



Inventory routing problem under dynamic, uncertain and green considerations

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► To cite this version:

Mohammad Rahimi. Inventory routing problem under dynamic, uncertain and green considerations. Business administration. Université de Lyon, 2017. English. NNT : 2017LYSEI049 . tel-02001046

HAL Id: tel-02001046

<https://theses.hal.science/tel-02001046>

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INSA

N°d'ordre NNT: 2017LYSEI049

THESE de DOCTORAT DE L'UNIVERSITE DE LYON
opérée au sein de
L'Institut national des sciences appliquées de Lyon

Ecole Doctorale N° EDA 512

INFORMATIQUE ET MATHEMATIQUES DE LYON

Spécialité/ discipline de doctorat :

Génie Industriel

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**Inventory Routing Problem under Dynamic,
Uncertain and Green Considerations**

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Abstract

The inventory management and transportation are two main activities of supply chain management. The joint optimization of these two activities is known as Inventory Routing Problem (IRP). The main objective of IRP is to determine the set of retailers to be delivered to in each period, the delivery sequence for each vehicle, and the quantities of goods delivered to each retailer for each period of a planning horizon. The traditional IRPs are faced different problems, caused mainly by lack of complete and/or timely information such as shifts in demand, traffic caused by a sudden vehicles accident, etc. sharing of updated and reliable logistics information can meaningful improve the efficiency of IRP. Moreover, because of the specificity of IRP in urban logistic, it is important to take into account other criteria as social, environmental criteria and service level that could be in conflict.

The main objective of this thesis is to (i) choose appropriate social, environmental and service level criteria, (ii) integrate them in mathematical models, and (iii) study the impact of these criteria on dynamic optimization of IRPs for perishable products under uncertain parameters.

For this purpose, three mathematical models are proposed. The first model is multi-objective mathematical model in order to make a trade-off between service level, environmental criteria and economic. To decrease quantity of expired products, a nonlinear step function as holding cost function is integrated in the model. Moreover, to solve the problem a fuzzy possibilistic approach is applied to handle uncertain parameters. In the second model, a bi-objective mathematical model is proposed to study impact of social issues on the IRPs. In the proposed model, first objective function concerns economic criteria while the second one social issues. A scenario-based stochastic approach is developed to cope with uncertainty in the model. Finally, the third model concerns impact of using real-time information in efficiency of IRPs. It is noteworthy that, according significant role of perishable products in the both financially and ecology sides of IRPs, perishable products are considered in all three proposed model while even proposed models are appropriate to nonperishable ones as well. The results show that a dynamic management is more efficient than the static one.

Keywords: *Inventory routing problem; Sustainable IRP; Dynamic IRP; Customer satisfaction level; Perishable Products; Stochastic mathematical modeling; Multi-objective optimization*

Résumé

La gestion des stocks et la maîtrise de la distribution sont les deux activités importantes dans le management de la chaîne logistique. L'optimisation simultanée de ces deux activités est connue sous l'intitulé du problème de gestion de stock et de tournée de livraison (Inventory Routing Problem, IRP). L'IRP traditionnelle est confronté aux différents problèmes, causé principalement par le manque d'informations complètes et/ou temps réel, tels que les changements de la demande, l'embouteillage soudain causé par un accident, etc. Le partage et la mise à jour d'information logistique peut améliorer l'efficacité d'IRP. De plus, en raison de la spécificité de l'IRP dans la logistique urbaine, il est important de considérer d'autres critères comme les critères sociaux, environnementaux et le niveau de service qui pourraient être en conflictuel.

L'objectif principal de cette thèse est de développer des modèles et des méthodes des IRP avec la prise en compte des incertitudes, du niveau de service et de l'impact environnemental, social en finalement les informations du temps réel (IRP dynamique).

Dans cette thèse, trois modèles mathématiques sont proposés. Le premier modèle multi-objectif est pour identifier un compromis entre le niveau de service, les critères environnementaux et économiques. Pour gérer des paramètres incertains, on applique une approche floue. Dans le deuxième modèle, nous avons étudié l'impact des critères sociaux sur les IRPs en proposant un modèle mathématique bi-objectif. Une approche stochastique basée sur des scénarios est développée pour faire face à l'incertitude dans le modèle. Enfin, le troisième model concerne l'impact de l'utilisation d'informations du temps réel dans les IRP. Il est à noter que, selon la durée de vie du produit tant sur le plan financier que sur le plan écologique, les produits périssables sont considérés dans les trois modèles proposés. Les résultats montrent une gestion dynamique est beaucoup plus efficace que la statique.

Mots-clés: *Gestion des stocks et des tournées de livraison; IRP durable; IRP dynamique; Niveau de service à la clientèle; Produits périssables; Modélisation stochastique; Méthode d'optimisation multi-objectif*

Dedicated to ...

*My sweetheart, Mahya, who is always with me
in my joys and sorrows with her incredible
support, encouragement and uplifting
spirit,*

*My parents, brother and sister for their endless
support and unconditional love.*

Acknowledgment

I wish to express my deepest gratitude to my supervisors Prof. Armand Baboli and Prof. Yacine Rekik. Their advice, encouragement, support, and mentorship have immensely valuable. I am very thankful for their genuine concern, efforts, and patience towards my development from student to a researcher.

I am also grateful to members of my jury, Prof. Siadat, Prof. Tavakkoli-Moghaddam, Prof. Frein and Dr. Ounnar. Their insights, time and feedback are invaluable.

Special thanks are also to all faculties and staff members of DISP laboratory for their constant academic interactions with me.

I would like to thank the Région Rhône-Alpes, France (ARC7) for providing the funding that allowed me to undertake this research.

Finally, I must express my gratitude to Mahya, my wife, for her incredible support and encouragement, which has helped me through many challenges. I can only hope to pay her back in the years to come. I am immensely indebted to my mother, father, brother and sister who experienced all of the ups and downs of my life.

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Résumé étendu en français

1 Introduction

Pour rester compétitives, les entreprises sont obligées d'accroître l'efficacité et la flexibilité de leurs systèmes de productions de biens ou de services. De plus, dans le contexte d'une nouvelle révolution industrielle, appelée Industrie 4.0 (Brecher C 2015), ou encore système cyber-physique (Lee & Shin 2017), une entreprise doit être très agile pour faire face aux changements du marché. Pour se conformer à l'objectif de l'industrie 4.0, les entreprises sont obligées de numériser plusieurs étapes de leurs processus permettant d'avoir la traçabilité de chaque opération et l'interaction entre les composants du système de production. Cette opportunité offre plus de transparence pour tous les acteurs de la chaîne de valeur et cette dernière se transforme en un système complètement intégré (Schrauf & Berttram 2017). Pour la réussite d'une telle transformation, un élément clé consiste à la transformation de la chaîne logistique traditionnelle en une chaîne logistique intelligente. Le point critique pour une chaîne logistique intelligente est l'échange efficace d'informations entre les différents acteurs de la chaîne. La chaîne logistique traditionnelle souffre de problèmes causés principalement par le manque d'informations complètes et en temps opportun tels que les changements de la demande, l'état du trafic routier causé par un accident de véhicules, etc. Le partage d'information et sa mise à jour fiable et en temps réel peut significativement améliorer l'efficacité de la chaîne logistique.

Pour tirer profit du partage d'information et sa mise à jour, il est nécessaire de coordonner et d'intégrer des décisions prises à plusieurs niveaux de la chaîne logistique. Nous nous intéressons dans ce rapport à deux décisions capitales qui sont la gestion des stocks et de la distribution. L'intégration de ces deux décisions consiste à décider conjointement la gestion des stocks et la distribution : une telle intégration est communément connue sous le nom d'Inventory Routing Problem (IRP). L'objectif principal de l'IRP est l'identification de la meilleure stratégie commune pour le stock et la distribution: c'est-à-dire le contrôle des stocks des produits, la détermination du type et du nombre de véhicules, le type de produits à distribuer, les quantités à livrer et la meilleure tournée de véhicule de chaque période.

La finalité de l'IRP classique est la minimisation des coûts totaux de stock et du transport et/ou le temps/distance de la tournée de véhicule (Madadi et al. 2010, Li et al. 2014) en supposant que tous les paramètres du problème sont connus à l'avance.

L'approche classique de la modélisation de l'IRP se focalise sur l'optimisation de la performance économique et néglige ainsi certains critères importants tels

que les questions sociales, les critères environnementaux, le niveau de service etc. Actuellement, les gestionnaires doivent prendre leurs décisions en considérant des critères complémentaires et parfois conflictuels avec le critère économique

Ces nouveaux critères prennent une importance plus importante lorsque ‘il s’agit de résoudre un problème d’IRP dans la logistique urbaine. Cette dernière se caractérise par des contraintes opérationnelles et parfois légales (distribution dans des fenêtres de temps très strictes et nécessité d’utiliser des véhicules propres) qui obligent le gestionnaire prendre en compte ces nouveaux critères. De plus, la modélisation des IRP peut être plus difficile lorsqu’elle est effectuée pour des articles périssables où la non-fraîcheur du produit et le besoin de recycler les produits périssables doivent également être modélisés et pris en compte. Il est également à noter que l’IRP classique ne tient pas compte de l’impact de l’utilisation d’information en temps réel sur l’efficacité économique du problème. Cependant, nous devons aborder une nouvelle approche de l’IRP pour prendre en compte des paramètres qui ne sont pas connus d’avance et qui peuvent se révéler au fil du temps. Afin de traiter cette nouvelle modélisation de l’IRP, communément appelée l’IRP dynamique (DIRP), nous devons définir de nouvelles stratégies de contrôle.

Nous étudions dans ce mémoire une extension de l’IRP classique qui permet de considérer d’autres critères d’optimisation complémentaires au critère économique. Nous nous focalisons sur le contexte de la distribution urbaine de produits périssables et nous considérons deux modes statique et dynamique de décision.

