, 2008). Those parameters can be determined from life data using techniques such as maximum likelihood, methods of moments and Bayesian approaches (Rinne, 2008). Hence, the proportion of defectives produced by each machine M_k can be described by the follwoing function:

$$p_k\left(A_k(t)\right) = p_k^0 + \eta_k\left(1 - \exp\left(-\mu_k\, A_k(t)^{\delta_k}\right)\right) \qquad (2)$$

where p_k^0 is a very small proportion of defectives produced by M_k at the initial condition. μ_k and δ_k are given positive constants and η_k is the boundary considered in the quality degradation.

Also, the cumulative probability distribution of operation-dependent failures of each machine M_k is given by:

$$F_{R,k}\left(A_k(t)\right)=1-\exp\left(-\beta_{R,k}\,A_k(t)^{\gamma_{R,k}}\right) \tag{3}$$

where $\beta_{R,k}$ and $\gamma_{R,k}$ are given positive constants.

Similarly, the cumulative probability distribution of quality-dependent failures of M_k is given by:

$$F_{Q,k}\left(Z_k(t)\right)=1-\exp\left(-\beta_{Q,k}\,Z_k(t)^{\gamma_{Q,k}}\right) \tag{4}$$

where $\beta_{Q,k}$ and $\gamma_{Q,k}$ are given positive constants. $Z_k(t)$ is the cumulative number of defective products coming to M_k at time t from the previous stage, since the last maintenance on M_k (see Eq. (7)).

Based on Eqs. (3) and (4), the reliability function of each machine M_k at time $t$can be estimated as follows:

$$R_k\left(A_k(t),Z_k(t)\right)=\left(1-F_{R,k}\left(A_k(t)\right)\right)\cdot\left(1-F_{Q,k}\left(Z_k(t)\right)\right) \tag{5}$$

Without loss of generality, we assume that the raw materials used in production are defect-free. Thus, $Z_1(.)$ will be always equal to zero, and only M_2 will be subject to quality-depended failures. This is because we wish to focus, in this study, on the effect of production quality on the machines' reliability.

7.4.2 Integrated production, quality and maintenance control policy

7.4.2.1 Maintenance Policy

Each machine is submitted to an age-based PM policy. Thus, each machine M_k is maintained upon failure or upon reaching a predetermined age m_k, whichever occur first. Indeed, m_k is a threshold of cumulative number of parts produced by M_k that when it is reached, a PM action is immediately carried out on M_k. m_k is also called the critical PM age.

Let $\Omega_k(t)$ denotes a binary function with 1 if a PM action has to be carried out at time t, and 0 if not. Therefore, the PM control policy of each machine M_k is given by:

$$\Omega_k(t) = \begin{cases} 1 & \text{if } A_k(t) \geq m_k \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

7.4.2.2 Quality Control Policy

Basically, a fraction f_k of parts produced by M_k is randomly inspected ($0 \leq f_k \leq 1$). An optimal inspection strategy at M_k can be either: no-inspection, if the fraction f_k is set to 0; continuous sampling inspection, if f_k is set to a value between 0 and 1 ($0 < f_k < 1$); or 100% inspection, if f_k is set to 1. Let $Y_k(t)$ denote the proportion of defective parts in the inspection sample drawn form the production process of M_k at time t ($0 \leq Y_k(t) \leq 1$). If the quality control policy used at M_k is no-inspection, then $Y_k(.)$ will be equal to 0. Under 100% inspection policy, $Y_k(t)$ will be exactly equal to $p_k\left(A_k(t)\right)$. However, under sampling inspection policy, $Y_k(t)$ will be a random number that can be described by the conditional distribution $P\left\{Y_k(t) \mid p_k\left(A_k(t)\right)\right\}$ with an expected mean equal to $f_k\ p_k\left(A_k(t)\right)$. Thus, the impact of the quality control policy used at M_1 on the reliability of M_2 can be described by the following equation:

$$\frac{\partial Z_2(t)}{\partial t} = \left(p_1\left(A_1(t)\right) - Y_1(t)\right) \cdot u_1\left(t, \alpha_1(t)\right),\ \forall\ t \geq T_2,\ Z_2(T_2) = 0 \tag{7}$$

where $p_1\left(A_1(t)\right) - Y_1(t)$ represents the proportion of defective parts produced by M_1 that are directly transmitted to M_2 with no inspection, at time t.

From Eq. (7), one can realize that $Z_2(.)$ intrinsically depends on the production quality of M_1, the level of quality control between the two machines and the maintenance policy of M_2. Figures 2 and 3 depict the effects of the incoming product quality and the quality and maintenance control settings on the reliability of M_2, based on Eqs. (2), (4) and (7). Figure 7.2 shows the impact of quality degradation at M_1 on the number of defective parts passed to M_2 and on the probability of quality-dependent failures $F_{Q,2}(.)$, accordingly. In addition, Figure 7.2 illustrates the effects of maintenance actions on both machines on the rate of defectives passed to M_2 and on the rate of the reliability degradation of this machine, accordingly: improving the production quality of M_1 through PM actions slows down the reliability degradation of M_2, while maintenance actions on M_2 restores the machine to the 'as-good-as-new' state (i.e., remove the cumulative effect of the

incoming defective parts). Also, Figure 7.3 shows the impact of the quality control policy used at M_1 on $F_{Q,2}(.)$: increasing the inspection level at M_1 reduces the number of defectives passed to M_2 and minimizes the effect of poor-quality products on the reliability of the last machine, and vice-versa.

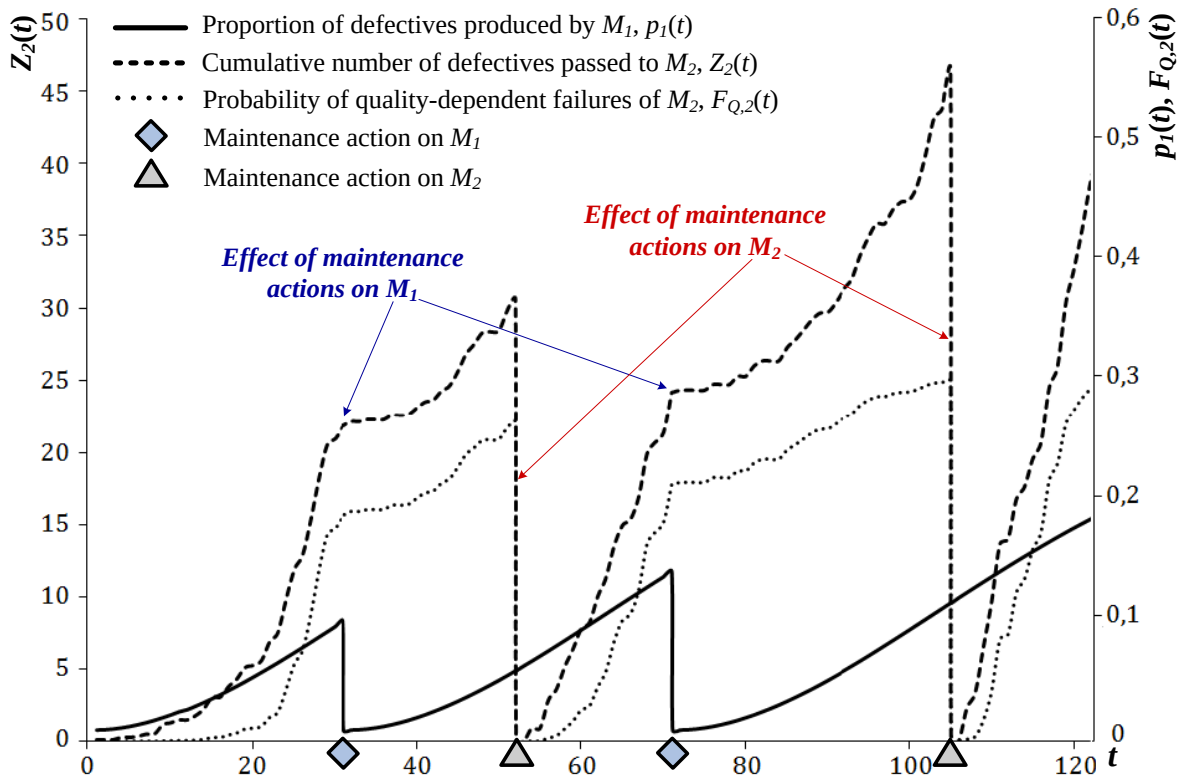


Figure 7-2. Impact of poor-quality products and maintenance actions on the reliability of M_2.

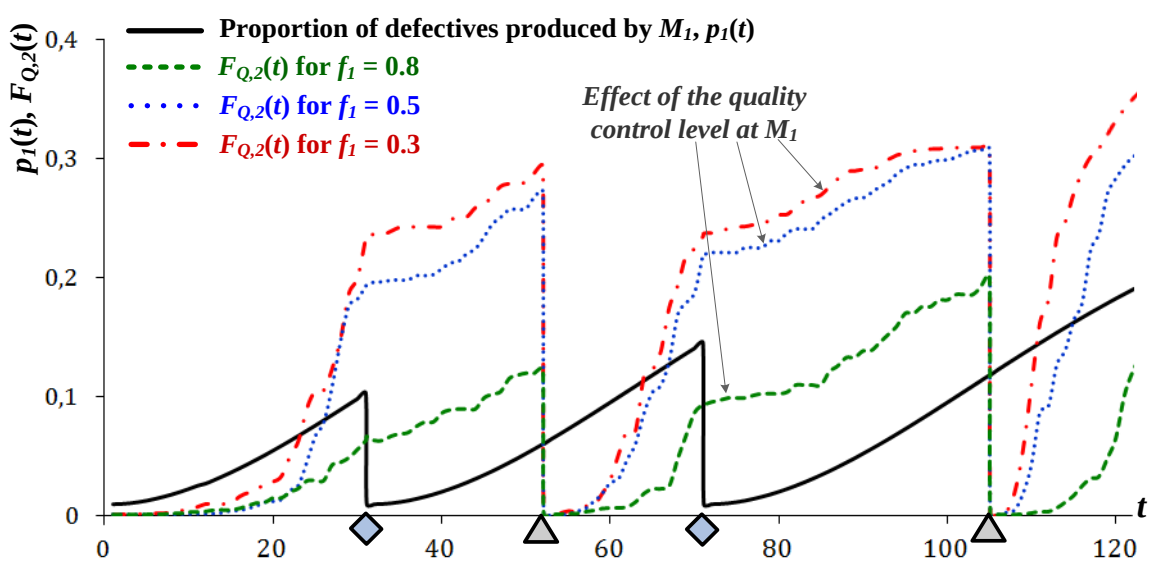


Figure 7-3. Impact of the quality control level at M_1 on the reliability of M_2.

The defective products found in quality control in both production stages are rejected. However, the defective products that have not been inspected will be transmitted to the serviceable stock and will therefore be sold to consumers. Under the ubiquitous inspection strategy, the long-run average proportion of defective products delivered to consumers, called the long-run Average Outgoing Quality (AOQ_∞), can be calculated as follows:

$$AOQ_\infty\left(s_1, s_2, m_1, m_2, f_1, f_2\right) = \left(1-f_1\right)E\left[p_1\right] + \left(1-f_2\right)E\left[p_2\right] \tag{8}$$

where $E[p_k]$ is the long-run average proportion of defective parts produced by M_k. Deriving a closed-form expression for $AOQ_\infty(.)$ using analytical approaches such as the renewal theory could be possible provided that the calculation of the expected production run length of each machine is analytically tractable. However, this is very challenging especially for M_2 due to the correlated failures. Nevertheless, $AOQ_\infty(.)$ can be bounded by an upper-bound function, denoted $UAOQ_\infty(.)$, which represents the worst average quality level perceived by the final consumers. From Eq.(8), $UAOQ_\infty(.)$ can be obtained by considering the longest possible production cycle of each machine, which corresponds to the interval between two consecutive PM actions (i.e., no failure occurs between the two consecutive PM actions), as follows:

$$UAOQ_\infty\left(m_1, m_2, f_1, f_2\right) = \left(1-f_1\right)\frac{1}{m_1}\int_0^{m_1} p_1(a).da + \left(1-f_2\right)\frac{1}{m_2}\int_0^{m_2} p_2(a).da \tag{9}$$

The exact expression for Eq.(9) is given by:

$$UAOQ_\infty\left(m_1, m_2, f_1, f_2\right) = \left(1-f_1\right)\left(p_{10} + \eta_1 - \frac{\eta_1 \Gamma\left(\frac{1}{\delta_1}, \mu_1 m_1^{\delta_1}\right)}{\delta_1\left(\mu_1 m_1^{\delta_1}\right)^{1/\delta_1}}\right) + \left(1-f_2\right)\left(p_{20} + \eta_2 - \frac{\eta_2 \Gamma\left(\frac{1}{\delta_2}, \mu_2 m_2^{\delta_2}\right)}{\delta_2\left(\mu_2 m_2^{\delta_2}\right)^{1/\delta_2}}\right) \tag{10}$$

where $\Gamma(s,x) = \int_0^x a^{s-1} e^{-a}.da$ is the lower incomplete Gamma function.