Dans ce qui suit, nous proposons de détailler les mots clés qui caractérisent la contribution de ce mémoire de thèse et nous motivons sur un plan pratique la nécessité d’étendre l’IRP comme nous le proposons. Nous poursuivons par la suite par une brève revue de littérature dans laquelle nous démontrons l’opportunité de recherche et la contribution scientifique de ce travail.

1.1 Critères sociaux

De nouvelles contraintes, lois, règles et normes ont été adoptées au cours des dernières années, qui devraient par conséquent être prises en compte dans la modélisation et l’optimisation de l’IRP. Parmi les nouvelles réglementations, on peut citer l’administration de la sécurité et de la santé au travail (NIOSH 2014), la réglementation du Parlement européen sur la nuisance sonore des véhicules (European Parlem 2012) ainsi que l’orientation de responsabilité sociale de la norme ISO 26000 (ISO 2010). Les gestionnaires doivent reconstruire la modélisation du problème conjoint de stock et de distribution en intégrant ces nouvelles réglementations. En outre, les entreprises des collectivités

gouvernementales et non gouvernementales et, plus généralement, de l'opinion publique font de plus en plus de pression pour les inciter à inclure des considérations durables dans leurs activités. Selon Cruz & Wakolbinger (2008), certaines entreprises internationales tels que Shell, McDonalds, Nike et Disney ont fait face à une réputation négative liée aux critères sociaux et qui a engendré un impact sur les bénéfices.

1.2 Critères environnementaux

Les entreprises sont de plus en plus sous la pression des communautés gouvernementales et non gouvernementales et, plus généralement, de l'opinion publique, pour maîtriser et réduire leurs émissions de gaz à effet de serre (GHG). Cette réduction vise non seulement à protéger l'environnement, mais elle est également motivée sur le plan économique, car de nouvelles réglementations prévoient des sanctions environnementales si ces émissions dépassent certains seuils. Il est par ailleurs montré que le transport est le principal secteur qui produit des émissions de GHG et devrait être pris en considération par les décideurs. De cette façon, les décideurs sont obligés de se soucier des critères environnementaux des IRP pour respecter les réglementations internationales et en même temps éviter les pénalités supplémentaires liés à leurs empreintes environnementales (Mirzapour Al-e-hashem & Rekik 2013).

En effet, l'ajout de l'empreinte écologique dans l'IRP est lié à un réel besoin des entreprises. Dans certains pays de l'Union européenne, l'accès au centre-ville est conditionnel à l'empreinte verte du véhicule effectuant la livraison. En effet, de plus en plus de règles législatives sont fixées pour suivre et limiter les émissions de GHG, en particulier dans les zones urbaines.

1.3 Niveau de service

L'accroissement de la compétitivité entre les entreprises sur un marché mondial génère de plus en plus de pression. Les entreprises doivent améliorer leur efficacité autant que possible pour assurer la satisfaction de la clientèle. Un niveau de service élevé est en effet l'un des facteurs clés pour renforcer la satisfaction et la fidélité des clients. Cependant, en dépit de l'impact positif sur les ventes à long terme, fournir un niveau de service plus élevé au client peut augmenter les coûts du stock et de distribution associés. Par exemple, les gestionnaires essaient de satisfaire autant de clients que possible, car ils maximisent leurs ventes. En même temps, le maintien du stock est à la fois coûteux et risqué: les produits ont besoin d'espace pour être stockés et ils peuvent expirer et devenir obsolètes, etc. (Schalit & Vermorel 2014).

Afin de prendre en compte le niveau de service dans les IRP, il faut des indicateurs spécifiques en gestion des stocks et en matière de distribution. Contrôler les stocks en considérant des niveaux de service est une pratique très utilisée en gestion des stocks mais l'est rarement en matière de pilotage de l'IRP. Le niveau de service cyclique et le taux de satisfaction des ventes sont des mesures bien connues et très utilisées pour les praticiens qu'il faudrait compléter par des mesures complémentaires associées à la distribution.

1.4 Produits périssables

Il existe différents types de produits périssables, qui se classent en fonction de la façon dont ils se détériorent. Ces produits perdent leur utilité avec une vitesse spécifique pendant le temps et ne sont pas utilisables pour le but initial après leur durée de vie fixe. Certains produits perdent leur fonctionnalité au fil du temps comme les fruits, les légumes et les fleurs. D'autres produits expirent après une date donnée, même s'ils sont encore en parfait état comme les calendriers. Toutefois, pour les deux types, les produits expirés doivent être collectés et recyclés. L'activité de recyclage entraîne un coût supplémentaire et une émission supplémentaire de GHG qui devraient être pris en compte dans les critères environnementaux.

Sachant que la périssabilité des produits ajoute plus de complexité aux IRP, le rôle important de ce type de produits ne doit pas être négligé.

1.5 Mode dynamique de décision

Comme il est mentionné plus haut, pour considérer de mode dynamique de décision, nous devons définir de nouvelles stratégies de contrôle.

Comme première stratégie, nous pouvons optimiser le modèle chaque fois que de nouvelles informations sont disponibles. Un autre est de résoudre le problème une fois et d'obtenir la solution initiale et chaque fois que de nouvelles informations sont disponibles, ré-optimiser le problème, qui est la stratégie plus commune. Sinon, nous pouvons utiliser les méthodes de prévision traditionnelles pour prédire la valeur des paramètres inconnus. En effet, l'utilisation de ces stratégies augmente la capacité du gestionnaire à prendre des décisions plus précises en tenant compte de l'information en temps réel (Coelho et al. 2013)

Malgré l'importance pratique et le rôle important des critères expliqués précédemment, nous avons constaté un très petit nombre de publications qui les considèrent.

2 Revue de la littérature

Tout d'abord, nous présentons une brève revue de la littérature sur la gestion des stocks et des tournées de livraison (IRP). En raison du grand nombre de recherches dans ce domaine, nous nous concentrons uniquement sur des études récentes (à partir de 2013). Pour les publications antérieures à 2013, nous renvoyons les lecteurs à la revue de la littérature réalisée par Coelho et al. (2013). Mirzapour Al-e-hashem et Rekik (2013) étudient l'impact des critères environnementaux dans les IRP, tout en minimisant le coût total et ajoutant une contrainte sur les émissions totales de gaz à effet de serre (GHG) produites par les véhicules. Coelho & Laporte (2013) proposent un algorithme de branch-and-cut pour les IRP de résolution où un fournisseur distribue plusieurs produits à différents clients par différents véhicules en capacité. Tavakkoli-Moghaddam et al. (2013) proposent un modèle mathématique bi-objectif afin de minimiser les coûts d'ouverture de l'emplacement, du transport et du stock tandis que la seconde fonction objective minimise le temps de transport. Les auteurs considèrent une demande stochastique et utilisent la méthode de somme pondérée pour résoudre le problème bi-objectif.

Amorim & Almada-Lobo (2014) considèrent un IPR avec des produits périssables et introduisent un modèle mathématique multi-objectif où le premier objectif minimise les coûts associés tandis que le second objectif tente de maximiser la fraîcheur des produits livrés. Ils résolvent le modèle en utilisant la ε -constraint pour les petites tailles et en adaptant un algorithme évolutif multi-objectif pour les problèmes de grande instance. Coelho & Laporte (2014) étudient l'IRP pour les produits périssables visant à maximiser les profits en supposant que les produits ont des âges différents. Les auteurs résolvent le modèle proposé en utilisant l'algorithme branch-and-cut. Sazvar et al. (2014) proposent un modèle mathématique multi-objectif pour montrer l'effet des critères environnementaux sur le coût total dans l'industrie pharmaceutique. Dans ce problème, la demande des clients est incertaine et une approche basée sur des scénarios est utilisée pour gérer l'incertitude. Ils tiennent compte du coût de recyclage des produits périmés et de la quantité d'émissions de GHG générées par le recyclage des produits périmés. Ils utilisent la méthode de somme pondérée pour résoudre le modèle proposé. Nolz et al. (2014) présentent un modèle IRP multi-objectifs pour faire un compromis entre le coût et la question sociale. Ils minimisent le risque pour la santé publique en considérant la collecte de déchets pharmaceutiques comme une question sociale dans les IRP.

Mirzaei & Seifi (2015) proposent un modèle mathématique multi-objectif pour étudier l'impact de la minimisation des ventes perdues dans le coût total de la distribution des produits périssables. Brinkmann et al. (2015) résolvent le problème de partage de vélos en utilisant l'IRP où ils utilisent les véhicules pour équilibrer les vélos entre les stations. Dans cette étude, les auteurs définissent

une stratégie pour déterminer la priorité de chaque station et pour considérer l'urgence de chaque station qui doit être rééquilibrée. Andersson et al. (2015) étudient l'IRP dans le domaine du gaz naturel liquéfié où le décideur est responsable de la partie de production, du routage et de l'ordonnancement des navires et du stock des terminaux de régazéification. En outre, ils considèrent qu'il y a un nombre limité de couchettes pour le chargement et le déchargement. Ils concernent le concept de périssabilité dans leur étude où le taux constant des pétroliers s'évapore chaque jour. Les auteurs proposent un algorithme basé sur la méthode branch-and-cut pour résoudre le modèle proposé. Singh et al. (2015) utilisent des IRP dans la distribution de gaz industriels liquéfiés pour maximiser le niveau de service qui est converti en coût. Dans cette étude, les auteurs considèrent trois hypothèses : toutes les commandes doivent être satisfaites, les stocks ne devraient pas être produits et l'efficacité de la distribution de gaz en vrac devrait être considérée.

Chitsaz et al. (2016) proposent une heuristique en deux phases pour résoudre les IRP. Dans la première phase, l'approche la plus décente est utilisée pour définir les visites. Dans la deuxième phase, les auteurs utilisent une heuristique basée sur le meilleur ajustement décroissant. Dans cette phase, les véhicules sont programmés et assignés à des circuits définis. Roldán et al. (2016) étudient des IRP stochastiques et dynamiques sans utiliser de méthode de prévision pour prédire la demande future. Ils proposent trois méthodes différentes de sélection de client telles que le grand ordre, le stockage le plus bas et la remise sur quantité. Zhalechian et al. (2016) proposent un modèle mathématique multi-objectif non linéaire mixte-entier pour les IRP en intégrant les problèmes d'allocation de localisation dans une chaîne logistique en boucle fermée. Les auteurs définissent trois fonctions objectives, le premier objectif minimisant les coûts totaux. La deuxième fonction objectif considère la minimisation des problèmes environnementaux et la troisième fonction objectif maximise les questions sociales qui est mesurée par les opportunités d'emploi créées et la maximisation du développement économique équilibré. Pour résoudre le modèle, les auteurs développent une mét-heuristique en combinant l'algorithme génétique auto-adaptatif et l'algorithme de variable neighborhood search. Ghorbani & Akbari Jokar (2016) proposent un algorithme hybride d'impérialisme compétitif-Simulated Annealing (IC-SA) pour résoudre les IRP. Azadeh et al. (2017) intègrent l'option de transbordement dans les IRP où le fournisseur livre un produit périssable aux clients. Les auteurs considèrent que le produit, se détériore au taux exponentiel pendant le temps à l'entrepôt. Ils proposent un algorithme génétique pour résoudre le problème. Cheng et al. (2017) présentent un modèle complet pour examiner la question de l'environnement dans les IRP. Les auteurs s'intéressent à la consommation de carburant lorsqu'ils sont mesurés en fonction de la charge, de la distance, de la vitesse et des caractéristiques du véhicule.

Iassinovskaia et al. (2017) proposent un problème lorsqu'un producteur produit des produits consignés et les livre aux clients. Chaque client définit une fenêtre de temps spécifique qui doit être respectée par le distributeur. De plus, le distributeur est responsable de la collecte des articles retournables vides. Les auteurs ont proposé une heuristique spécifique pour résoudre le problème proposé. Hiassat et al. (2017) dans les décisions de localisation dans les IRP pour trouver l'emplacement des entrepôts requis en plus des décisions classiques des IRP.

Nous proposons dans le Chapitre 1 une étude bibliographique plus approfondie que nous résumons dans Tableau 1.1 (chapitre 1) ou nous observons quatre principales lacunes dans la recherche dans les IRP:

- Prise en compte de la durabilité et le niveau de service en addition à l'aspect économique de l'IIR.
- Modélisation et optimisation multi-objective pour les produits périssables.
- Contrôle de la variation des paramètres qui ont la nature incertaine tels que la demande, les coûts de transport, le trafic des routes et etc.
- Prise en compte de l'optimisation dynamique de l'IRP en particulier s'agissant de la variation de la demande et les conditions de circulation durant la tournée du véhicule.

3 Positionnement du problème et méthodologie

Notre motivation dans ce travail est le développement de nouveaux modèles d'IRP qui colleraient plus avec la réalité des entreprises de nos jours. Nous proposons dans un premier temps d'intégrer des considérations de durabilité sur les modèles IRP pour produits périssables. Dans un second temps, nous développons un modèle dynamique d'IRP qui profite des données temps réel à disposition des managers.

Sur un plan opérationnel, les questions de recherche que nous traiterons dans ce mémoire sont :

- Comment intégrer des critères de durabilité dans les IRP
- Quel impact de ces critères de durabilité sur les IRP
- Comment modéliser les produits périssables dans les IRP
- Quel lien entre coûts et niveau de service dans les IRP
- Quel impact de l'optimisation dynamique des IRP

Sur un plan théorique, nous contribuons par :

- Comment élaborer une approche de résolution pour faire face aux paramètres incertains du problème
- Comment traiter la présence de plusieurs objectifs dans le problème IRP

Afin d'atteindre notre objectif et proposer des éléments de réponse à ces questions de recherche, notre méthodologie suivra les étapes qui suivent :

1. Identification / proposition d'indicateurs de performance pour mesurer les critères de durabilité et de niveau de service applicable en IRP.
2. Proposition de trois nouveaux modèles d'IRP intégrant plusieurs considérations en terme d'objectif de décision: considérations de niveau de service, environnemental et économiques dans le premier modèle ; considérations environnementales, sociales et économiques dans le second et proposition d'une optimisation dynamique de l'IRP dans le troisième modèle.
3. Proposition de méthodes de résolution efficaces pour chaque modèle.
4. Etude numérique qui met en lumière l'applicabilité de nos modèles et qui permet de déduire des implications managerielles pour les managers.

Dans ce qui suit, nous proposons dans des sections différentes un résumé des trois modèles que nous avons développé. Nous nous focalisons en particulier sur la motivation qui nous a poussés à considérer chaque modèle ainsi que la contribution de ce dernier à la littérature existante.

Finalement, nous concluons notre travail de recherche, proposons de nouveaux sujets de recherche pour les travaux futurs et présentons la liste des publications.

4 Modèle IRP multi-objectif et stochastique qui mixe des considérations économiques, de niveau de service et environnementales (1^{er} modèle)

4.1 Motivation et Contribution

Dans ce premier modèle, nous contribuons à la littérature existante grâce aux considérations qui suivent :

- Nous intégrons le niveau de service dans les IRP et nous exploitons le lien entre coûts de l'IRP et un ensemble de niveau de service qui mesure la performance de gestion des stocks et de distribution.
- Nous explorons en particulier le lien conflictuel qui pourrait exister entre un département de ventes qui encouragerait l'amélioration du niveau de service et un département logistique qui souffrirait de niveaux cibles placé très élevés.
- Nous modélisons l'empreinte environnementale de l'IRP sous forme d'une fonction objective et nous analysons son lien avec la performance économique du problème.
- Nous modélisons les véhicules avec différentes technologies (électrique et diesel) pour obtenir des informations sur le lien entre la

technologie considérée et son empreinte de GHG. Le résultat pourrait aider certains praticiens à réaliser des études de type retour sur investissement. En effet, certains praticiens seraient intéressés par étudier l'impact de l'utilisation de l'énergie électrique dans le transport urbain pour la distribution de produits périssables. En supposant que ce type de véhicule a un coût de transport fixe et variable plus élevé que l'alternative, il produit des volumes très faibles d'émissions de GHG par rapport aux véhicules diesel.

- Nous modélisons la périssabilité des produits dans les IRP en utilisant deux points de vue : nous modélisons la non-fraîcheur des produits qui sont transférés d'une période à l'autre en utilisant un coût de détention additionnel et non linéaire. Nous montrons que ce point de vue est équivalent à un rabais sur prix que doit proposer les managers sur ces produits non frais. Notre modèle IRP permet également de modéliser la gestion de la logistique inverse des produits périmés qui devraient être recyclés. En outre, nous supposons que le recyclage de ces produits périmés a un impact sur la performance économique de l'IRP ainsi que sur son empreinte environnementale.
- Contrairement à la plupart des études dans la littérature IRP et pour une meilleure modélisation des produits périssables, nous permettons à la fonction de coût de détention de se comporter comme une fonction non linéaire. Cette modélisation est motivée par des opérations d'inspection supplémentaires dont les produits ont besoin avant de les transférer à la période suivante. Cette modélisation pourrait également être interprétée comme une réduction de prix offerte pour les produits non frais dans les périodes à venir.
- En outre, pour être proche de cas réels de l'IRP, nous supposons que certains paramètres tels que la demande, les coûts de transport variables et la vitesse du véhicule sont incertains, et nous les modélisons avec une distribution possibiliste floue.

4.2 Description du problème

Dans cette étude, nous proposons un nouveau modèle mathématique multi-objectif qui établit un compromis entre le niveau de service, les considérations environnementales et économiques des IRP. Nous détaillons dans ce qui suit les ingrédients de ce modèle.

4.2.1 Critères économiques: maximisation du bénéfice

La performance économique de l'IRP est mesurée par la fonction de profit qui est égale au chiffre d'affaires moins les coûts des stocks et de distribution connexes,

y compris les coûts de stockage, de rupture, le recyclage, les coûts de transport fixe et variable, le coût de commande et les coûts de chargement et de déchargement.

Pour mieux modéliser la périssabilité du produit, nous modélisons le coût de stockage unitaire comme une fonction linéaire par étage (step wise linear) qui dépend du stock restant à la fin de chaque période.

4.2.2 Niveau de service

Le niveau de service définit un degré de satisfaction offert au client. Par conséquent, dans une décision conjointe stock et distribution, le niveau de service peut inclure de nombreuses mesures possibles parmi lesquelles nous avons choisi les éléments suivants:

- Le délai de livraison; Un retard se produit si le véhicule visite un détaillant après la fenêtre de temps autorisée
- La fréquence de rupture définie par la probabilité pour qu'un client ne trouve pas le produit en stock
- Le volume de rupture définie par le volume des produits non satisfaits directement depuis le stock (backlog)

La première mesure de service est associée au volet distribution de l'IRP. Les retards sont l'un des plus grands problèmes auxquels la distribution alimentaire est confrontée au Royaume-Uni. Selon McKinnon, Ge et Leuchars (2003), 29% des détaillants interrogés dans la chaîne logistique alimentaire au Royaume-Uni avaient connu des retards de livraison qui avaient directement influencé la satisfaction de leurs clients.

Les deuxièmes et troisièmes mesures de niveau de service sont liées au volet gestion des stocks de l'IRP.

4.2.3 Critères environnementaux

En plus des considérations économiques et de niveau de service décrit dans les sections précédentes, nous introduisons un critère environnemental dans notre IRP étendu. Si les produits périssent, nous supposons qu'ils doivent être collectés et recyclés. En ce qui concerne l'exhaustivité, en plus des émissions de GHG résultant de la distribution et des opérations de chargement / déchargement, nous incluons celles associées au recyclage des produits périssables.