Therefore, the manufacturer must select the critical PM ages m_1 and m_2 and the inspection fractions f_1 and f_2 such that:

$$UAOQ_\infty\left(m_1, m_2, f_1, f_2\right) \le AOQL \tag{11}$$

7.4.2.3 Production-Inventory Control Policy

The hierarchical control policy proposed by Samaratunga et al. (1997) basically consists of building and maintaining a surplus inventory in the downstream of each unreliable machine in order to be able to respond to the downstream demand during maintenance operations. The production rate of each machine shall be set to its maximum level during the periods of inventory surplus build-up. Once built, the inventory surplus shall be maintained by aligning as much as possible the production rate with the rate of the downstream demand. This control policy has been primarily constructed for unreliable production lines with no quality consideration. In our context, some quality aspects should be taken into consideration in the production-inventory control. First, because the inspection delay is not negligible and because defective parts sorted during quality control are rejected, feedback information about the amount of products under quality inspection at each stage should be incorporated in the production-inventory control policy. Based on such information, it is possible to enhance visibility on the material flow and to avoid overproduction situations, accordingly. Also, the production rate can be quickly adjusted to compensate for loss in production due to the rejection of defective parts. Second, the production rate control of each machine should take into consideration the level of quality control at the upstream machine as this impacts the supply flow of the incoming products. Thus, the hierarchical control structure observed in Samaratunga et al. (1997) can be extended to include these quality considerations as in the following equations:

$$u_1(t) = \begin{cases} 0 & \text{if } y_1(t) > s_1 \text{ or } y_2(t) > s_2 \text{ or } \alpha_1(t) \in \{0,2\} \\ d & \text{if } y_1(t) = s_1 \text{ and } y_2(t) = s_2 \text{ and } \alpha_1(t) = 1 \\ u^1_{\max} & \text{if } y_1(t) < s_1 \text{ and } y_2(t) \le s_2 \text{ and } \alpha_1(t) = 1 \\ \min\{u^1_{\max}, u^2_{\max}\} & \text{if } y_1(t) = s_1 \text{ and } y_2(t) < s_2 \text{ and } \alpha_1(t) = 1 \end{cases} \tag{12}$$

$$u_2(t) = \begin{cases} 0 & \text{if } y_2(t) > s_2 \text{ or } \alpha_2(t) \in \{0,2\} \text{ or } I_{M1}(t) = 0 \\ d & \text{if } x_1(t) > 0 \text{ and } y_2(t) = s_2 \text{ and } \alpha_2(t) = 1 \\ u^2_{\max} & \text{if } x_1(t) > 0 \text{ and } y_2(t) < s_2 \text{ and } \alpha_2(t) = 1 \\ \min\{(1-f_1)u^1_{\max}, u^2_{\max}\} & \text{if } x_1(t) = 0 \text{ and } y_2(t) < s_2 \text{ and } \alpha_2(t) = 1 \text{ and } I_{M1}(t) = 1 \end{cases} \tag{13}$$

where s_1 and s_2 are two inventory thresholds, also called hedging levels. $y_k(t)$ is the inventory position in the kth production stage at time t, which is the sum of the inventory level $x_k(t)$ and the total number of parts produced by M_k that are held for quality control at the kth stage at time t. In

Eq.(13), $I_{M1}(t)$ is a binary function that indicates whether M_2 is completely starved or not at each time t. It is defined as follows: $I_{M1}(t)$ =0, if $x_1(t)$=0 and $\alpha_1(t)\neq 1$, and $I_{M1}(t)$ =1 otherwise.

From Eqs.(12) and (13), a machine is stopped if it is under maintenance or if one of the downstream buffers is full (blocking). For both machines, the production rate is set at its maximum level until the downstream inventory position reaches its hedging level. The production rate is set to d if the downstream inventory positions are equal to their hedging levels. For machine M_1, once the inventory position $y_1(.)$ reaches the threshold s_1, the production rate should be aligned with that of M_2 in order to not deplete the buffer $x_1(.)$. In situations where the buffer $x_1(.)$ is empty and M_1 is still operational, the maximum production rate of M_2 cannot exceed the supply rate of semi-finished products which is equal to $(1-f_1)\,u_1(.)$.

Under this production control policy, the dynamics of the inventories $x_1(.)$ and $x_2(.)$ can be described by the following equations:

$$\frac{\partial x_1(t)}{\partial t} = \left(1-f_1\right) u_1(t) + f_1 \left(1-Y_1\left(t-\tau_{insp}^1\right)\right) u_1\left(t-\tau_{insp}^1\right) - u_2(t),\ \ x_1(0)=x_1 \qquad (14)$$

$$\frac{\partial x_2(t)}{\partial t} = \left(1-f_2\right) u_2(t) + f_2 \left(1-Y_2\left(t-\tau_{insp}^2\right)\right) u_2\left(t-\tau_{insp}^2\right) - d,\ \ x_2(0)=x_2 \qquad (15)$$

where $\left(1-f_k\right) u_k(t)$ represents the rate of production that is directly transmitted to the downstream buffer with no quality inspection at time t, while $f_k \left(1-Y_k\left(t-\tau_{insp}^k\right)\right) u_k\left(t-\tau_{insp}^k\right)$ represents the rate of production that is transmitted to the downstream buffer after quality inspection at time t. These two equations illustrate the impact of quality control on inventory dynamics.

7.4.3 Optimization problem

The optimization problem consists of finding the optimal values of the critical PM ages m_1 and m_2, the quality control levels f_1 and f_2 and the hedging levels s_1 and s_2 that minimize the expected total cost incurred per unit time, denoted ETC(.), under the constraints formulated above. This cost includes the inventory holding and backlog costs, the total maintenance cost and the total quality cost.

The average total cost per unit time of inventory holding and backlog during the period [0,T], denoted $IC(T)$, is given by:

$$IC(T)=\frac{1}{T}\cdot\int_0^T\left(C_h\left(y_1(t)+y_2^+(t)\right)+C_b x_2^-(t)\right)\cdot dt \tag{16}$$

where $y_2^+(t)=\max\left(y_2(t),0\right)$ and $y_2^-(t)=\max\left(-y_2(t),0\right)$.

The average total maintenance cost per unit time during [0,T], denoted $MC(T)$, includes the costs of CM and PM actions for both machines, as follows:

$$MC(T)=\frac{1}{T}\sum_{k=1,2}\left(C_{cm}^k\ N_{cm}^k(T)+C_{pm}^k\ N_{pm}^k(T)\right) \tag{17}$$

where $N_{cm}^k(T)$ and $N_{pm}^k(T)$ are respectively the numbers of CM and PM actions on M_k during [0,T].

The average total quality cost per unit time during the interval [0,T], denoted $QC(T)$, includes the cost of quality inspection, the rejection cost of defective parts and the cost of selling defective parts. It is given by:

$$QC(T)=\frac{1}{T}\cdot\begin{pmatrix} C_{insp}\int_0^T\left\{f_1\cdot u_1(t)+f_2\cdot u_2(t)\right\}.dt+C_{rej1}\int_0^T Y_1(t)\cdot u_1(t).dt+C_{rej2}\int_0^T Y_2(t)\cdot u_2(t).dt \\ +C_{def}\int_0^T\left\{\left(p_1\left(A(t)\right)-Y_1(t)\right)\cdot u_1(t)+\left(p_2\left(A(t)\right)-Y_2(t)\right)\cdot u_2(t)\right\}.dt \end{pmatrix} \tag{18}$$

Hence, the optimization problem (P1) is to solve the following model:

$$\begin{cases} \text{Minimize} & ETC\left(s_1,s_2,m_1,m_2,f_1,f_2\right)=\lim_{T\to+\infty}\left\{IC(T)+MC(T)+QC(T)\right\} \\ \text{Subject to} & \text{Eqs. (1)-(6), (11)-(14)} \\ & UAOQ_\infty\left(m_1,m_2,f_1,f_2\right)\le AOQL \\ & 0\le f_k\le 1,\ k\in\left\{1,2\right\} \\ & s_1,s_2,m_1,m_2>0 \end{cases} \tag{P1}$$

7.5 Resolution approach

The optimization problem (P1) formulated above is constrained, non-linear and highly stochastic. The stochastic events are mainly the operations-dependent failures, the quality-dependent failures

in M_2, and the durations of CM and PM actions which follow general. The long-run average numbers of CM induced by operation-dependent failures and PM actions as in Eq. (17) can be analytically derived for each machine using previous findings in the literature as in Barlow and Proschan (1965). However, deriving an analytical expression of the long-run average number of CM actions induced by quality-dependent failures in M_2 is challenging due to the correlation with the dynamic of M_1. Moreover, computing the long-run average inventory/backlog cost, either analytically or numerically, is very challenging because the complexity of the inventory dynamic as in Eqs. (14) and (15) and the stochastic durations of maintenance activities. Furthermore, the computation of the long-run average quality cost as in Eq. (18) is very difficult due to the random number $Y(.)$ which follows a complex conditional probability distribution. Thus, it is not possible to employ the classical mathematical programming methods to solve the optimization problem (P1), as there is no way to derive a closed-form analytical expression for the objective function ETC(.). We alternatively used a simulation-based optimization approach to solve this problem optimally.

7.5.1 Simulation-based optimization

Simulation-based optimization is becoming one of the most commonly used optimization approaches for design of manufacturing systems and operating strategies especially in the recent years (Negahban and Smith, 2014; Alrabghi and Tiwari, 2015). This trend can be explained by the fact that using traditional modeling approaches for complex stochastic systems generally lead to models which are not analytically tractable. Numerous simulation-based optimization techniques have been proposed in the literature (see for example Fu, 2015). In this study, the simulation optimization approach consists of the following step-by-step procedure:

- *Step* 1 – *Problem Formulation*: Analytically formulate the problem under study, as shown in Section 4. This provides a rigorous modeling of the system dynamic, the objective function to be minimized and the problem constraints.
- *Step* 2 – *Simulation Modeling*: From the analytical modeling (Step 1), build a combined discrete/continuous simulation model according to the following logic: the continuous-time functions, describing the machines aging as in Eq. (1), the proportions of defectives produced as in Eq. (2), the probabilities of failure as in Eqs. (3) and (4), the production-inventory control policy as in Eqs. (12) and (13) and the inventory dynamic as in Eqs. (14) and (15) are modeled

and executed instantly with subroutines, mathematical functions and operators in C++, while the discrete events such as failures occurrence and CM and PM actions are modelled with the SIMAN simulation language in ARENA software (see Bouslah et al., 2013 and 2015 for more details). Then, the simulation is used to calculate the expected total cost incurred for given values of the decision variables.

- *Step* 3 – *Regression Metamodeling*: Use Design Of Experiments (DOE) and Response Surface Methodology (RSM) to fit the expected total cost function ETC(.) by a convex, polynomial regression metamodel called response surface and denoted $\psi(.)$ (Myers et al., 2009). The regression metamodel must include the main effects and the significant interactions between the six decision variables. The interaction effects play an important role to obtain an optimal trade-off solution for the integrated control policy.
- *Step4 – Constrained Optimization*: Solve the following optimization problem (P2) using non-linear constrained optimization techniques such as the penalty and barrier methods (Luenberger and Ye, 2008) :

$$\begin{cases} \text{Minimize} \quad \psi\left(s_1, s_2, m_1, m_2, f_1, f_2\right) \\ \text{Subject to} \quad UAOQ\left(m_1, m_2, f_1, f_2\right) \leq AOQL \\ \qquad 0 \leq f_k \leq 1,\ k \in \{1, 2\} \\ \qquad s_1, s_2, m_1, m_2 > 0 \end{cases} \tag{P2}$$

The optimal solution from (P2) should be determined within the local space defined by the DOE. Because RSM basically uses a sequence of local metamodels to converge to the optimal solution, the sequential procedure of DOE, regression metamodeling and constrained optimization should be iteratively repeated in order to fully explore the entire admissible space and to bring out at the end a global optimal solution.

7.5.2 Simulation model

A discrete/continuous simulation model has been developed and executed with the ARENA software. The differential equations (1), (14) and (15) are continuously integrated in C++ using the Runge–Kutta–Fehlberg method (Pegden et al., 1995). Advanced features in ARENA have been used to properly interface the discrete simulation with C++ subroutines.