4.2.4 Les hypothèses du modèle

En plus de la description et des hypothèses présentées précédemment, nous considérons que la chaîne logistique à l'étude est sujette aux hypothèses supplémentaires suivantes pour la rendre aussi proche que possible des études de cas réelles de l'IRP:

- Il existe un réseau logistique urbain dans lequel différents types de produits périssables sont distribués d'un fournisseur ou un centre de distribution à un ensemble de détaillants à chaque période.
- Le fournisseur utilise une flotte hétérogène de véhicules à capacités différentes, différentes technologies (*électrique et diesel*), différents coûts fixes et variables et différents niveaux d'émissions de GHG par kilomètre.
- Le fournisseur et les détaillants disposent de deux types d'équipements (*gaz et électricité*) pour le chargement et le déchargement, avec différents coûts et émissions de GHG.
- Les philosophies du juste à temps (*JIT*) et du cross-docking sont considérées du côté des fournisseurs, ce qui conduit à un scénario sans stock pour le fournisseur et à l'hypothèse que les produits livrés aux détaillants sont frais.
- Pour chaque détaillant, nous considérons que la capacité du stock et le niveau du stock initial pour chaque produit sont connus.
- La demande pour chaque détaillant est indépendante du niveau de service atteint dans l'IRP.
- Chaque produit a une durée de conservation donnée (L_j) et nous supposons que les produits ne peuvent pas être vendus après la date de péremption et doivent être recyclés avec un coût supplémentaire. Une telle opération de recyclage produira des émissions de GHG, qui sont incluses dans le calcul du critère environnemental.
- Il existe une contrainte de fenêtre de temps définie par les temps de distribution le plus hâtif et le plus tardif pour chaque détaillant. On suppose qu'un retard survient si le véhicule arrive après le temps tardif. Si le véhicule arrive plus tôt que le temps hâtif, il doit attendre.
- Le temps de déchargement dans les entrepôts des détaillants est pris en compte et est calculé en fonction de la quantité de produits livrés.

4.3 Formulation mathématique

Le premier objectif maximise le profit qui est égal au chiffre d'affaires des produits moins les coûts, y compris le coût de détention, le coût de rupture (backordering), le recyclage des coûts des produits expirés, les coûts de commande, les coûts de transport fixes et variables et les frais du chargement et du déchargement. La seconde fonction objective optimise les critères de niveau de service pondérés en minimisant le taux de retard pouvant survenir lors de la visite des détaillants, le taux de nombre de produits en attente de satisfaction et le taux de fréquence des commandes en attente. Le troisième objectif minimise la quantité d'émissions de GHG résultant du transport, du chargement /

déchargement des produits et des émissions de GHG dues au recyclage des produits périmés. Le problème est sujet aux contraintes qui suivent :

- Le niveau du stock entre deux périodes successives doit être équilibré.
- Le nombre de commandes en attente, la fréquence des commandes en attente et le nombre de produits expirés doivent être déterminés.
- Le temps d'arrivée au prochain détaillant et le nombre de retards doivent être déterminé en tenant compte de la fenêtre de temps prédefinie.
- La capacité de chaque véhicule et la capacité des détaillants pour chaque produit devraient être respectées.
- Les circuits doivent être définis tout en évitant les visites secondaires.

4.4 Méthode de résolution

Afin de traiter les paramètres incertains (demande, coût de transport variable et vitesse du véhicule) dans le modèle, l'approche floue possibiliste est appliquée et adoptée. Pour résoudre le modèle et illustrer la performance et l'applicabilité du cadre de l'IRP L'algorithme génétique de triage non dominé II (NSGA-II) est utilisé après validation. Cet algorithme est montré par des études antérieures comme un algorithme efficace pour les IRP.

Nous avons obtenu une frontière de Pareto optimale pour différentes tailles de problèmes et d'instance. En outre, nous avons classé les solutions et trouvé un groupe de solutions, où une petite variation de profit a un impact significatif sur la variation du niveau de service. Sur la base des résultats obtenus, le niveau de service peut être amélioré d'environ 25% à 27% avec une réduction de moins de 7% du bénéfice. Ce sont des solutions précieuses pour les entreprises qui sont dans un marché concurrentiel et doivent considérer le niveau de service pour augmenter la satisfaction du client et veulent reporter leurs actions correctives afin d'améliorer le niveau de service.

Nous avons également élaboré un intérêt conflictuel pour les niveaux de service très élevé. Si ce niveau de servie est fixé par un département marketing indépendamment des considérations logistiques, le coût subi en terme de stockage et distribution pourrait être très élevé. Nous recommandons une coordination interne sur le choix du niveau de service cible fonction des coûts logistiques.

Via le coût de stockage linéaire par étage, nous avons également proposé un mécanisme permettant d'intégrer le non fraîcheur des produits dans l'optimisation de l'IRP.

Sur un plan théorique, nous avons montré la performance de l'approche floue pour prendre en compte de différents niveaux d'incertitude.

5 Modèle bi-objectif pour l'IRP durable : Produits périssables et logistique inverse (2ème modèle)

5.1 Motivation et Contribution

Dans le deuxième modèle, nous contribuons à la littérature existante avec les considérations suivantes:

- Nous modélisons et incluons certaines considérations sociales dans le modèle IRP. En raison de l'interaction entre l'humain et la machine au cours des différentes activités de distribution et de stockage, considérer les questions sociales dans les IRP est particulièrement important. Pour ce faire, la problématique sociale dans les IRP, les risques d'accident, le bruit des véhicules et le nombre de produits périmés sont considérés comme des enjeux sociaux.
- Nous intégrons le concept de logistique de retour dans le modèle. Afin de traiter les produits périmés, nous proposons le ramassage et le recyclage de ces produits après leur date d'expiration.
- Comme dans le premier modèle, nous considérons une modélisation linéaire par étage pour le coût unitaire de stockage, ce qui permettrait de modéliser la non-fraîcheur des produits par une obligation de proposer un rabais sur les produits qui sont transférés entre périodes.
- Comme dans le premier modèle nous supposons certains paramètres du problème incertains, tels que la demande, la vitesse du trafic, la vitesse du véhicule et le coût de transport variable. Afin de modéliser ces paramètres incertains dans le modèle, un modèle d'optimisation stochastique utilisant une approche stochastique basée sur les scénarios est développée et adoptée.

5.2 Description du problème

Le but de cette section est de présenter un modèle mathématique bi-objectif en tenant compte des considérations de durabilité dans l'IRP des produits périssables. Dans ce cadre, la première fonction objective traite de la maximisation des bénéfices alors que la seconde modélise certaines considérations sociales.

5.2.1 Critère économique: maximisation du bénéfice

Pour ce qui est de l'aspect économique de l'IRP, nous considérons la fonction de bénéfice calculé par le revenu des ventes moins les coûts des stocks et de distribution connexes, y compris les coûts de détention, le coût de rupture en attente, les coûts de transport fixe et variable, le coût de commande et le coût de

pénalité payé si la livraison au détaillant se produit en dehors des fenêtres de temps autorisées. Nous proposons également un mécanisme de rabais sur quantité liant le fournisseur aux différents détaillants.

5.2.2 Critères sociaux

La modélisation des considérations sociales n'est pas simple et n'est pas un exercice commun dans la littérature des IRP. Nous avons essayé de construire notre approche de modélisation en se basant sur certains rapports tels que ISO 26000 (ISO 2010), le rapport sur l'administration de la santé et la sécurité au travail (NIOSH 2014) et le Global Reportant Initiative 2011).

Selon ces rapports, nous pourrions modéliser trois considérations sociales dans le cadre de l'IRP pour les articles périssables :

- Le taux d'accidents lors de la logistique directe et de retour
- L'émission de bruit des véhicules qui contribue à la nuisance sonore
- Le nombre de produits périmés, Le fait qu'un nombre plus élevé de produits expirés génère plus de gaspillage de produits (alimentaires), plus d'opérations dans la logistique inverse, ce qui augmenterait à terme le risque d'accidents ainsi que la nuisance sonore.

Le premier enjeu social concerne la valeur du taux d'accident associé à une solution de routage de véhicule. En ce qui concerne la distribution, il faut utiliser toutes les voies possibles, où chacune peut être associée à un taux d'accidents plus ou moins élevé. Ce taux est fonction de nombreux critères, notamment la nature de route, la limite de vitesse sur cette route, le type de la plupart des véhicules qui l'empruntent et les données statistiques d'accidents qui y sont associées.

Afin de modéliser ce premier enjeu social, nous avons considéré dans notre réseau de la chaîne logistique différents types de routes caractérisés par deux paramètres: i) la vitesse moyenne de circulation (ATS) sur chaque route et ii) la vitesse moyenne du véhicule (AVS) pour chaque route. La première mesure de vitesse dépend de plusieurs facteurs des routes, y compris le type de route, la météo et le jour de la semaine, alors que la deuxième mesure de vitesse dépend de l'attitude du conducteur du véhicule sur cette route. Cela dépend en partie de certaines caractéristiques démographiques du conducteur (âge, sexe, exposition, etc.), de sa conduite et de certains facteurs psychologiques (tolérance au risque, recherche de sensations, etc.) ainsi que des états temporaires (humeur, fatigue), Maladie, etc.). Intuitivement, on peut s'attendre à ce que le taux d'accidents augmente avec AVS et diminue avec ATS (Quimby, A., Maycock, G., Palmer, C., Buttress 1999).

Le deuxième enjeu social concerne l'émission de bruit du véhicule. Le bruit de la circulation est un problème répandu qui touche plus de 44% des citoyens de l'Union Européenne et constitue un grave risque pour la santé (European Parlem,

2012). Pour la modélisation analytique des émissions sonores, nous utilisons l'étude de Y Oshino, S Kono, T Iwase, H Ohnishi, T Sone (2000) où les auteurs relient l'émission sonore au type de véhicule et la vitesse moyenne du véhicule sur la route.