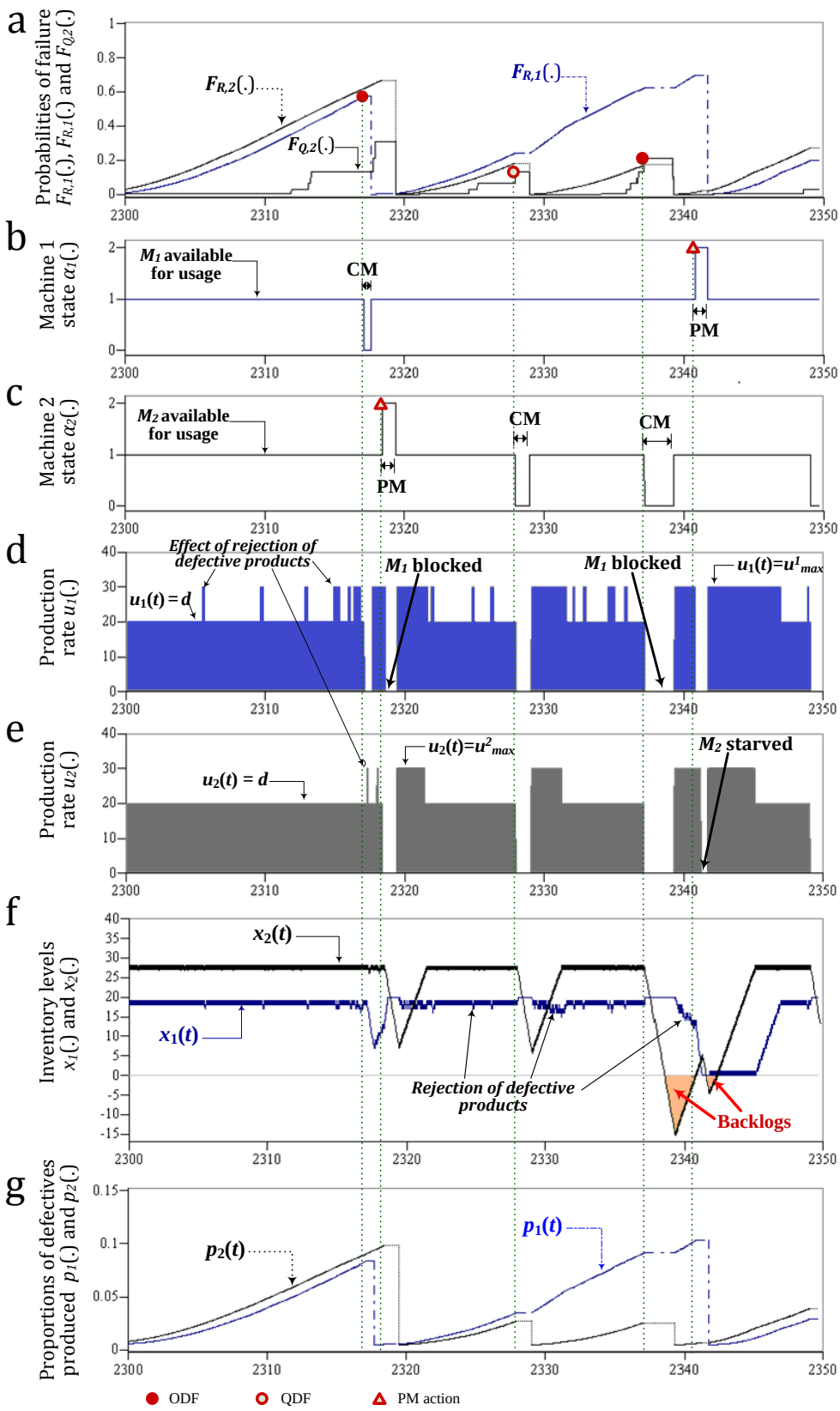


Figure 7-4. A sample of the dynamic of the manufacturing line during the simulation run.

The duration of simulation runs t_∞ is set in such a way to ensure that the steady-state is reached. At the end of each simulation run, the average inventory/backlog cost $IC(t_\infty)$, the average maintenance cost $MC(t_\infty)$ and the average quality cost $QC(t_\infty)$ are calculated from simulation data using Eqs. (16), (17) and (18), respectively.

A set of verification and validation techniques has been used to check the accuracy of the simulation model. This includes tracing the model operation, testing for reasonableness, testing the model structure and data, and using the animation and debug features of ARENA (Pegden et al., 1995). For example, Figure 4 represents a simulation sample of the dynamic of the manufacturing line over time. Figures 4.(b)-(f) show that the production-inventory control policy performs correctly with respect to the inventories $x_1(.)$ and $x_2(.)$ and the machines states $\alpha_1(.)$ and $\alpha_2(.)$, as in Eqs. (12) and (13). They also exhibit the effects of the CM and PM actions on depleting the inventories, resulting sometimes in blocking, starving and shortage situations. In Figure 4.(f), we see the effect of rejection of defective products on inventory. This loss in production is compensated by accelerating the production as shown in Figures 4.(d) and 4.(e). Figures 4.(a) and 4.(g) depict the impact of operations on reliability and quality degradations, respectively. These two Figures also illustrate the effects of CM and PM actions on improving the machines reliability and the production quality (i.e., restoration to the 'as-good-as-new' condition). Finally, from Figures 4.(b) and4.(c), we verify that the age-based PM policy operates properly as in Eq.(6).

7.6 Experimentation and sensitivity analysis

7.6.1.1 Numerical example

This section provides an illustrative example for the proposed integrated model. In this basic example, we assume that both machines are identical in the sense that they have the same production capacity and they are subject to the same probability distribution functions of operation-dependent failures and the same quality degradation pattern as well. The only difference feature between the two machines is that M_2 is additionally subject to quality-dependent failures. Also, the inspection costs at the two manufacturing stages are considered identical. So, let us consider the following parameters in the appropriate units: $u^1_{\max} = u^2_{\max}$ =30, d=20, AOQL=2.5%, C_h=1.5, C_b=25, $C^1_{cm} = C^2_{cm}$ =2000, $C^1_{pm} = C^2_{pm}$ =800, $C^1_{insp} = C^2_{insp}$ =3.5,

C^1_{rej} =40, C^2_{rej} =50, C_{def}=95, $\tau^1_{insp} = \tau^2_{insp}$ =5×10^{-4}, (τ^1_{cm}, τ^2_{cm})~Gamma(0.4,2.8), (τ^1_{pm}, τ^2_{pm})~Log-Normal(1,0.1), p_{10}=p_{20}=0.05%, η_1=η_2=0.15, μ_1=μ_2=2×10^{-6}, δ_1=δ_2=1.8, $\beta_{R,1}$= $\beta_{R,2}$=5×10^{-5}, $\gamma_{R,1}$= $\gamma_{R,2}$=1.6, $\beta_{Q,2}$=5×10^{-3} and $\gamma_{Q,2}$=2.4.

Simulations are conducted according to a 3^{6-2} factorial design of experiments in nine blocks augmented with four center points. This 3-level fractional design is suitable to reasonably reduce the number of simulation runs, and to obtain at the same time a good indication of curvature which facilitates fitting a quadratic regression model relating the response to the design factors (Montgomery, 2008b). The simulation horizon t_∞ is set to 500'000 units of time to ensure that the steady state is reached. One simulation run takes, on average, less than 30 seconds on a computer with a 2.80 GHz CPU. Collected simulation data are used to fit the expected total cost function ETC(.) by a continuous second-order regression model $\psi(.)$. To check the fitness of the regression model, we used a set of validation techniques as in Myers et al. (2009). First, the model's overall performance is evaluated in terms of the adjusted R-squared coefficient. Second, a complete residual analysis is conducted to check the homogeneity of variances and the normality assumption of residuals. Third, once the optimization is carried out on the regression model, the optimal solution is cross-checked to ensure the validity.

The simulation results are handled using the statistical software STATISTICA in order to produce the analysis of variance (ANOVA) and to seek the regression model fitting ETC(.). The ANOVA analysis is presented in Table 7.1. All factors and quadratic effects and most of interactions are statistically significant for the response variable (P-Value ≤ 5%). These significant interaction effects show the importance of finding a trade-off solution for the integrated production, quality and maintenance control policy. Furthermore, the adjusted R-squared is equal to 0.96947 which states that the second-order regression model explains about 97% of the variability observed in the excepted total cost. From STATISTICA, we obtained the following second-order regression model $\psi(.)$:

$$\begin{aligned}
\psi(s_1, s_2, m_1, m_2, f_1, f_2) &= 620.92 - 4.42\, s_1 + 51.08\times10^{-3} s_1^2 - 2.82\, s_2 + 31.06\times10^{-3} s_2^2 - 12.24\, m_1 \\
&+610.96\times10^{-3} m_1^2 - 9.29\, m_2 + 361.2\times10^{-3} m_2^2 + 14.08\, f_1 + 45.6\, f_1^2 - 67.09\, f_2 + 11.82\, f_2^2 \\
&+42.73\times10^{-3} s_1 s_2 + 70.95\times10^{-3} s_1 m_1 + 8.08\times10^{-3}\, s_1 m_2 + 72.3\times10^{-2}\, s_1 f_1 - 27.91\times10^{-2} s_1 f_2 \\
&-57.93\times10^{-5} s_2 m_1 + 2.06\times10^{-3} s_2 m_2 + 55.85\times10^{-2}\, s_2 f_1 + 13.66\times10^{-2} s_2 f_2 + 11.73\times10^{-2} m_1 m_2 \\
&-8.03\, m_1 f_1 - 72.27\times10^{-2} m_1 f_2 - 5.86\times10^{-2}\, m_2 f_1 + 16.5\times10^{-2} m_2 f_2 + 18.95\, f_1 f_2
\end{aligned} \tag{19}$$

Table 7.1: ANOVA table for the regression model.

Effect	SS	D.f.	MS	F-ratio	p-value	Significant
$s_1 + s_1^2$	3953.40	2	1976.70	48.36	0.0000	Yes
$s_2 + s_2^2$	4231.05	2	2115.53	51.76	0.0000	Yes
$m_1 + m_1^2$	10059.39	2	5029.69	123.06	0.0000	Yes
$m_2 + m_2^2$	5559.53	2	2779.77	68.01	0.0000	Yes
$f_1 + f_1^2$	2861.93	2	1430.96	35.01	0.0000	Yes
$f_2 + f_2^2$	1853.88	2	926.94	22.68	0.0000	Yes
$s_1 \cdot s_2$	3172.04	1	3172.04	77.61	0.0000	Yes
$s_1 \cdot m_1$	1185.78	1	1185.78	29.01	0.0000	Yes
$s_1 \cdot m_2$	15.29	1	15.29	0.37	0.5432	No
$s_1 \cdot f_1$	345.42	1	345.42	8.45	0.0052	Yes
$s_1 \cdot f_2$	0.43	1	0.43	0.01	0.9184	No
$s_2 \cdot m_1$	0.15	1	0.15	0.00	0.9525	No
$s_2 \cdot m_2$	3.29	1	3.29	0.08	0.7776	No
$s_2 \cdot f_1$	213.69	1	213.69	5.23	0.0260	Yes
$s_2 \cdot f_2$	8.51	1	8.51	0.21	0.6499	No
$m_1 \cdot m_2$	565.18	1	565.18	13.83	0.0005	Yes
$m_1 \cdot f_1$	8290.59	1	8290.59	202.85	0.0000	Yes
$m_1 \cdot f_2$	291.59	1	291.59	7.13	0.0098	Yes
$m_2 \cdot f_1$	343.70	1	343.70	8.41	0.0053	Yes
$m_2 \cdot f_2$	695.02	1	695.02	17.01	0.0001	Yes
$f_1 \cdot f_2$	538.98	1	538.98	13.19	0.0006	Yes
Error	2329.65	57	40.871			
Total SS	51031.42	84			R^2-adjusted = 0.96947	

Figure 5 depicts the projection of the cost response surface $\psi(.)$ on different two-dimensional spaces. The regions with gray-shaded contours in Figures 5.(b) and 5.(c) represent the space of infeasible solutions where the AOQL constraint is not satisfied. These two figures additionally exhibit the effect of the tightness of the AOQL constraint on the size of the feasible region and on the optimal solution, accordingly. Solving the optimization problem as in (P2) yields to the following optimal solution: s_1^*=19.0, s_2^*=28.2, m_1^*=511.4, m_2^*=491.8, f_1^*=0.531, f_2^*=0 and ψ^* =$ 422.7. From 20 replications of simulation, we verified that the optimal cost $ 422.7 falls within the confidence interval [$422.23, $425.21]. The $UAOQ_\infty$ corresponding to the optimal solution is equal to 1.81%. Using Eq.(8), we calculated the AOQ_∞ with simulation. The calculated AOQ_∞ is 1.74%.