Enfin, le troisième enjeu social concerne le nombre de produits périmés qui causent en premier lieu du gaspillage de produits et en deuxième lieu plus de logistique inverse et, indirectement, plus d'accidents et de bruits. Nous considérons les produits avec une durée de conservation limitée et supposons que les produits périmés doivent être collectés et recyclés. Par conséquent, cet IRP traite à la fois de la logistique avant et de la logistique inverse afin de modéliser la livraison des produits frais et la collecte des produits périmés. Les produits périmés sont collectés par une flotte de véhicules différents de ceux utilisés dans la logistique avancé, principalement pour deux raisons: i) les produits périmés n'ont pas besoin de soins particuliers et coûteux pour les produits frais (véhicules frigorifiques par exemple) et ii) Les produits frais et les produits périmés ne doivent pas être mélangés en raison d'une éventuelle contamination.

5.2.3 Critères environnementaux

Comme pour le premier modèle, nous considérons également un critère environnemental dans notre IRP. En particulier, nous considérons les émissions de GHG produites par le transport direct et inverse des produits.

5.2.4 Hypothèse du problème

Nous reprenons les mêmes hypothèses du premier modèle (présentées dans section 4) auxquelles nous ajoutons celles qui suivent :

- Le fournisseur utilise une flotte d'hétérogènes de véhicules de capacités différentes, différents coûts fixes et variables, et différents niveaux d'émissions de GHG par kilomètre.
- Pour chaque détaillant, il existe un taux de demande satisfaisant qui détermine le pourcentage minimum de produits frais dans les entrepôts d'un détaillant.

5.3 Formulation mathématique

La première fonction objective maximise le profit, qui est égal au revenu des ventes des produits diminué par les coûts, y compris le coût de détention, le coût de rupture (backordering), le coût de commande, les coûts de transport fixes et variables pour la logistique directe et la logistique inverse. La seconde fonction objective permet d'optimiser le critère social pondéré en minimisant le taux d'accidents et l'émission totale de bruit des véhicules produits au cours de la logistique directe et inversée, ainsi que le nombre de produits périmés.

En plus des contraintes de la section 4, les contraintes qui définissent les caractéristiques de notre nouveau problème sont présentées comme suit:

- Le temps d'arrivée au prochain détaillant et la durée des retards doivent être déterminés en tenant compte de la fenêtre de temps prédefinie.
- Les émissions de GHG produites devraient être inférieures au seuil maximal autorisé pour chaque période.
- Une seule route devrait être choisie entre deux détaillants.

5.4 Méthode de résolution

Pour modéliser les paramètres incertains (demande, vitesse du trafic, vitesse du véhicule et coût de transport variable), nous proposons une approche stochastique basée sur les scénarios. Cette approche a montré son efficacité dans la modélisation des paramètres incertains. Nous avons également ajusté et appliqué la méthode Multi-Objective Simulated Annealing (MOSA) pour résoudre le modèle.

Nous avons obtenu une frontière de Pareto optimale pour différentes tailles des instances du problème. Ensuite, nous avons classé les solutions et avons trouvé un groupe de solutions, où une petite variation de profit a un impact significatif sur la variation des enjeux sociaux. Sur la base des résultats obtenus, les questions sociales peuvent être améliorées d'environ 19% à 31% avec une réduction de moins de 5% du bénéfice. Ce sont des solutions précieuses pour les entreprises qui sont confrontées à la pression des gouvernements et des organisations non gouvernementales pour examiner les questions sociales et veulent reporter leurs actions correctives afin d'améliorer les critères sociaux.

Dans notre étude, nous avons évalué la performance du modèle stochastique proposé. Pour cela, nous avons résolu des modèles déterministes et stochastiques. Ensuite, les solutions des deux modèles ont été évaluées dans chaque scénario. Les résultats obtenus montrent que le modèle stochastique a déterminé la configuration IRP de manière à pouvoir satisfaire tous les scénarios. Le modèle stochastique a obtenu des solutions qui sont immunisées contre tous les scénarios et peut gérer l'incertitude d'une manière souhaitable avec une augmentation raisonnable du coût total par rapport au modèle déterministe. En d'autres termes, le modèle stochastique est capable d'atteindre des solutions appropriées dans toutes les tailles et dans tous les scénarios, alors que le modèle déterministe est probablement infaisable. Les résultats obtenus illustrent que le gestionnaire, indépendamment de 13% du montant du profit et 11% du montant de la question sociale dans la situation déterministe, pourrait parvenir à une solution robuste qui est faisable dans différents scénarios.

6 IRP stochastique et dynamique: Produits périssables et durabilité (3ème modèle)

6.1 Motivation et Contribution

L'objectif principal du troisième modèle est d'étudier l'impact d'une optimisation dynamique sur l'efficacité des IRP. Nous avons étendu vers le mode dynamique de contrôle le deuxième modèle proposé dans section 6 en omettant la logistique inverse. La contribution de ce troisième modèle peut se résumer comme suit :

- Contrairement aux études antérieures qui n'ont tenu compte que de la demande en optimisation dynamique, nous prenons en compte les informations sur la variation de la demande et l'état du trafic routier comme deux paramètres d'optimisation engendrant un mode dynamique de contrôle.
- Une stratégie de ré-optimisation est définie pour étudier l'effet de l'utilisation d'information en temps réel dans le problème proposé. L'idée générale de cette stratégie est d'optimiser le modèle et de trouver les solutions initiales où la valeur des paramètres incertains est prédite. Ensuite, nous sélectionnons la solution initiale et ré-optimisons le problème à chaque période sur la base d'informations en temps réel. La stratégie de ré-optimisation nous permet de satisfaire toutes les nouvelles exigences basées sur la demande mise à jour. En outre, sur la base des informations mises à jour sur le trafic, le routage initial sera ré-optimisé.
- En plus de l'optimisation dynamique en considérant l'information en temps réel, nous considérons l'incertitude dans certains paramètres dans l'étape de trouver la solution initiale. Pour atteindre ce but, nous appliquons l'approche factuelle floue pour prédire la valeur des paramètres incertains.
- En raison de la spécificité de l'IRP dans la logistique urbaine, il est important de tenir compte d'autres critères comme critères sociaux et environnementaux. À cette fin, nous utilisons le modèle mathématique bi-objectif proposé à la section 6.
- Enfin, nous prenons en compte la périssabilité des produits dans les IRP. Nous supposons que les produits périmés doivent être recyclés, ce qui entraîne un coût supplémentaire et une émission supplémentaire de GHG qui devraient être pris en compte dans les critères environnementaux.

Il faut préciser que nous distinguons entre incertitude et dynamique. Dans la première étape de l'algorithme proposé, nous considérons l'incertitude dans la demande et l'état du trafic, modélisée par la vitesse moyenne du véhicule, pour

prévoir leur valeur et trouver une solution initiale. Par la suite, à chaque période, nous ré-optimisons le problème en considérant les informations mises à jour (information en temps réel) liées à la variation de la demande après le démarrage du premier routage et la dernière condition du trafic sur les routes. En fait, la dynamique de cette étude peut être interprétée en ré-optimisant le problème à chaque période, et en prenant en compte l'information en temps réel.

6.2 Description du problème

Dans ce modèle, nous avons étendu le deuxième modèle mathématique, présenté précédemment dans section 6. De plus, pour modéliser l'incertitude, nous avons utilisé l'approche possibiliste floue, qui a été également utilisée dans section 5. Comme mentionné précédemment, nous avons utilisé une stratégie dynamique particulière pour gérer l'aspect dynamique dans notre modèle, qui est détaillé dans ce qui suit.

6.3 Stratégie dynamique

Dans cette section, nous présentons la stratégie dynamique et l'algorithme qui sont définis et appliqués dans cette étude. Dans la première étape de l'algorithme proposé, nous optimisons le problème stochastique et trouvons la solution initiale. Dans l'étape suivante, à chaque période, nous ré-optimisons le problème en considérant les informations mises à jour relatives à la dernière condition du trafic sur les routes et la variation de la demande après le démarrage du premier routage. L'algorithme dynamique contient deux étapes principales; La classification des détaillants et la ré-optimisation qui sont détaillés dans ce qui suit.

- **Classification des détaillants**

Dans la première étape, nous classons les détaillants dans la solution initiale. Nous utilisons le temps de mise à jour (UT: Updating Time) à chaque période pour la classification, où le temps de mise à jour peut être défini par le décideur. Depuis, chaque tour dans la solution initiale contient différents détaillants, la classification des détaillants peut être en baisse par les visites définies. Les circuits définis peuvent être classés en trois groupes. Les tournées qui sont déjà réalisées (tournée terminée), les tournées qui ne sont pas encore commencées (tournée non encore commencée), et les tournées qui sont en cours de réalisation (tournée en cours). La méthode de classification est fondée sur la comparaison entre l'UT et le temps d'arrivée et de départ des véhicules chez les détaillants.

- *Tournée terminée:* Dans ce groupe de tournées, le véhicule a servi tous les détaillants de cette tournée et est retourné à l'entrepôt. La nouvelle demande de ces détaillants sera satisfaite avec un autre véhicule.

- *Tournée non encore commencée:* Dans ce groupe de tournées, en considérant la solution initiale et le temps de mise à jour, le véhicule est programmé pour quitter l'entrepôt et servir les détaillants après la mise à jour. Dans ce cas, les visites seront réorganisées en fonction des informations de circulation actualisées et la nouvelle demande sera satisfaite avec un autre véhicule, si nécessaire.
- *Tournée en cours:* Dans ce groupe de tournées, le véhicule a quitté l'entrepôt après la mise à jour alors que le dernier détaillant n'a pas encore été servi. Cela signifie, au moment de la mise à jour, que le véhicule est sur la route. Dans ce cas, le nouveau routage doit être défini en fonction des conditions de circulation mises à jour pour visiter les autres détaillants.

- **Ré-optimisation**

Après la classification des détaillants, nous avons besoin des nouveaux plans de distribution:

- Le nouveau plan de routage des véhicules qui se trouvent sur la route
- Le nouveau plan de distribution pour satisfaire la nouvelle demande des détaillants

À cette fin, nous nous occupons de deux nouveaux problèmes d'optimisation pour trouver la solution nouvelle qui prend en compte la mise à jour.

La partie de la ré-optimisation est liée aux détaillants, qui sont classés dans la troisième catégorie. En fait, l'objectif de ce problème d'optimisation est de trouver la meilleure séquence et type de déroute pour visiter les détaillants restants. Dans ce problème, le véhicule livre une quantité spécifique de produits aux détaillants en tenant en compte les conditions de circulation mises à jour. Afin de trouver une réponse rapide pendant le processus de ré-optimisation, nous transformons notre modèle bi-objectif en objectif mono et nous transformons le second objectif en une contrainte.

Une autre partie de la ré-optimisation est liée à la satisfaction de la nouvelle demande des détaillants. Dans ce problème, le fournisseur utilise une flotte de véhicules pour livrer une nouvelle demande de détaillants.

6.4 Méthode de résolution

Nous avons utilisé le NSGA-II pour résoudre le problème. Dans cette section, nous résolvons le problème dans la version statique, puis nous appliquons une stratégie dynamique pour examiner son impact sur les IRP. Nous avons réalisé quelques analyses pour démontrer la force de l'algorithme dynamique proposé, et certaines implications managériales ont été proposées. En particulier :

- Nous avons montré que le décideur doit tenir compte du concept dynamique des deux côtés du transport et de la gestion des stocks.

- Nous avons exploré qu'une gestion dynamique est plus efficace que la gestion statique tandis que le décideur est capable de réduire le taux de rupture (backlog) d'environ 19,79% et d'améliorer le bénéfice de 12,26%.
- Nous avons montré que l'optimisation dynamique des IRP apporte un gain pour le taux des produits périmés qui recule de 39,63% grâce à l'optimisation dynamique.
- Comme dans les modèle 1 et 2, nous avons proposé un outil qui permet aux décideurs de calculer numériquement l'impact de la variation du profit de x% sur les questions sociales. Il est montré qu'il possible d'atteindre le meilleur niveau de la considération sociale en scarifiant un maximum de 33% du bénéfice.

7 Conclusion et perspectives

Dans cette thèse, l'impact des considérations sociales et environnementales ainsi que le lien avec le niveau de service dans les IRP est exploré. Nous considérons les modes d'optimisation statique et dynamique prenant en compte des informations en temps réel dans IRP.

Trois modèles mathématiques qui sont expliqués dans les sections cinq, six et sept sont développés. Nous avons essayé de développer divers modèles pour se rapprocher des aspects plus pratiques et opérationnels des managers d'IRP. Cette étude est motivée par le changement des exigences du monde économique en termes de nouvelles législations sociales et environnementales ainsi que par une pression croissante pour proposer un meilleur niveau de service dans un contexte plus compétitif.

Dans les deux premiers modèles proposés, nous avons tenté d'intégrer le niveau de service, les critères environnementaux et les questions sociales dans les IRP. Dans ces deux modèles, nous avons présenté des modèles mathématiques multi-objectifs en convertissant les critères qualitatifs en mesures quantitatives pour mesurer l'empreinte environnementale, le niveau de service et les critères sociaux. De plus, nous avons considéré les produits périssables de deux façons:

- Définition de l'expiration. Les produits périmés doivent être recyclés par un coût supplémentaire alors que cette activité produit davantage d'émissions de GHG, ce qui est ajouté à d'autres critères environnementaux.
- Appliquer le mécanisme d'actualisation dans les IRP. L'effet négatif sur le plan financier et écologique du traitement des produits périssables nous oblige à appliquer une fonction non linéaire comme fonction de coût de détention pour diminuer la quantité de produits périmés. En fait, cette hypothèse est équivalente au cas où le coût unitaire de détention est

supposé être fixe alors que les détaillants proposent un prix de rabais pour les produits non frais qui sont transférés d'une période à une autre.

Étant donné que les modèles proposés traitent des produits périssables, le gestionnaire doit envisager de ramasser et de recycler ces produits après leur date d'expiration. À cette fin, le concept de logistique de retour est appliqué dans les modèles proposés. En outre, certains paramètres tels que la demande, le coût de transport et la vitesse du véhicule sont considérés comme incertains. Pour gérer l'incertitude dans ces problèmes, les approches stochastiques basées sur des scénarios et l'approche flou possibiliste sont adaptées et appliquées. Enfin, les algorithmes NSGA-II et MOSA sont réglés et adoptés pour obtenir une frontière de Pareto optimale. En se basant sur les résultats obtenus, certaines implications managériales sont fournies pour aider les gestionnaires à prendre des décisions plus précises et plus solides.

Dans le troisième modèle, on a tenté d'étudier l'impact d'une décision dynamique dans les IRP. Pour atteindre cette finalité, nous avons simplifié le modèle mathématique proposé et appliqué un algorithme de ré-optimisation. Ce mode de décision dynamique est en phase avec la transformation technologique de notre société où les objets connectés produisent de plus en plus de « *big data* » qui peuvent être exploitée par les preneurs de décision.

Du point de vue de l'applicabilité, les modèles proposés et les approches d'optimisation statique et dynamique ainsi que les approches de résolution présentés dans cette thèse peuvent être facilement déployés en entreprise. Nous pensons que les extensions réalisées dans ce mémoire est un moyen de rendre l'IRP plus proche de la réalité des entreprises. Nos modèles sont principalement inspirés de la distribution de produits frais dans des zones urbaines. Cette dernière est sujette à plus de contraintes quant à l'empreinte environnementale ainsi que son impact sociale et sociétale en général.

Les modèles présentés pourraient être utilisés pour les entreprises dans les différents secteurs tels que les entreprises qui distribuent des gaz industriels, la distribution de produits alimentaire et végétal, pharmaceutique et etc. En outre, la stratégie dynamique d'optimisation peut être utilisée dans plusieurs cas en présence de donnée temps réel. Cette stratégie accroît la capacité du gestionnaire à corriger sa décision en se basant sur des informations continuellement mis à jour.

Basé sur cette recherche et confrontés à des défis, nous proposons quatre champs de perspectives de recherche principaux: (i) des recherches qui envisagent d'améliorer la qualité des résultats; (ii) des recherches qui mettent l'accent sur l'utilisation de nouvelles méthodes pour diminuer le temps de calcul; (iii) Intégrer les nouveaux enjeux dans la modélisation de ces problèmes et (iv) des recherches qui concernent l'analyse des résultats obtenus afin de proposer des

recommandations managériales plus efficaces aux gestionnaires. Dans ce qui suit, chaque champ sera détaillé.

Comme mentionné précédemment, dans cette thèse, nous nous sommes concentrés sur des questions de modélisation qui n'ont pas été prises en compte dans les investigations de recherche précédentes. Pour cette raison, nous avons utilisé les approches de résolution (NSGA-II et MOSA) dont l'efficacité est déjà prouvée. Afin d'avoir des résultats plus précis, de nouvelles approches telles que les approches exactes, heuristiques, métahéuristique et hybrides des méthodes existantes peuvent être appliquées comme une direction de recherche future.

Comme mentionné au chapitre 4, nous ré-optimisons le problème proposé à chaque période. Dans ce cas, pour les problèmes avec une grande taille d'instance, le temps du CPU était d'environ 30 minutes. Comme prolongation de cette direction de recherche, nous pouvons nous intéresser à l'utilisation de nouvelles technologies telles que le GPS (Global Positioning System) dans les véhicules et de recevoir des informations en temps réel sur la circulation des itinéraires. Ainsi, le conducteur devrait être en mesure d'obtenir une solution ré-optimisée du routage pré-planifié en tenant compte des informations à partir du positionnement GPS de véhicule et de trouver une nouvelle solution. Cela signifie que nous devons ré-optimiser le problème dans un temps de calcul très court. Dans ce cas, il est nécessaire de développer une nouvelle approche de résolution qui doit être à la fois efficace et rapide. Étant donné que dans cette situation, il est nécessaire d'analyser une quantité énorme d'informations, l'application de nouvelles méthodes telles que les techniques d'apprentissage automatique et les réseaux de neurones, la simulation et data mining peuvent largement contribuer à diminuer le temps de calcul.

En plus, selon l'importance de l'intégration des différents acteurs de la chaîne logistique, la prise en compte de la phase de production dans les modèles proposés peut améliorer leur efficacité. De plus, dans l'extension de la recherche actuelle, nous pouvons envisager les différents modèles de gestion de stock et des politiques de réapprovisionnement pour étudier leur impact sur les IRP. En outre, d'autres aspects sociaux, ergonomiques, environnementaux et niveau de service, tels que le temps de travail, les émissions dues aux activités d'inventaire, etc., peuvent aussi être pris en compte. Il est également intéressant de proposer une option de transbordement (transshipment) dans l'optimisation dynamique qui peut améliorer l'efficacité de l'aspect dynamique dans l'IRP.

Finalement, il est nécessaire d'analyser les résultats obtenus, de vulgariser les méthodes développées et de proposer des règles managériales aux gestionnaires. Mais la transformation des données et informations en connaissances nécessite encore plus d'analyse à ce qui est présenté dans cette thèse.