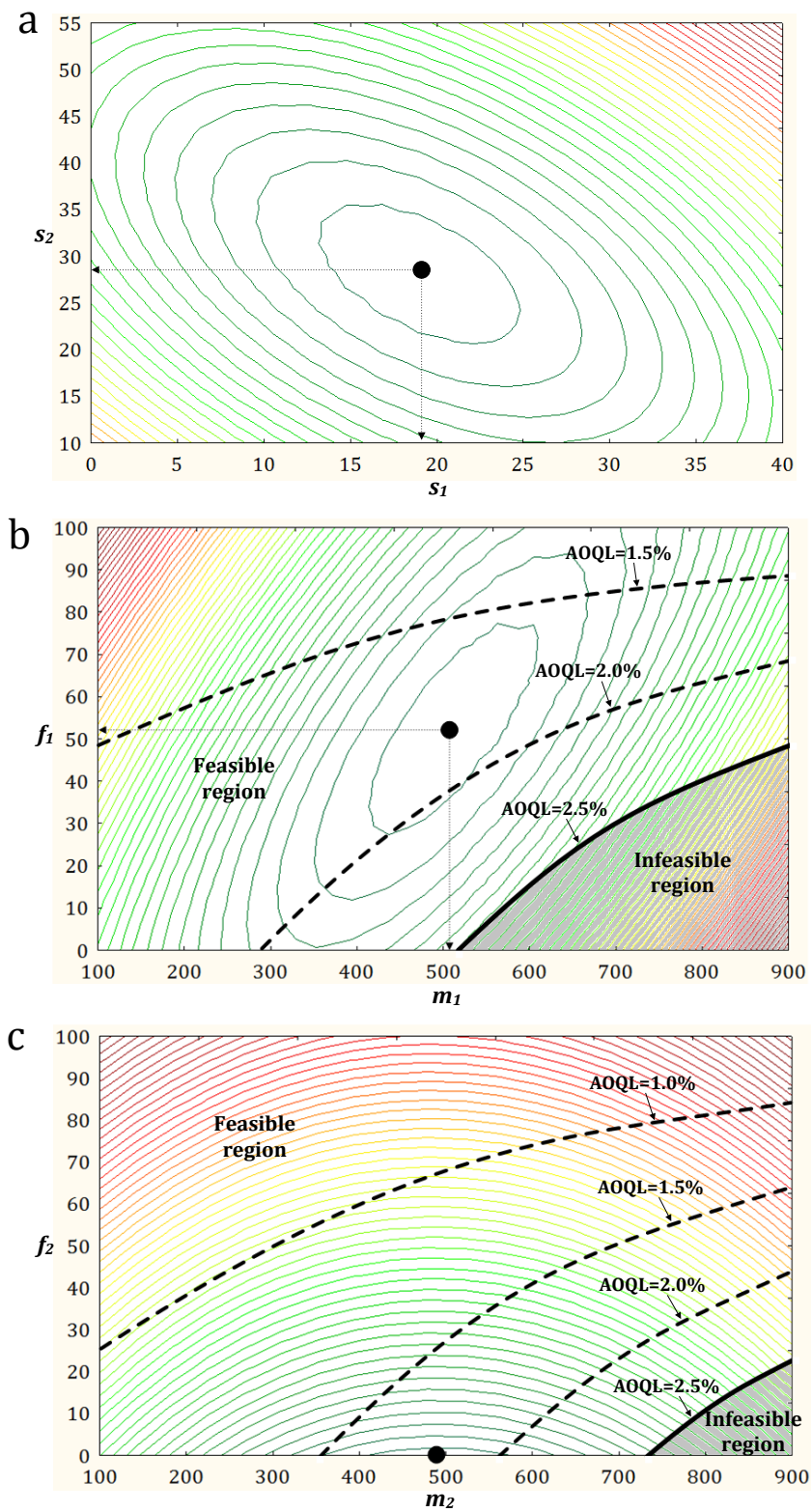


Figure 7-5. Contour plots of the estimated expected total cost function $\psi(.)$.

The optimal solution obtained indicates that one inspection station should be assigned after M_1 and that 53.1% of intermediate products should be randomly inspected at that point (as f_1^* is equal to 0.531). There is no inspection station to be assigned to M_2 as f_2^* is equal to 0. Focusing the quality control efforts at M_1 can be explained by the fact that the rejection cost at this machine is less expensive than that at M_2. But, more importantly, the quality control at M_1 reduces the proportion of defective products passed to M_2 and improves the reliability of that machine accordingly. Otherwise, M_2 will become a production bottleneck machine due to the quality-dependent failures, and the production line will be unbalanced (recall that both machines are initially identical).

7.6.2 Impact of cost parameters

Another set of experiments derived from the basic case was conducted to analyze the sensitivity of the optimal solution with respect to changes in the system parameters. The main objective of the sensitivity analysis is to investigate the effects of the system parameters on the optimal control settings and to study important aspects related to the interrelations between production, quality and maintenance control settings.

Table 7.2 presents 40 configurations of cost parameters. For each configuration, we calculated $UAOQ_\infty$ and AOQ_∞ to verify that the AOQL constraint is satisfied. Moreover, we used simulation to calculate additional performance measures, such as the long-run average backlog $E[x^-]$, the long-run average rate of operations-dependent failures of each machine M_k denoted by $\lambda_{R,k}$, the long-run average rate of quality-dependent failures of M_2 denoted by $\lambda_{Q,2}$, and the long-run average reliability of each machine M_k denoted by $E[R_k]$. These performance indicators are used to help analyze and explain the variations of the optimal control settings in response to changes in cost parameters.

The first observation that can be made from Table 2 is that when the reliability of M_1 decreases, the reliability of M_2 increases and vice-versa. This is because, when the reliability of M_1 worsens, M_2 becomes more likely to be starved so that it should be more reliable to be able to fulfill the downstream demand. Generally speaking, the lower the reliability of the upstream processes which means higher uncertainty in the upstream material flow, the higher the reliability of the subsequent machines is required. Another interesting observation from Table 2 is that each reliability improvement of M_2 always corresponds to an increase of the frequency of PM actions

on M_2 (i.e., m_2^* decreases) and an increase the quality control level at M_1 as well (i.e, f_1^* increases). This shows how the preventive maintenance and quality control complement each other to improve the performance of that machine. Moreover, it highlights the important role of the quality control on reliability improvement.

The variations of the optimal settings in Table 2 are compared to the basic case and analyzed as follows:

• *Variation of the holding inventory cost*: When C_h increases as in cases 3 and 4, both optimal hedging levels s_1^* and s_2^* decrease to minimize the total holding inventory cost. The optimal age threshold m_1^* increases to reduce the PM actions on M_1 as the decrease of s_1^* slows down both quality and reliability degradations in this machine. However, m_2^* decreases in order to perform the PM actions more frequently on M_2. This results in improving the reliability of M_2, which is essential to increase its capacity to mitigate the risk of shortage becoming higher as s_2^* decreased ($E[x^-]$ increased significantly). The optimal inspection fraction f_1^* significantly increases to lower the number of defective parts passed to M_2 and to minimize the occurrence of quality-dependent failures accordingly ($\lambda_{Q,2}$ decreased significantly). Note that a lower holding inventory cost has the opposite effects (cases 1 and 2).

• *Variation of the backlog cost*: When C_b increases as in cases 7 and 8, the optimal hedging level s_2^* increases to provide better protection to the serviceable inventory against stock-outs (as the inventory $x_2(.)$ is facing the market demand). Consequently, s_1^* increases to avoid situations where M_2 is starved. The optimal inspection fraction f_1^* increases and the optimal PM critical age m_2^* decreases to improve the reliability of M_2 and to reduce the risk of shortage accordingly (as a result, $E[x^-]$ decreased). m_1^* increases due to reliability improvement of M_2. Note that decreasing C_b produces the opposite effects (cases 5 and 6).

• *Variation of the CM cost of M_1*: When C_{cm}^1 increases as in cases 11 and 12, the reliability of M_1 should be improved to minimize the occurrence of failures which explains the significant decrease of the PM critical age m_1^* (as a result, $\lambda_{R,1}$ decreases and $E[R_1]$ increases significantly). s_1^* increases because frequent PM actions on M_1 reduce the machine's availability. f_1^* decreases as the frequent PM actions enhance the production quality of M_1 as well. On the other side, m_2^* increases due to the reliability improvement of M_1. Accordingly, s_2^* decreases to slow down the

degradation of M_2 during the periods of safety stock build-up (periods when the production is accelerated). Note that the decrease of C_{cm}^1 produces the opposite effects (cases 9 and 10).

• *Variation of the CM cost of M_2*: When C_{cm}^2 increases (cases 15 and 16), m_2^* decreases and f_1^* increases significantly in order to improve the reliability of M_2 and to reduce the occurrence of failures on that machine accordingly (both $\lambda_{R,2}$ and $\lambda_{Q,2}$ decreased and $E[R_2]$ increased significantly). The increase of the quality control level at M_1 results in reducing the PM actions on M_1 which explains the increase of m_1^*. The optimal surplus inventory s_2^* decreases due to the reliability improvement of M_2, while s_1^* decreases to decelerate the degradation of M_1. The opposite effects are observed when C_{cm}^2 decreases (cases 13 and 14).

• *Variation of the PM cost of M_1*: Increasing C_{pm}^1 as in cases 19 and 20 has the opposite effects on the optimal control settings when compared with increasing the CM cost C_{cm}^1 (cases 11 and 12). This is because both cost variations influence in the opposite way the optimal balance between PM and CM activities on M_1. Similarly, decreasing C_{pm}^1 as in cases 17 and 18 has the opposite effect on the optimal control settings as decreasing C_{cm}^1 (cases 9 and 10).

• *Variation of the PM cost of M_2*: Also, increasing C_{pm}^2 as in cases 23 and 24 produces the opposite effect on the optimal control settings when compared with increasing C_{cm}^2 (cases 15 and 16), and vice-versa, decreasing C_{pm}^2, as in cases 21 and 22, produces the opposite effect on the optimal control settings when compared with decreasing C_{cm}^2 (cases 13 and 14).

• *Variation of the inspection cost at M_1*: When C_{insp}^1 increases as in cases 27 and 28, f_1^* significantly decreases to reduce the total inspection cost at M_1. The decrease of the quality control level at M_1 is compensated by increasing the PM actions on that machine which explains the significant decrease of m_1^* (so that $E[R_1]$ increased significantly). s_1^* increases as frequent PM actions on M_1 reduces its availability. Because the reliability improvement of M_1, m_2^* increases to reduce the PM actions on M_2. Note that a lower inspection cost at M_1 has the opposite effects (cases 25 and 26).

• *Variation of the inspection cost at M_2*: When C_{insp}^2 increases as in cases 31 and 32, the inspection cost at M_2 becomes more expensive than at M_1, and then the optimal solution remains unchanged as no inspection station is initially allocated at M_2 (in the basic case). However, when C_{insp}^2 decreases as in cases 29 and 30, the optimal inspection fraction f_2^* increases because the

inspection cost at M_2 becomes less expensive than that at M_1. As a result, some quality control efforts at M_1 are transferred to M_2 in order to reduce the total inspection cost which explains the decrease of f_1^* and the increase of f_2^*. For example, in case 29, 49.5% and 40.7% of products manufactured by M_1 and M_2, respectively, are inspected. Accordingly, the outgoing quality is significantly improved (i.e., AOQ_∞ dropped from 1.74% to 1.17%). m_2^* increases to reduce the PM actions on M_2 as f_2^* increased, while m_1^* decreases to carry out more PM actions on M_1 as f_1^* decreased. Thus, s_2^* decreases to slow down the degradation of M_2, while s_1^* increases because the increase of PM activities in M_1.

• *Variation of the rejection cost at M_1*: When C_{rej}^1 increases as in cases 35 and 36, f_1^* decreases in order to reduce the total rejection cost. The decrease of quality control level at M_1 is compensated by an increase of PM actions on this machine, so that m_1^* decreases. s_1^* increases due to the effect of the increasing frequency of PM actions on the availability of M_1. Because M_2 is less likely to be starved, m_2^* decreases in order to reduce the PM actions on M_2. Note that the decrease in C_{rej}^1 has the opposite effects (cases 33 and 35).