8 Publications associées à ce travail

Les résultats de cette recherche ont été présentés et publiés dans une revue et des conférences:

- M. Rahimi, A. Baboli, Y.Rekik, "Multi-objective inventory routing problem: A stochastic model to consider profit, service level and green criteria" International Journal of Transportation Research Part E, Volume 101, May 2017, Pages59-83
- M. Rahimi, A. Baboli, Y.Rekik, "A bi-objective model for the sustainable inventory routing problem: products perishability and reverse logistics considerations" International Journal of Production Economics (submitted)
- M. Rahimi, A. Baboli, Y.Rekik, "Dynamic stochastic inventory routing problem for perishable products considering sustainable issue" International Journal of Production Research (submitted)
- M. Rahimi, A. Baboli, Y.Rekik, (2016) "Sustainable inventory routing problem for perishable products by considering reverse logistic" 8th IFAC conference on Manufacturing modeling, management & control (MIM), Jun. 28-30, Troyes, France, 6 pages
- M. Rahimi, A. Baboli, Y.Rekik, (2016) "Inventory routing problem for perishable products by considering customer satisfaction and green criteria" The 5th International Conference on Dynamics of Logistics (LDIC) jointly held with 7th IFAC conference on MCPL, Feb. 23-25, Bremen, Germany, 10 pages
- M. Rahimi, A. Baboli, Y.Rekik, (2015) "Inventory routing problem for perishable products by considering social issues" The 10th IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI), Nov. 15-17, Yasmine Hammamet, Tunisia, pp. 116-121
- M. Rahimi, A. Baboli, Y.Rekik, (2015) "Inventory routing problem by considering customer satisfaction and environmental criteria" The ISIR Workshop on Sustainable Logistics and Supply Chain Management, Oct. 7-9, EMLyon Business School, Ecully, France
- M. Rahimi, A. Baboli, Y.Rekik, (2014) "A bi-objective inventory routing problem by considering customer satisfaction level in context of perishable product" CIPLS'14, IEEE Symposium Series on Computational Intelligence in production and logistics systems, Dec. 09-12, Orlando, Florida, USA, pp. 91-97.

1

Introduction, problem statement and literature review

1 Introduction, problem statement and literature review

1.1 Introduction

To remain competitive, enterprises have been forced to increase the efficiency and flexibility of their systems. Moreover, in the context of new revolution in industry, called Industry 4.0 (Brecher C 2015), or cyber physical system (Lee & Shin 2017), a company must have a high degree of agility to deal with market changes. As objective of industry 4.0, companies are forced to digitalize several steps of their processes allowing to have the tractability of each operation and interaction between the components of production system. This opportunity offer the possibility to be more transparent for all the players and becomes a completely integrated system (Schrauf & Berttram 2017). A key element is transforming traditional supply chains to a smart supply chain. The critical point for a smart supply chain is effective exchange of information between different players of supply chain. The traditional supply chain is faced different problem, caused mainly by lack of complete and timely information such as shifts in demand, traffic caused by a sudden vehicles accident, *etc.* sharing of updated and reliable logistics information can meaningful improve the efficiency of supply chain.

To use the advantages of updated information sharing in supply chain, it is important to coordinate and integrate the inventory and distribution management as two main activities of logistics. This type of integration known as Inventory Routing Problem (IRP). The main objective of the IRP is identification of the best joint strategy for inventory and distribution: i.e. the inventory control of products on the first hand, and the determination of type and number of vehicles, type of products, their quantity to be delivered to each customer and the best routing in each period, on the second hand.

The principal objective in classical IRP is the minimization of the total inventory and transportation costs as well as the traveling time or distance (Madadi *et al.* 2010; Li *et al.* 2014) where all the inputs are known beforehand.

The classical approach of IRP modelling focuses mainly on the economic aspect and does not consider certain important criteria such as the social issues, the environmental criteria, service level and *etc.*. Currently, managers must make their decisions by considering different criteria in addition to the economic criterion; these may, in certain cases, conflict with each other.

These new criteria become more important when solving an IRP in urban logistics. The latter is characterized by operational and sometimes legal constraints (distribution in very strict time windows and the need to use specific

vehicles), which forces the manager to model and take into account these new criteria.

In addition, the IRPs modeling may be more challenging when it is performed for perishable items where both the product non-freshness and the need to recycle perished products should also be modeled and considered.

It should also be noted that the classical IRP overlooks the impact of using real-time information on economic efficiency of IRPs. However, we need to deal with a new approach of IRP to consider parameters which are not known beforehand and will be revealed over the time. In order to deal with this aspect of IRP, refereed as the Dynamic IRP (DIRP), we need to define some new strategies involving the data received or changing over time.

We study in this thesis an extension of the classical IRP that allows considering other optimization criteria in addition to the economic criterion. We focus on the context of the urban distribution of perishable products and consider a static and dynamic mode of decision.

In the following, we propose the detail of the key words that characterize the contributions of this research and practically explain the need to extend the classical IRP as we propose it. Then, we expose an updated literature review study in which we demonstrate the research opportunity and the scientific contribution of this work.

1.1.1 Social issue

New regulations, law and standards have been adopted during the recent years, which should be consequently taken into account in the IRP modeling and optimization. Among the new regulations, one could cite the occupational safety and health administration (NIOSH 2014), the European Parliament regulation about the vehicle noise (European Parlem 2012) as well as the social responsibility guidance provided in the ISO 26000 standard (ISO 2010). Managers need to reconsider the modeling of joint inventory and distribution problem by including these new regulations in the framework. Moreover, there is an increasing pressure on companies from the governmental and non-governmental communities and more generally from the public opinion to encourage them to include sustainable considerations in their activities. According to Cruz & Wakolbinger (2008), some famous trades such as Shell, McDonalds, Nike and Disney faced a negative reputation with a profit impact because of some media reports.

1.1.2 Environmental issue

Currently, there is increasing pressure on companies, stemming from the governmental and non-governmental communities and, more generally, from public opinion, to encourage them to master and decrease their Greenhouse gas (GHG) emissions. This reduction is not only to protect the environment but is also economically motivated, because new regulations provide for environmental penalties if this emission is higher than certain thresholds. However, transportation is main sector that produce GHG emissions and should be considered by decision makers. In this way, decision makers are obliged to concern on environmental criteria in IRPs to respect international regulations and avoid imposing the additional cost to the system (Mirzapour Al-e-hashem & Rekik 2013).

Indeed, adding the green footprint in the IRP is linked to a real need of companies. In some of European Union countries, the access to the city center is conditional to the green footprint of the vehicle performing the delivery. More and more legislation rules are set to at least track and to limit the GHG emission particularly in urban zones.

1.1.3 Service level

Increasing competitiveness between firms in a global marketplace generates increasingly more pressure. The firms need to improve their efficiency as much as possible to ensure customer satisfaction. A high service level is indeed one of the key factors to strengthening customer satisfaction and loyalty. However, despite the positive impact on sales in the long-term, providing a higher service level to the customer may increase the associated inventory and distribution costs. For example, the managers try to satisfy as many customers as possible as it maximizes their sales. At the same time, maintaining the inventory is both costly and risky: products need space to be housed, they expire and get obsolete, and so on (Schalit & Vermorel 2014).

In order to taking into account service level in IRPs, it is needed specific indicators in both side of inventory and distribution management. Service levels are very used in the inventory control area where they can be preferred for their ease of use from a technical point of view. The service level and the fill rate are well known and very used measures for practitioners. However, it is necessary to define the indicators which concern on distribution part of IRPs.

1.1.4 Perishable products

There exist different types of deteriorative products, which classify based on according to how they decay. These kind of products lose their utility with a

specific speed during the time and are not usable for the original purpose after their fixed lifetime. The first type includes products whose lose their functionality over time such as fruits, vegetables and flower. The second type are products, which become expired after a given date, even though they are still in perfect condition. However, for the both type, the expired products should be collected and be recycled. Recycling activity, results in an additional cost and an additional GHG emission that should be taken into account in the environmental criteria.

Knowing that the products perishability adds more complexity to the IRPs, but the significant role of this type of products should not be overlooked. Moreover, the frameworks should be developed in a way, which can handle the both type of perishable products.

1.1.5 Dynamic decision

As it is mentioned before, for considering dynamic management in IRPs, we need to define some new strategies.

As first strategy, we can optimize the model whenever new information becomes available. Another one is to solve the problem once and obtain the initial solution and whenever new information becomes available we re-optimize the problem, which is more common strategy. Otherwise, we can use traditional forecasting methods to predict value of unknown parameters. Indeed, using these strategies increase capability of manager to take more accurate decisions by considering real time information (Coelho *et al.* 2013).

Despite of importance and significant role of explained criteria in IRPs, only few numbers of studies involved these aspects in IRP.

1.2 Literature review

In this section, we review the relevant literature to show existing research gaps in IRPs and to distinguish the present research work from previous ones. Finally, a classification of described studies in the IRP literature is presented.

1.2.1 Literature review on relevant IRP

Due to existing many studies in this domain, we limit this targeted review to papers are more related to product perishability, service level, environmental criteria, sustainability and dynamic issues. We refer reader to the excellent literature review performed by Coelho *et al.* (2013).

For this purpose, we review the relevant literature in four main classes; the first one concerns general IRP, the second and third ones concern IRP considering environmental, social issue and service level, and last one is the IRP for

perishable products. The presentation of research works is based on their publication date.

1.2.1.1 General IRP

One of the first research works related to IRP was presented by Bell *et al.* (1983) as a framework combining decisions on inventory management and vehicle scheduling for the distribution of chemical products. This study is extended and continued by different researchers (Dror *et al.* 1985; Anily & Federgruen 1990; Speranza & Ukovich 1996), who also consider inventory and distribution optimization by additional aspects such as multi product, multi vehicle and etc., simultaneously. Other researchers have since integrated different ideas with various applications in IRPs: cost or profit as objective functions (Archetti *et al.* 2007; Liu & Chung 2008; Cho *et al.* 2013); and traveling time minimization (Li *et al.* 2014; Hemmelmayr *et al.* 2008). From industrial aspect, others have investigated IRPs in different industrial fields such as the gas industry (Halvorsen-Weare & Fagerholt 2013), maritime transportation (Christiansen *et al.* 2011), healthcare (Hemmelmayr *et al.* 2010) and the food industry (Gaur & Fisher 2004).