• *Variation of the cost of selling a defective finished product*: When C_{def} increases as in cases 39 and 40, the quality control activities should be intensified to improve the outgoing quality which explains the increase of the optimal inspection level f_1^* (e.g., in case 40, AOQ_∞ dropped from 1.74% to 0.94%). m_1^* increases to reduce the frequency of PM actions on M_1 as the quality control at this machines becomes tighter. However, m_2^* decreases to increase the frequency of PM actions on M_2 and to improve the product quality accordingly. Both the optimal hedging levels s_1^* and s_2^* decrease to slow down the quality degradation of machines M_1 and M_2 respectively. Note that the decrease in C_{def} produces the opposite effects (cases 37 and 38).

Table 7.2: Sensitivity analysis of cost parameters.

Case number	Parameter	Value	Optimal control settings						Performance								
			PIC		PM		QC		*Cost**	Quality		Reliability					$E[x^-]$
			s_1*	s_2*	m_1*	m_2*	f_1*	f_2*		$UAOQ_\infty$	AOQ_∞	$\lambda_{R.1}$	$E[R_1]$	$\lambda_{R.2}$	$\lambda_{Q.2}$	$E[R_2]$	
1	C_h	0.5	28.1	41.1	384.9	522.1	15.4%	0.0%	372.9	2.12%	2.08%	0.03185	0.8154	0.03747	0.00633	0.7374	0.12
2		1.0	23.9	34.4	440.2	508.6	32.2%	0.0%	400.4	2.00%	1.95%	0.03469	0.7886	0.03730	0.00451	0.7458	0.20
basic		1.5	19.0	28.2	511.4	491.8	53.1%	0.0%	422.7	1.81%	1.74%	0.03756	0.7593	0.03716	0.00254	0.7595	0.43
3		2.0	12.9	22.5	606.0	470.4	80.0%	0.0%	441.6	1.47%	1.39%	0.04001	0.7268	0.03625	0.00061	0.7726	0.77
4		2.5	7.4	17.4	680.6	449.9	100.0%	0.0%	452.7	1.12%	1.07%	0.04261	0.7092	0.03660	0.00000	0.7844	1.59
5	C_b	15	16.4	19.9	488.7	508.7	46.1%	0.0%	399.3	1.96%	1.85%	0.03538	0.7655	0.03766	0.00327	0.7502	0.86
6		20	17.7	24.0	503.1	500.6	50.5%	0.0%	410.3	1.88%	1.79%	0.03745	0.7624	0.03668	0.00278	0.7535	0.61
basic		25	19.0	28.2	511.4	491.8	53.1%	0.0%	422.7	1.81%	1.74%	0.03748	0.7593	0.03737	0.00254	0.7601	0.43
7		30	20.3	31.7	516.6	481.8	56.0%	0.0%	433.8	1.74%	1.69%	0.03759	0.7566	0.03587	0.00227	0.7621	0.26
8		35	21.6	34.3	519.7	469.7	58.7%	0.0%	441.6	1.66%	1.63%	0.03875	0.7574	0.03596	0.00181	0.7695	0.24
9	C^1_{cm}	1000	12.4	28.6	710.8	465.3	100.0%	0.0%	391.1	1.15%	1.10%	0.04168	0.6980	0.03615	0.00000	0.7766	0.54
10		1500	15.6	28.4	614.1	478.2	77.0%	0.0%	406.7	1.54%	1.45%	0.03985	0.7228	0.03680	0.00059	0.7691	0.45
basic		2000	19.0	28.2	511.4	491.8	53.1%	0.0%	422.7	1.81%	1.74%	0.03756	0.7593	0.03716	0.00254	0.7595	0.43
11		2500	22.2	28.0	409.6	505.4	30.4%	0.0%	437.1	1.97%	1.92%	0.03323	0.8028	0.03729	0.00426	0.7482	0.37
12		3000	25.4	27.8	307.6	519.0	8.7%	0.0%	447.9	2.03%	2.01%	0.02911	0.8585	0.03781	0.00544	0.7416	0.38
13	C^2_{cm}	1000	20.2	31.4	437.0	565.5	4.0%	0.0%	380.2	2.50%	2.30%	0.03488	0.7905	0.03975	0.01095	0.7100	0.32
14		1500	19.8	29.8	444.8	563.6	17.4%	0.0%	403.2	2.32%	2.19%	0.03518	0.7867	0.03811	0.00759	0.7171	0.35
basic		2000	19.0	28.2	511.4	491.8	53.1%	0.0%	422.7	1.81%	1.74%	0.03756	0.7593	0.03716	0.00254	0.7595	0.43
15		2500	15.5	28.1	685.7	424.6	100.0%	0.0%	437.2	1.06%	1.03%	0.04182	0.7065	0.03453	0.00000	0.7954	0.48
16		3000	14.4	27.9	706.7	368.1	100.0%	0.0%	446.2	0.93%	0.93%	0.04282	0.7030	0.03280	0.00000	0.8249	0.56
17	C^1_{pm}	600	25.6	26.8	322.8	539.5	2.1%	0.0%	397.4	2.17%	2.04%	0.02949	0.8497	0.03784	0.00723	0.7298	0.36
18		700	23.6	27.7	384.7	520.9	14.1%	0.0%	411.7	2.14%	1.98%	0.03274	0.8166	0.03737	0.00653	0.7355	0.41
basic		800	19.0	28.2	511.4	491.8	53.1%	0.0%	422.7	1.81%	1.74%	0.03756	0.7593	0.03716	0.00254	0.7595	0.43
19		1000	14.2	28.5	662.0	470.8	86.5%	0.0%	435.4	1.40%	1.32%	0.04093	0.7104	0.03704	0.00026	0.7727	0.47
20		1200	12.2	28.6	721.8	462.4	100.0%	0.0%	443.7	1.15%	1.10%	0.04275	0.6980	0.03671	0.00000	0.7792	0.55

PIC: Production-Inventory Control, QC: Quality Control

Table 7.2: (continued)

Case number	Parameter	Value	Optimal control settings						Performance								
			PIC		PM		QC		*Cost**	Quality		Reliability					$E[x^-]$
			s_1*	s_2*	m_1*	m_2*	f_1*	f_2*		$UAOQ_\infty$	AOQ_∞	$\lambda_{R.1}$	$E[R_1]$	$\lambda_{R.2}$	$\lambda_{Q.2}$	$E[R_2]$	
21	C^2_{pm}	600	16.9	27.7	592.8	340.1	72.2%	0.0%	401.1	1.29%	1.18%	0.03863	0.7274	0.03148	0.00057	0.8386	0.47
22		700	18.1	28.0	543.9	412.9	61.1%	0.0%	412.8	1.56%	1.52%	0.03891	0.7480	0.03369	0.00137	0.7966	0.44
basic		800	19.0	28.2	511.4	491.8	53.1%	0.0%	422.7	1.81%	1.74%	0.03756	0.7593	0.03716	0.00254	0.7595	0.43
23		1000	19.9	28.6	470.8	587.6	44.4%	0.0%	436.7	2.12%	1.96%	0.03611	0.7749	0.03831	0.00353	0.7172	0.37
24		1200	20.5	29.1	446.3	643.9	32.3%	0.0%	446.1	2.39%	2.15%	0.03583	0.7872	0.03985	0.00557	0.6973	0.34
25	C^1_{insp}	2.0	13.4	27.7	669.9	472.2	100.0%	0.0%	391.2	1.17%	1.11%	0.04106	0.7081	0.03611	0.00000	0.7744	0.56
26		3.2	15.6	27.9	605.9	479.4	81.5%	0.0%	415.5	1.47%	1.39%	0.03984	0.7262	0.03684	0.00037	0.7694	0.47
basic		3.5	19.0	28.2	511.4	491.8	53.1%	0.0%	422.7	1.81%	1.74%	0.03756	0.7593	0.03716	0.00254	0.7595	0.43
27		3.8	22.1	28.4	422.5	503.8	26.2%	0.0%	427.2	2.03%	1.98%	0.03396	0.7966	0.03745	0.00500	0.7454	0.35
28		5.0	24.9	28.6	343.0	512.4	2.5%	0.0%	429.5	2.13%	2.11%	0.03169	0.8392	0.03779	0.00732	0.7386	0.34
29	C^2_{insp}	2.0	19.9	26.8	490.7	505.9	49.5%	40.7%	412.1	1.35%	1.17%	0.03579	0.7650	0.03799	0.00275	0.7536	0.46
30		2.5	19.3	28.0	498.5	493.0	51.9%	8.6%	417.4	1.71%	1.65%	0.03707	0.7642	0.03723	0.00260	0.7584	0.42
basic		3.5	19.0	28.2	511.4	491.8	53.1%	0.0%	422.7	1.81%	1.74%	0.03756	0.7593	0.03716	0.00254	0.7595	0.43
31		3.8	19.0	28.2	511.4	491.8	53.1%	0.0%	422.7	1.81%	1.74%	0.03756	0.7593	0.03716	0.00254	0.7595	0.43
32		5.0	19.0	28.2	511.4	491.8	53.1%	0.0%	422.7	1.81%	1.74%	0.03756	0.7593	0.03716	0.00254	0.7595	0.43
33	C^1_{rej}	30	13.0	28.0	686.5	470.4	100.0%	0.0%	415.9	1.17%	1.11%	0.04145	0.7038	0.03624	0.00000	0.7741	0.54
34		35	16.5	28.1	583.2	482.8	72.6%	0.0%	418.9	1.60%	1.51%	0.03969	0.7337	0.03697	0.00078	0.7665	0.46
basic		40	19.0	28.2	511.4	491.8	53.1%	0.0%	422.7	1.81%	1.74%	0.03756	0.7593	0.03716	0.00254	0.7595	0.43
35		45	21.6	28.2	463.3	498.1	39.6%	0.0%	425.9	1.93%	1.86%	0.03552	0.7777	0.03723	0.00341	0.7521	0.39
36		50	22.8	28.3	429.0	502.8	29.8%	0.0%	426.7	2.00%	1.94%	0.03503	0.7961	0.03765	0.00501	0.7476	0.37
37	C_{def}	65	20.5	30.2	434.2	591.5	23.3%	0.0%	393.7	2.31%	2.15%	0.03444	0.7914	0.03839	0.00719	0.7101	0.35
38		80	20.1	29.2	461.8	544.0	35.1%	0.0%	407.9	2.10%	1.98%	0.03553	0.7790	0.03811	0.00481	0.7318	0.36
basic		95	19.0	28.2	511.4	491.8	53.1%	0.0%	422.7	1.81%	1.74%	0.03756	0.7593	0.03716	0.00254	0.7595	0.43
39		110	16.2	27.1	609.4	429.8	84.1%	0.0%	435.4	1.31%	1.27%	0.04026	0.7265	0.03414	0.00031	0.7914	0.46
40		125	15.1	26.1	660.2	371.8	100.0%	0.0%	443.0	0.94%	0.94%	0.04211	0.7135	0.03347	0.00000	0.8235	0.60

7.6.3 Impact of quality and reliability degradation parameters

Tables 7.3 and 7.4 present different configurations of quality and reliability degradation parameters, respectively. By varying one degradation parameter at a time, the machines become non-identical and one of them may turn into a quality/production bottleneck. So, the objective of this section is to study the reaction of the optimal settings of the integrated control policy when the machines are basically subject to different degradation patterns. The results obtained make sense and can be explained as follows.

• *Variation of the quality degradation rate in M_1*: Increasing the parameter μ_1 as in cases 57 and 58 yields to intensifying the quality degradation in M_1 which becomes a quality bottleneck machine (in the sense that it is the machine that has the largest effect on the product quality (Inman et al., 2013)). Therefore, the quality control level at M_1 should be increased to minimize the effects of the defective intermediate products on the reliability of M_2 and on the outgoing quality, which explains the significant increase of the optimal inspection level f_1^*. Also, the optimal hedging level s_1^* decreases to slow down the quality degradation of M_1. The optimal age threshold m_1^* firstly increases to reduce the PM actions on M_1 due to the increase of f_1^* (as in case 57), then once f_1^* reaches the 100% level (as in case 58), m_1^* changes its variation so it starts decreasing in order to carry out more PM actions and to improve the quality of intermediate products accordingly. In addition, in response to the increase of μ_1, m_2^* decreases to improve the reliability of M_2 and to mitigate the risk of shortage becoming higher as s_1^* has decreased. Also, s_2^* increases to provide greater protection to the serviceable stock against stock-outs. When quality degradation in M_1 is decelerated as in cases 55 and 56, we observe the opposite effects of case 57.

• *Variation of the quality degradation rate in M_2*: When the quality degradation rate in M_2 is intensified as in cases 61 and 62, this machine becomes a quality bottleneck. Thus, the optimal PM threshold m_2^* decreases in order to restore the process quality of M_2 more frequently and to improve the outgoing quality. The optimal hedging level s_2^* increases because the increase of the PM actions on M_2. Because the reliability of M_2 is improved, the first reaction of the optimal control setting for M_1 (as in case 61), is decreasing the optimal hedging level s_1^*, increasing the optimal PM threshold m_1^* and increasing the optimal inspection level f_1^* accordingly. However, when the quality degradation rate in M_2 becomes more critical as in case 62, some of inspection

efforts at M_1 are transferred to the second machine (i.e., f_1^* decreases and f_2^* increases) in order to enhance the outgoing quality and to reduce at the same time the total inspection cost. Consequently, m_1^* changes its variation so it starts decreasing in order to compensate the decrease of f_1^*, and hence s_1^* starts increasing as PM actions on M_1 become more frequent. When the quality degradation rate in M_2 is lowered as in cases 59 and 60, the opposite effects of case 61 are observed.

• *Variation of the 'operation-dependent' failure rate of M_1*: When the reliability degradation of M_1 is intensified as in cases 65 and 66 (Table 7.4), failures occur more frequently and incur extra CM costs. Thus, m_1^* decreases to perform more PM actions on M_1 and to mitigate the negative effects of failures. f_1^* decreases as the PM actions on M_1 become frequent. Also, m_2^* increases to lower the total PM cost. Both s_1^* and s_2^* increase to protect the production line against the increasing uncertainty in M_1 (i.e., higher risk of starvation). Note that a slower reliability degradation of M_1 produces the opposite effects (cases 63 and 64).

• *Variation of the 'operation-dependent' failure rate of M_2*: When the 'operation-dependent' failure rate of M_2 increases as in cases 69 and 70, the optimal PM threshold m_2^* decreases to minimize the occurrence of such failures in that machine. Also, the optimal inspection level f_1^* increases to minimize the occurrence of quality-dependent failures and to minimize the total CM cost at M_2 accordingly. The optimal PM threshold m_1^* increases because the increase of the quality control level at M_1. Both s_1^* and s_2^* increase to protect the production line against the increasing uncertainty in M_2 (i.e., higher risk of stock-outs). Slowing down the reliability degradation of M_2 as in cases 67 and 68 produces the opposite effects.

• *Variation of the 'quality-dependent' failure rate of M_2*: When the 'quality-dependent' failure rate of M_2 increases as in cases 73 and 74, the optimal quality control level f_1^* increases to provide better protection against the effect of poor quality on the reliability of the second machine. Also, the optimal PM threshold m_2^* decreases to improve the reliability of M_2, while the optimal hedging level s_2^* increases to provide better protection to the serviceable stock against shortages. The optimal PM threshold m_1^* increases due to the increase of f_1^*, while s_1^* decreases to slow down the quality degradation in M_1. Note that a lower 'quality-dependent' failure rate, as in cases 71 and 72, produces the opposite effects.

Table 7.3 : Sensitivity analysis of quality degradation parameters.

Case number	Parameter	Value	Optimal control settings						Performance								
			PIC		PM		QC		*Cost**	Quality		Reliability					$E[x^{-}]$
			s_1*	s_2*	m_1*	m_2*	f_1*	f_2*		$UAOQ_\infty$	AOQ_∞	$\lambda_{R.1}$	$E[R_1]$	$\lambda_{R.2}$	$\lambda_{Q.2}$	$E[R_2]$	
55	μ_1	1.50	21.7	26.1	469.6	509.1	15.3%	0.0%	496.5	2.25%	2.06%	0.03593	0.7752	0.03743	0.00618	0.7404	0.39
56		1.75	20.9	26.6	482.4	498.0	34.6%	0.0%	409.6	2.02%	1.91%	0.03669	0.7705	0.03728	0.00399	0.7515	0.42
basic		2.00	19.0	28.2	511.4	491.8	53.1%	0.0%	422.7	1.81%	1.74%	0.03756	0.7593	0.03716	0.00254	0.7595	0.43
57		2.25	13.8	28.5	666.2	480.7	100.0%	0.0%	432.9	1.19%	1.15%	0.04191	0.7085	0.03704	0.00000	0.7697	0.48
58		2.50	13.6	28.9	649.2	461.7	100.0%	0.0%	436.7	1.14%	1.11%	0.04055	0.7134	0.03637	0.00000	0.7785	0.53
59	μ_2	1.25	19.7	27.9	452.6	578.1	40.3%	0.0%	399.7	2.12%	1.70%	0.03457	0.7822	0.03894	0.00407	0.7218	0.46
60		1.75	19.7	28.0	464.5	527.8	41.6%	0.0%	411.4	1.98%	1.82%	0.03617	0.7785	0.03785	0.00335	0.7408	0.44
basic		2.00	19.0	28.2	511.4	491.8	53.1%	0.0%	422.7	1.81%	1.74%	0.03756	0.7593	0.03716	0.00254	0.7595	0.43
61		2.25	18.0	28.4	566.3	464.6	67.9%	0.0%	434.6	1.61%	1.59%	0.03884	0.7385	0.03569	0.00134	0.7728	0.39
62		2.75	19.7	28.9	494.4	411.5	45.8%	12.6%	440.8	1.65%	1.63%	0.03753	0.7667	0.03406	0.00305	0.7950	0.38

Table 7.4 : Sensitivity analysis of reliability degradation parameters.

Case number	Parameter	Value	Optimal control settings						Performance								
			PIC		PM		QC			Quality		Reliability					
			s_1*	s_2*	m_1*	m_2*	f_1*	f_2*	*Cost**	$UAOQ_\infty$	AOQ_∞	$\lambda_{R.1}$	$E[R_1]$	$\lambda_{R.2}$	$\lambda_{Q.2}$	$E[R_2]$	$E[x^-]$
63	$\beta_{R,1}$	4.0	12.6	26.1	678.9	475.6	100.0%	0.0%	405.4	1.18%	1.13%	0.03343	0.7729	0.03688	0.00000	0.7782	0.41
64		4.5	15.9	27.5	584.3	487.3	74.0%	0.0%	410.9	1.59%	1.52%	0.03638	0.7649	0.03699	0.00079	0.7663	0.42
basic		5.0	19.0	28.2	511.4	491.8	53.1%	0.0%	422.7	1.81%	1.74%	0.03756	0.7593	0.03716	0.00254	0.7595	0.43
65		5.5	20.7	28.6	482.1	502.3	45.9%	0.0%	433.2	1.89%	1.82%	0.03963	0.7462	0.03739	0.00276	0.7522	0.47
66		6.0	21.9	28.8	442.9	507.6	34.0%	0.0%	437.3	1.98%	1.91%	0.04206	0.7276	0.03745	0.00428	0.7487	0.52
67	$\beta_{R,2}$	4.0	18.6	25.0	458.4	506.0	40.8%	0.0%	406.3	1.93%	1.91%	0.03557	0.7803	0.03027	0.00388	0.7767	0.39
68		4.5	18.9	26.7	491.9	496.9	48.9%	0.0%	410.5	1.86%	1.81%	0.03686	0.7675	0.03337	0.00278	0.7670	0.41
basic		5.0	19.0	28.2	511.4	491.8	53.1%	0.0%	422.7	1.81%	1.74%	0.03756	0.7593	0.03716	0.00254	0.7595	0.43
69		5.5	19.3	28.9	522.4	481.0	55.4%	0.0%	433.2	1.75%	1.67%	0.03782	0.7614	0.03965	0.00206	0.7520	0.45
70		6.0	19.4	29.8	529.3	471.3	59.7%	0.0%	438.4	1.69%	1.60%	0.03824	0.7567	0.04283	0.00174	0.7476	0.48
71	$\beta_{Q,2}$	40	21.7	26.9	446.0	513.8	29.0%	0.0%	411.2	2.06%	2.00%	0.03431	0.7849	0.03731	0.00437	0.7427	0.36
72		45	19.6	27.9	485.6	496.2	44.2%	0.0%	413.8	1.90%	1.84%	0.03614	0.7682	0.03722	0.00283	0.7543	0.38
basic		50	19.0	28.2	511.4	491.8	53.1%	0.0%	422.7	1.81%	1.74%	0.03756	0.7593	0.03716	0.00254	0.7595	0.43
73		55	16.4	28.3	570.1	486.5	70.2%	0.0%	429.0	1.63%	1.56%	0.03886	0.7371	0.03695	0.00130	0.7649	0.45
74		60	14.3	28.5	641.2	480.6	93.0%	0.0%	431.9	1.30%	1.24%	0.04176	0.7191	0.03668	0.00003	0.7720	0.57

7.6.4 Impact of the AOQL constraint

Additional experiments were conducted to analyze the influence of the AOQL constraint on the optimal control settings of the integrated control policy. Table 7.5 presents the optimal control settings obtained for different levels of the AOQL. The first observation from Table 5 is that, as expected, the optimal cost increases in response to the decrease of the AOQL and vice-versa. Also, for AOQL levels strictly greater than 1.81%, the AOQL constraint is inactive (i.e., $UAOQ_{\infty}$<AOQL). This is because, in the basic case, the optimal solution obtained whose the $UAOQ_{\infty}$ is equal to 1.81% absolutely realizes the minimum possible cost, as it has not been influenced by the AOQL constraint as shown in Figure 5. However, for AOQL levels less than 1.81% (e.g., cases 76-85), the AOQL constraint becomes active (i.e., $UAOQ_{\infty}$=AOQL). In these cases, we clearly observe that all the production, quality and maintenance control settings have been significantly influenced by the tightness variation of the AOQL constraint.

As the AOQL is more and more restricted, the quality control levels in the downstream of both machines become more and more tighten in order to improve the outgoing quality. First (cases 76-80), the quality control efforts are only concentrated at M_1 as the rejection cost is cheaper and because the quality control at that point also improves the reliability of the subsequent machine M_2. So, the optimal inspection fraction f_1^* progressively increases until it reaches its maximal level which corresponds to the 100% inspection. In parallel, the optimal critical age m_1^* increases to minimize the PM actions on M_1 as the quality control level at this stage increased, while m_2^* decreases to perform more PM actions on M_2 and to improve the quality of finished products accordingly (as no inspection station is assigned, for the moment, to this point). Also, the optimal hedging level s_1^* decreases to decelerate the quality degradation of M_1, while s_2^* slightly increases because the increase of PM actions on M_2.

Then, once the 100% inspection level is reached at M_1 and there is no way to add further PM efforts for M_2 (as this may critically affect the availability of M_2 in addition to considerably increase the total PM cost), an inspection is now assigned to M_2 to satisfy the AOQL constraint (cases 81-85). Therefore, the optimal inspection fraction f_2^* starts increasing and approaches the 100% level as the AOQL constraint becomes more and more tightened. For a highly restricted AOQL (e.g., AOQL<0.01%), the optimal quality control policy at both machines leads to a near-100% inspection. This is because according to the ubiquitous inspection strategy, each inspection

station controls only the quality attribute made by the adjacent processing machine. From Table 5, a switch in the variation of the optimal PM thresholds m_1^* and m_2^* and the hedging levels s_1^* and s_2^* occurs at case 81 which corresponds to the AOQL from which an inspection station is assigned to M_2. So, m_1^* starts decreasing to improve the production quality of M_1 and to reduce the rejection cost accordingly, while, on the other hand, m_2^* starts increasing due to the increase of the quality control level at M_2. Also, s_1^* starts increasing due to the increase of PM actions on M_1, while, inversely, s_2^* starts decreasing to slow down the quality degradation of M_2.

Table 7.5: Impact of the AOQL constraint on the optimal control settings.

Case number	AOQL	PIC		PM		QC		Performance		
		s_1^*	s_2^*	m_1^*	m_2^*	f_1^*	f_2^*	*Cost**	$UAOQ_\infty$	AOQ_∞
75	≥1.81%	19.1	28.2	511.4	491.8	53.9%	0.0%	422.7	1.81%	1.74%
76	1.75%	18.1	28.2	533.1	484.3	58.6%	0.0%	423.4	1.75%	1.68%
77	1.50%	15.5	28.3	608.2	472.4	78.6%	0.0%	424.9	1.50%	1.45%
78	1.25%	13.5	28.3	667.9	464.3	94.2%	0.0%	426.7	1.25%	1.21%
79	1.00%	12.7	28.3	696.3	398.9	100.0%	0.0%	432.4	1.00%	1.00%
80	0.75%	12.6	28.4	709.5	289.2	100.0%	0.0%	439.4	0.75%	0.75%
81	0.50%	14.2	26.7	699.6	289.4	100.0%	33.4%	456.9	0.50%	0.49%
82	0.25%	16.0	24.4	673.5	404.1	100.0%	75.3%	485.8	0.25%	0.24%
83	0.15%	16.5	23.8	665.8	447.2	100.0%	86.5%	491.8	0.15%	0.15%
84	0.05%	16.9	23.3	659.3	483.7	100.0%	95.8%	495.3	0.05%	0.05%
85	0.01%	17.1	23.1	657.0	496.7	100.0%	99.2%	496.8	0.01%	0.01%

7.7 Concluding remarks

The joint design of production, quality and maintenance control policies for manufacturing lines subject to quality and reliability degradations and correlated failures have never been studied before in the literature. Nevertheless, in many industrial contexts, the correlated failures such as failures caused by defective products manufactured in the previous processes may have a significant impact on the production system reliability. In this work, we have developed an integrated model for the joint economic design of production, inventory, quality control and preventive maintenance of a small production line whose machines are subject to operation-dependent and quality-dependent failures. Our study contributes to the research on integrated models for multistage systems in three ways.

First, we provided a practical modeling framework to accurately model complex and dynamic phenomena in real-life manufacturing systems such as aging, quality and reliability degradations

and correlated failures, and to bring out an effective integrated policy for operations management and control.

Second, we have shown that quality control between production stages can play an important role not only in improving the outgoing quality but also in mitigating the effects of poor quality on the reliability of the downstream machines. This demonstrates the need to incorporate the relationship between quality and reliability in designing the quality inspection system, as well as in designing maintenance policies for machines subject to quality-dependent failures. The results obtained from the numerical experimentations demonstrate that inspection stations should be mainly placed in the upstream of machines which are mostly affected by the quality of the incoming products. This is because the quality control at such locations may improve both the product quality and the system reliability more significantly compared to any other location in the manufacturing line. Moreover, the experimental results indicate that the optimal economic quality control policy for production lines subject to dynamic quality degradation can lead in many situations to a sampling inspection policy. This is an interesting finding because, in the literature, the production quality of degrading manufacturing systems is commonly controlled by 100% inspection which is more costly than sampling inspection. In practice, this means that it is possible by integrating quality control design with production control and PM scheduling policies to extend the application of standard sampling inspection procedures such as continuous sampling plans to degrading production processes, as they are presently limited only to stable processes (Schilling and Neubauer, 2009).

Third, we have shown through analytical modeling and experimentations how the production, quality and maintenance control settings across all the manufacturing stages interact with each others and how these interactions impact the overall performance of the manufacturing line (incurred cost, machines' reliability, backlog, outgoing quality, etc.). The outgoing quality which has always been considered as a function only of the quality control parameters has additionally been expressed as a function of the production and maintenance control settings. This should help both researchers and practitioners to realize that, in reality, the product quality as perceived by the final consumers is governed by all the production, quality and maintenance control settings across all the manufacturing stages.

Possible extensions of this work can be envisaged to investigate the joint design of production, quality and maintenance control for large manufacturing lines composed of more than two machines. Further research can be conducted to study additional correlated failures in manufacturing systems such as failures induced by worse repairs in the upstream machines or quality inspection errors. Another research direction is to jointly optimize production, quality and maintenance control settings under non-ubiquitous quality inspection strategies. For example, in situations where inspection stations can detect defective features made by many previous machines, it may be possible to achieve savings even the inspection cost of intermediate products at later stages will be more expensive.

CHAPITRE 8 DISCUSSION GÉNÉRALE ET CONCLUSION

Cette thèse vise principalement l'intégration des plans d'échantillonnage avec les politiques de production et de maintenance dans les systèmes manufacturiers en dégradation. Cette recherche est motivée par trois raisons principales. Premièrement, plusieurs recherches précédentes dans la littérature ont montré déjà que les politiques d'intégration du contrôle de la production, de la qualité et de la maintenance permettent d'améliorer considérablement les performances globales des usines manufacturières, de réduire significativement les coûts des opérations et de mieux gérer les ressources de production. Toutefois, des aspects importants de contrôle statistique de la qualité tels que les plans d'échantillonnage n'ont pas été étudiés dans la littérature dans un contexte d'intégration avec les politiques de production et de maintenance. Deuxièmement, les plans d'échantillonnage sont largement utilisés dans l'industrie pour substituer le contrôle à 100% et assurer en même temps un contrôle statistique de la qualité des produits livrés. L'amélioration de la conception de ces plans pour prendre en considération les interactions avec les paramètres de la production et de la maintenance répond à un besoin réel puisque ces interactions ont été toujours négligées dans les méthodes et les procédures existantes de conception de ces plans. De plus, l'extension de l'utilisation des plans d'échantillonnage dans les situations où la qualité de la production n'est pas stable permet aux industriels d'éviter le coût excessif du contrôle à 100% et de surmonter les restrictions d'utilisation de ces plans telles que dans les normes et les tables standards. Troisièmement, la thèse s'intéresse en particulier aux systèmes de production en dégradation, car la dégradation est un phénomène inhérent des systèmes manufacturiers réels qui sont sujets, par nature, à l'usure et au vieillissement. La modélisation adéquate de la dégradation permet de mieux comprendre les relations de dépendance entre les politiques du contrôle de la production, de la qualité et de la maintenance et leurs effets sur les performances des systèmes manufacturiers. Ainsi, la modélisation appropriée des phénomènes complexes de dégradation tels que la corrélation entre la qualité des produits semi-finis et la fiabilité des machines permet de mieux estimer les performances réelles de ces systèmes et de développer par la suite des politiques d'intégration plus réalistes et plus efficaces. Dans les sections suivantes, nous présentons une synthèse des travaux de recherche réalisés dans le cadre de cette thèse. Ensuite, nous discutons les principales contributions scientifiques apportées par ces travaux. Enfin, nous proposons les perspectives de recherche future.

8.1 Synthèse des travaux de recherche

Les travaux de recherche de cette thèse ont traité le problème d'intégration de contrôle de la qualité par échantillonnage avec les politiques de la production et de la maintenance pour différentes configurations de systèmes manufacturiers.

Dans le premier article intitulé « *Joint production and quality control of unreliable batch manufacturing systems with rectifying inspection* », nous avons présenté un premier modèle d'intégration du plan d'échantillonnage simple avec une politique de production de type seuil critique pour un *système de fabrication par lots*, non-fiable et imparfait. Seulement la maintenance corrective est considérée dans ce modèle. La durée de cette maintenance est supposée aléatoire suivant une distribution générale. Aussi, le pourcentage des produits non-conformes dans les lots fabriqués est supposé aléatoire selon une distribution de probabilité prédéfinie. Les produits conformes détectés lors du contrôle de la qualité sont rectifiés avant d'être transmis au stock final. Contrairement à la majorité des modèles d'intégration dans la littérature, les durées d'inspection et de rectification sont considérées non négligeables. Cette considération nous a permis d'étudier l'impact des opérations de contrôle de la qualité sur la dynamique de stock. Une combinaison de méthodes de modélisation analytique stochastique, de la simulation discrète-continue et d'optimisation avec la méthodologie de surface de réponse a été employée afin de trouver les paramètres optimaux du plan d'échantillonnage, de la taille optimale du lot de production et du seuil optimal de surplus de stock. Les expérimentations on montré que les interactions entre les paramètres du plan d'échantillonnage et ceux de production (taille du lot de production et seuil critique) sont statistiquement significatives. De plus, l'analyse de sensibilité a montré que les coûts de stockage et de pénurie ont un impact non négligeable sur la conception économique du plan d'échantillonnage. De même, les coûts de contrôle de la qualité ont un impact aussi non négligeable sur les paramètres de production. Aussi, les expérimentations ont montré que la fiabilité et la disponibilité (temps moyen entre les pannes et temps moyen de réparation) du système de production ont un impact significatif sur la conception économique du plan d'échantillonnage.

Dans le second article intitulé « *Integrated production, sampling quality control and maintenance of deteriorating production systems with AOQL constraint* », nous avons introduit dans le modèle du premier article une contrainte sur la qualité après-contrôle. De plus, les dégradations de la qualité

des produits et de la fiabilité du système de production sont supposées dépendantes des opérations. Nous avons aussi intégré une stratégie de maintenance préventive qui comporte des actions de maintenance 'imparfaite' lors des activités de mise-en-course au début de chaque cycle de production et une maintenance majeure dès que le pourcentage des produits non-conformes atteint un certain seuil prédéterminé. Ce pourcentage est déterminé en comptant le nombre de produits non-conformes dans les lots rejetés. Ainsi, nous avons montré que le fait que le taux de rejet des lots produits augmente systématiquement avec la dégradation de la qualité, l'information sur le pourcentage des produits non-conformes devient de plus en plus disponible pour surveiller l'état de la dégradation du système et aussi pour prendre la décision appropriée pour déclencher immédiatement ou non la maintenance majeure. Ceci signifie qu'il est possible d'organiser les interventions de maintenance basée sur les informations du contrôle de la qualité sans avoir recours nécessairement au contrôle à 100% tel que suggéré dans la littérature. Les expérimentations ont montré que les interactions entre les paramètres de contrôle de la production, de la qualité et de la maintenance sont toutes significatives. En outre, les expérimentations ont démontré une forte corrélation entre la sévérité du plan d'échantillonnage et le seuil de la maintenance majeure. Ceci est expliqué par le fait que la sévérité du plan d'échantillonnage détermine aussi le degré de visibilité de l'état de dégradation de la qualité. Dans un contexte de couplage du contrôle de la qualité avec les décisions de maintenance, cela implique aussi que le plan d'échantillonnage peut jouer un rôle important, non seulement pour améliorer la qualité des produits, mais aussi pour fournir des informations pertinentes sur l'état du processus de production. Par ailleurs, les expérimentations ont montré que l'utilisation du plan d'échantillonnage dans un contexte de dégradation de la qualité est plus économique que le contrôle à 100%. Dans certains cas, les gains économiques peuvent dépasser 20%.

Dans le troisième article intitulé « *Joint economic design of production, continuous sampling inspection and preventive maintenance of a deteriorating production system* », nous avons proposé trois niveaux d'intégration du contrôle de la qualité avec une politique de production de type seuil critique et une politique de maintenance préventive périodique d'un *système de production continue*. Le premier niveau consiste à utiliser le contrôle à 100% tel que dans la majorité des modèles d'intégration de la littérature. Le deuxième niveau consiste à utiliser plutôt un plan d'échantillonnage continu de type-1 (CSP-1). Pour le troisième niveau d'intégration, nous avons introduit dans la procédure de CSP-1 une règle d'arrêt qui indique quand on doit arrêter le

contrôle de la qualité pour lancer une maintenance préventive. C'est le cas où le CSP-1 demeure longtemps en mode 'contrôle à 100%', indiquant que la qualité de la production a atténué un niveau critique de dégradation. La comparaison des trois scénarios a montré que le CSP-1 est toujours plus économique que le contrôle à 100%. Ce résultat prouve l'efficacité des plans d'échantillonnage continu pour les processus de production en dégradation, à condition que ces plans soient conçus conjointement avec la politique de maintenance préventive. De plus, l'analyse comparative a montré que l'intégration d'une règle d'arrêt dans la procédure de CSP-1 permet d'améliorer l'organisation des actions de maintenance préventive et de réaliser des gains économiques additionnels par rapport au CSP-1 classique.

Finalement, dans le quatrième article intitulé « *Joint production, quality and maintenance control of a two-machine line subject to operation-dependent and quality-dependent failures* », nous avons présenté un modèle d'intégration du contrôle de la production, de la qualité et de la maintenance d'une *ligne de production* composée de deux machines en dégradation. La dégradation des deux machines est dépendante des opérations. De plus, les pièces non-conformes fabriquées par la première machine augmentent l'usure et la dégradation de la fiabilité de la deuxième machine. Le taux de production de chaque machine est commandé par une politique de type seuil critique. Aussi, une politique de maintenance préventive de type âge est employée pour chacune des deux machines. Le modèle d'optimisation développé permet d'optimiser conjointement les paramètres du contrôle de la production, de la qualité et de la maintenance. Le problème du contrôle de la qualité ici consiste à déterminer le niveau d'inspection de la qualité en aval de chaque machine. Un niveau optimal d'inspection peur être : 0% (pas d'inspection), contrôle à 100%, ou contrôle par échantillonnage continu. Les expérimentations ont montré que la corrélation entre les dégradations de la qualité et de la fiabilité a un impact significatif sur l'ensemble des paramètres de contrôle de la production, de la qualité et de la maintenance de la ligne de production. Les expérimentations ont montré aussi que les efforts du contrôle de la qualité devraient être concentrés essentiellement en amont des machines les plus affectées par la qualité des produits semi-finis. Ceci montre que le contrôle de la qualité peut jouer un rôle important dans l'amélioration de la fiabilité des lignes de production.

8.2 Contributions scientifiques de la thèse

Les travaux réalisés dans le cadre de cette thèse apportent des contributions scientifiques originales à la recherche sur l'intégration des politiques de contrôle de la production, de la qualité et de la maintenance. Ces contributions peuvent être résumées comme suit :

1. **Intégration conjointe du plan d'échantillonnage avec les politiques de production et de maintenance :** Selon une analyse comparative récente de la littérature sur l'intégration de la qualité dans les modèles de la Quantité Économique de Production menée par Karimi-Nasab et Sabri-Laghaie (2014), notre premier article (Chapitre 4) paraît être l'unique dans la littérature qui intègre simultanément la conception d'un plan d'échantillonnage avec les problèmes de la Quantité Économique de Production et de la commande du taux de production. Ainsi, les modèles présentés dans les chapitres 5 et 6 permettent de déterminer, respectivement, la conception optimale du plan d'échantillonnage simple et du plan d'échantillonnage continue de type-1 (CSP-1) dans un contexte d'intégration avec les politiques de commande de la production et de la maintenance préventive. Ces modèles nous ont permis de mettre en évidence et d'étudier les différentes interactions entre les paramètres de ces plans d'échantillonnage et les paramètres de commande de la production et de la maintenance. Au meilleur de notre connaissance, il n'existe aucun modèle dans la littérature qui aborde le problème d'intégration des plans d'échantillonnage avec les politiques de production et de maintenance.

2. **Extension de l'utilisation des plans d'échantillonnage aux systèmes de production en dégradation :** Tel que mentionné dans la section 2.3.2, les méthodes existantes de conception des plans d'échantillonnage telles que les tables militaires, les standards de l'organisation internationale de normalisation, les tables de Dodge-Romig et les méthodes de conception économique sont basées sur l'hypothèse que la qualité de la production est stable. Dans le cas des plans d'échantillonnage continu, il est clairement mentionné dans les tables et les normes standards que la stabilité du processus de production est une condition nécessaire pour l'utilisation de ces plans (Montgomery, 2008a; Schilling et Neubauer, 2009). Dans les chapitres 5, 6 et 7, nous avons montré qu'il est possible d'utiliser les plans d'échantillonnage pour les processus de production non stables et même en dégradation. En fait, l'approche de conception de plans d'échantillonnage que nous avons proposée permet d'assurer que la

contrainte sur la qualité après-contrôle est toujours satisfaite indépendamment de l'état instantané et du comportement de la dégradation de la qualité. De plus, le couplage du plan d'échantillonnage avec la maintenance préventive permet de mieux organiser les interventions de maintenance afin de restaurer la qualité quand celle-ci atteint un niveau critique de dégradation.

3. **Intégration des informations issues des plans d'échantillonnage dans la maintenance préventive conditionnelle** : Plusieurs modèles ont été proposés dans la littérature afin d'intégrer les informations issues du contrôle de la qualité dans les décisions de la maintenance préventive. Ces informations sont généralement faciles à collecter et à interpréter, contrairement aux techniques classiques de maintenance conditionnelle qui nécessitent des dispositifs et des technologies coûteux pour la collection et l'analyse des données (telles que l'analyse vibratoire, l'analyse acoustique, l'analyse thermographique, etc.). Les techniques de contrôle de la qualité utilisées dans les modèles susmentionnés sont soit les cartes de contrôle, soit le contrôle à 100%. Dans les chapitres 5 et 6, nous avons montré qu'il est possible d'utiliser aussi des informations issues des plans d'échantillonnage dans la maintenance préventive conditionnelle. En fait, dans ces deux chapitres, nous avons présenté deux modèles de maintenance conditionnelle basée sur l'information du pourcentage des produits non-conformes. Cette information est recueillie seulement dans les périodes où le plan d'échantillonnage (plan d'échantillonnage simple ou CSP-1) est en mode 'contrôle à 100%'. Nous avons démontré théoriquement et à travers les expérimentations l'efficacité de cette stratégie malgré que cette information n'est pas toujours disponible. En outre, nous avons montré, dans le Chapitre 5, que cette stratégie est plus économique que celle basée sur le contrôle à 100% tel que dans les travaux de Hsu et Kuo (1995) et Radhoui et al. (2009, 2010).

4. **Modélisation plus réaliste de la dynamique complexe des systèmes manufacturiers :** L'une des contributions importantes de cette thèse est de modéliser soigneusement les dégradations de la qualité et de la fiabilité en fonction des opérations (telle que dans les chapitres 5, 6 et 7), ainsi que la modélisation des pannes dépendantes de la qualité (telle que dans le Chapitre 7). Ces hypothèses de modélisation de la dégradation de la qualité et de la fiabilité sont basées sur les résultats de plusieurs études de cas réels tels que discutés dans la Section 2.2. La modélisation de la dégradation qui se produit en réalité d'une façon continue

avec différentes intensités de dégradation en fonction du taux de production a été souvent négligée dans la littérature. Dans les chapitres 5, 6 et 7, nous avons utilisé la simulation continue pour modéliser l'aspect continu de la dégradation. Aussi, dans la littérature de modèles intégrés, les pannes corrélées n'ont jamais été intégrées dans la modélisation de la fiabilité des systèmes de production (Colledani et al., 2014). Dans les chapitres 5, 6 et 7, les expérimentations ont montré que la dépendance de la dégradation aux opérations de production affecte la détermination des paramètres optimaux de la commande de production. De même, dans le Chapitre 7, les expérimentations ont montré que l'effet de la qualité sur la fiabilité a un impact significatif sur l'ensemble des paramètres optimaux du contrôle de la production, de la qualité et de la maintenance, ce qui montre l'importance de la modélisation de ce phénomène sur l'efficacité des politiques d'intégration.

5. **Effet de l'ensemble des politiques de gestion des opérations sur la qualité après-contrôle :** La qualité moyenne après-contrôle est un indicateur important pour mesurer le niveau de la qualité perçue par les clients finaux. D'ailleurs, elle est considérée comme l'un des principaux critères de conception des plans d'échantillonnage tels que dans les tables de Dodge-Romig et les tables militaires. La qualité moyenne après-contrôle a été toujours calculée dans la littérature seulement en fonction des paramètres de contrôle de la qualité, alors qu'en réalité elle dépend aussi des paramètres de contrôle de la production et de la maintenance. Au meilleur de notre connaissance, il n'existe aucun modèle dans la littérature qui cherche à déterminer cet indicateur en fonction de tous ces paramètres. Dans les chapitres 5, 6 et 7, nous avons montré que la contrainte sur la qualité moyenne après-contrôle a un effet significatif sur tous les paramètres du contrôle de la production, de la qualité et de la maintenance. Dans le Chapitre 7, nous avons calculé par simulation la qualité moyenne après-contrôle en fonction des niveaux de contrôle de la qualité, des paramètres de la maintenance préventive et des seuils critiques de commande de production de toutes les machines de la ligne de production. Nous avons aussi fourni une formule analytique de la limite-supérieure de la qualité moyenne après-contrôle en fonction des paramètres de contrôle de la qualité et de maintenance préventive dans le cas où la dégradation de la qualité suit la loi de Weibull.

8.3 Limitations et perspectives de recherche

Les travaux de recherche de cette thèse ouvrent de nombreuses perspectives de recherches futures. Parmi celles-ci, les trois directions suivantes de recherche peuvent être envisagées :

1. **Intégration du contrôle de la production, de la qualité et de la maintenance des systèmes manufacturiers de grande taille :** Dans cette thèse, nous avons étudié des systèmes manufacturiers de petite taille tels que les systèmes composés d'une seule unité de production (chapitres 4, 5 et 6) et les lignes de production composées de deux machines (Chapitre 7). Le modèle de Chapitre 7 peut être étendu pour étudier les lignes de production composées de plus de deux machines. Dans ce cas, l'approche d'optimisation basée sur les plans d'expériences et la méthodologie de surface de réponse ne sera plus pratique vu que le nombre de variables de décision sera élevé (au moins trois variables de décision par machine). La simulation discrète-continue peut donc être combinée avec des meta-heuristiques, telles que les algorithmes génétiques, de Recherche Tabu, de Recuit Simulé, etc., ou les méthodes de recherche basées sur l'estimation du gradient afin d'optimiser les paramètres de contrôle de la production, de la qualité et de la maintenance de toutes les machines (Gosavi, 2014, 2015; Fu, 2015). Aussi, ces approches peuvent être utilisées pour étudier et optimiser les systèmes manufacturiers multi-produits et les stratégies d'inspection multi-niveaux (c'est-à-dire, plusieurs types de contrôle de la qualité peuvent être effectués dans chaque station d'inspection en fonction du nombre d'attributs des produits).

2. **Vers une nouvelle génération de conception des plans d'échantillonnage:** Tel que mentionné dans la Section 6.1, la conception des plans d'échantillonnage a évolué considérablement dans les dernières décennies, partant de la conception basée seulement sur des critères liées à la qualité jusqu'à la conception économique de ces plans en prenant en compte des contraintes sur la qualité moyenne après-contrôle. Dans cette thèse, nous proposons une nouvelle méthodologie de conception des plans d'échantillonnage qui, à part l'aspect économique et la satisfaction de la contrainte sur la qualité après-contrôle, prend en considération les interactions avec les politiques de production et de la maintenance préventive. Cette méthodologie peut être généralisée pour d'autres types de plans d'échantillonnage. En fait, dans cette recherche, nous avons étudié seulement le plan d'échantillonnage simple par attributs tel que dans les chapitres 4 et 5, et les plans

d'échantillonnage continu de type-1 tel que dans les chapitres 6 et 7 (l'échantillonnage continu dans le Chapitre 7 est considéré comme un cas particulier de CSP-1 avec un paramètre *i* égal à 0). Des recherches futures peuvent explorer les plans d'échantillonnage multiple, les plans d'échantillonnage des lots avec mesures, les plans d'échantillonnage continu de type CSP-2, CSP-3, CSP-F, CSP-V et CSP-T et les plans d'échantillonnage continu multi-niveaux. Ces plans possèdent des propriétés statistiques plus particulières que celles étudiées dans cette thèse. De plus, ces plans qui sont basés sur des décisions multiples de contrôle de la qualité fournissent des informations plus pertinentes sur la qualité des produits qui peuvent être incorporées dans la politique de maintenance préventive conditionnelle.

3. **Impact de la qualité après-contrôle sur la demande :** Dans cette thèse, la demande est supposée constante. Cette hypothèse est valable dans le cas où la commercialisation du produit est dans la phase de maturité (selon la théorie du cycle de vie des produits). En réalité, la demande est sensible aux plusieurs facteurs liés à la stratégie de commercialisation, mais aussi aux performances du système manufacturier. Par exemple, Chung et Wee (2008) et Chen et al. (2012) ont étudié l'impact des périodes de garantie après-vente sur la demande. Kevin Weng (1995), Viswanathan et Wang (2003), et Qin et al. (2007) ont étudié divers sujets liés à l'impact du prix de vente du produit sur le taux de la demande. L'impact de la pénurie sur la demande a été étudié par Gershwin et Tan (2009). D'autres chercheurs ont considéré que le taux de la demande dépend de la dynamique du stock disponible des produits finis (une revue de la littérature a été présentée par Urban, 2005). Teng et Chang (2005) sont probablement les premiers qui ont essayé de comprendre l'impact des politiques de gestion de la production sur la dynamique de stock et le coût du produit, et par conséquent, sur le taux de la demande. Toutefois, un facteur important qui affecte très significativement la demande de nos jours, mais qui n'a pas été suffisamment étudié dans la littérature, est la qualité des produits offerts. Il est bien évident chez les experts de marketing que la qualité est devenue aujourd'hui le premier critère de compétitivité des entreprises industrielles (Banker et al., 1998 ; Narasimhan et Méndez, 2001; Matsa, 2011). D'ailleurs l'histoire de positionnement des entreprises japonaises sur le marché nord-américain dans les années quatre-vingt du 20ème siècle présente un exemple bien connu de l'expansion du marché (demande) à cause de la supériorité de la qualité des produits offerts par ces entreprises (Hayes et al., 1988). Les

changements du comportement du marché à cette époque ont donné naissance au concept de la stratégie de différenciation par la qualité (Smith, 1986). Des recherches futures peuvent étudier l'intégration du contrôle de la production, de la qualité et de la maintenance dans le cas où la demande dépend de la qualité moyenne après-contrôle qui résulte, en fait, des paramètres de ces trois fonctions.

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