Berman & Larson (2001) investigate IRP in gas industry. They minimize some related cost such as expected cost, shortage cost, delay cost, and cost of returning. The authors use stochastic dynamic programming to model the problem. Bertazzi *et al.* (2002) propose a mathematical model to minimize distribution and inventory costs in order to deliver one product from one supplier to set of customers. They introduce two-step heuristic algorithm to solve the problem. Jaillet *et al.* (2002) investigate IRP for distribution some products such as oil from depot to large number of the customers. They consider cost approximation to minimize the total delivery costs.

Bertazzi & Speranza (2002) propose a mathematical model to find appropriate delivering strategy that minimizes the inventory and transportation costs while the demand are deterministic. Adelman (2003) takes into account minimization of replenishment and shortage costs in IRPs. The author uses price-directed control method to achieve the solution.

Gaur & Fisher (2004) develop a model for solving the distribution problem at the supermarket chain. They assume there is single product should be delivered to some supermarkets which are clustered in different regions with different size of vehicles. The main objective of this problem is to minimize the total costs. They construct a heuristic called randomized sequential matching algorithm. Campbell & Savelsbergh (2004) develop a two-phase algorithm to solve the inventory routing problems. In the first approach, they determine how much should deliver to each customer. In the second phase, they solve the Vehicle Routing Problem (VRP) with time window to find the routing strategy.

Archetti *et al.* (2007) introduce a mixed integer linear programming to distribute one product from one supplier to some retailers while the total costs should be minimized. They consider that stock out does not occur in the retailers. The Authors use branch-and-cut algorithm to solve the problem.

Bard & Nananukul (2008, 2010) study integration of production, inventory and distribution as three main activities of supply chain by proposing a mathematical model while total costs should be minimized. They pay attention that one production facility produce the products and deliver to customers. In order to solve the proposed model, they develop a heuristic with combination of branch-and-price and column generation. Hemmelmayr *et al.* (2008, 2010) formulate an integer programming model related to the distribution the blood products to hospitals by minimizing time traveling. The authors introduce a Variable Neighborhood Search (VNS) while product consumption is a stochastic parameter. Savelsbergh and Song (2008) consider that in IRP, at supplier warehouse there exist product availability limitation. They use randomized greedy heuristic to obtain the initial solution and then improve the initial solution using a local search algorithm. Li *et al.* (2008) concern on replenishment option in IRPs where each supplier can replenish only selected retailer at selected periods.

Chen & Lin (2009) propos a mathematical model to minimize the total costs of distribution and inventory where one supplier distributes multi products to retailers. In this study, authors concern effect of price changing in total profit as risk aversion in the model. Shen & Honda (2009) address a mixed-integer programming model to formulate the three-echelon supply chain system where a single planet produce one product and deliver to different warehouses for distribution to retailers. Abdelmaguid *et al.* (2009) consider multi-period IRP where one supplier distributes one product to retailers. The authors consider the demand of each retailer is deterministic and is smaller than vehicle capacity. They propose different heuristics to solve the problem and show efficiency of developed heuristics.

Ahmadi Javid & Azad (2010) propos a mixed-integer mathematical model in IRP to integrate some strategic decisions such as location-allocation. In their study, the customer's demand assumed as an uncertain parameter, and at each distribution center, the safety stock is considered. Huang & Lin (2010) propos a model with an uncertain demand by combining multi-item inventory management and vehicle-routing optimization. They use an Ant Colony Optimization (ACO) algorithm to solve their problem. Shiguemoto & Armentano (2010) address a multi-product model to coordinate production, inventory, and distribution by considering the time window for the distribution process. A Tabu search procedure developed to obtain the solution. Oppen *et al.* (2010) propose an IRP model to collect animals from farms for slaughter. The authors lead to a loading

problem where the vehicle capacity depends on the loading sequence. Their objective is to minimize the traveling distance. To solve the model, they present an exact solution method, based on column generation.

Christiansen *et al.* (2011) study IRP in maritime industry to transport multiple non-mixable products from producing factories to regional silo stations. There exist inventory constraints at the factories and the silos where upper and lower limits for all inventories are defined. They developed a heuristic based on genetic algorithm and show efficiency of proposed algorithm in obtaining the good results. Siswanto *et al.* (2011) study a ship inventory routing problem to decide about route selection, ship selection, loading and unloading activities. They develop a one-step greedy heuristic and show the efficiency and applicability of their model. Popović *et al.* (2011) present a simulation approach for IRPs when fuel consumption is stochastic. The authors consider emergency deliveries and safety stocks in the model. They show applicability of model when fuel consumption is stochastic. Moin *et al.* (2011) propose a model for many-to-one distribution network consisting the various supplier and one assembly plant. In this problem, each supplier supplies specific products. They use homogeneous fleet to distribute deterministic demand of assembly plant for each product. To solve the model, they use genetic algorithm. Zhong & Aghezzaf (2011) propose a non-linear inventory routing problem to distribute one product from one depot to some retailers to minimize the total costs. They consider that retails should not be occurred by stock outs. They propose a heuristic by combining DC-programming, branch-and-bound and a steepest descent algorithm.

Coelho *et al.* (2012a) focus on some consistencies such as quantity consistency, vehicle filling rate and *etc.* in IRP. They assume there are a homogeneous and a heterogeneous fleet for transportation. A branch-and-cut algorithm also applied as an exact solution approach. Stålhane *et al.* (2012) propose a model for producer and distributor of liquefied natural gas to minimize the total costs. They use start local search heuristic to solve the proposed model. In this problem, authors consider multi-products, berth capacity at the loading port and vehicles with different capacity. Coelho *et al.* (2012b) consider transshipment option between suppliers and customers and also between customers to minimize the total costs. They use an adaptive large neighborhood search as a heuristic approach to solve the model. Solyali *et al.* (2012) study the impact of customer demand variation as dynamic aspect in IRPs. Ahmadi-Javid & Seddighi (2012) develop three level location, distribution and inventory problem to minimize the total costs. They use a heuristic based on integration simulated annealing and ant colony system to solve the problem.

Coelho & Laporte (2013) propose a branch-and-cut algorithm for the solving IRPs where a supplier distributes multi-products to various customers by different vehicles in capacity. Hewitt *et al.* (2013) use inventory and routing for

a maritime problem where different vessels transports a single produced product to multiple sites. The authors use branch-and-price algorithm to solve the proposed problem. Tavakkoli-Moghaddam *et al.* (2013) propose a bi-objective mathematical model to minimize the costs of opening the location, transportation and inventory while second objective function minimizes transportation time from planets to customers. The authors consider demand as stochastic parameter. They use weighted-sum method to solve the problem.

Coelho *et al.* (2014) propose an efficient algorithm to predict future demand of customers using historical data. Then the authors take into account to demand updated information by applying lateral emergency transshipment when customer faces shortage.

Bertazzi *et al.* (2015) study IRPs for minimizing total cost where supplier has limitation in production capacity and demand of the retailers is stochastic. Brinkmann *et al.* (2015) solve the bike sharing problem by using IRP where they use the vehicles to balance the bikes between stations. For this purpose, they define a stochastic IRP where request for bike from customer is stochastic. In this study, authors define a strategy to determine priority of each station and to consider urgency of each station that should be rebalanced. Shao *et al.* (2015) propose a mathematical model to minimize total costs which caused by lost production, stock out and non-satisfied demand in distribution of liquefied natural gas. The authors consider that exist production terminals with specified storage capacities as well as a limited number of berths for ships. Moreover, there is a set of regasification terminal their need, that have fixe storage capacity. The authors develop a heuristic by hybridizing rolling time algorithm, greedy randomized adaptive search procedure, and neighborhood search techniques. They evaluate their algorithm and show the proposed heuristic is able to reach optimal solution faster than commercial optimization software. Jiang & Grossmann (2015) extend IRPs where different vessels deliver a single product to the ports. The authors propose two continuous and discrete time models. Objective of their problem is to minimize the total costs, which include sailing cost, waiting and operation costs. Agra *et al.* (2015) study the maritime IRP to distribute oil products between different islands and manage the storage level of tankers in the ports. The authors assume the traveling time and operating time are two stochastic parameters in the problem. Moreover, they combine rolling horizon, local branching and feasibility pump to solve the model.

Chitsaz *et al.* (2016) propose two-phase heuristic to solve the IRPs. In the first phase, steepest decent approach is used to define the tours. In the second phase, the authors use a heuristic based on best-fit decreasing. In this phase, vehicles are scheduled and are assigned to defined tours. Roldán *et al.* (2016) study dynamic stochastic IRPs without using forecasting method to predict future demand. They propose three different customer selection methods such as big

order, lowest storage and equal quantity discount. Ghorbani & Akbari Jokar (2016) propose a hybrid Imperialist Competitive-Simulated Annealing (IC-SA) algorithm to solve to IRPs.

1.2.1.2 IRP considering environmental and social issues

Benjamin & Beasley (2010) propose a model to minimize the total cost due to collection the waste from customers. In this problem, the vehicles leave the depot while they are empty. They pick up the waste from customers, and empty themselves at the waste disposal facilities. At the end, vehicle return to depot empty. The authors concern that the total working time of driver should not exceed at each period. Moreover, they hybridize Tabu search and variable neighborhood search. Aksen *et al.* (2012) investigate minimization of total costs for collection waste vegetable oil to use as raw material for a biodiesel company while production equipment should be satisfied. Erdogan & Miller-Hooks (2012) formulate a mixed integer linear mathematical model, considering green criteria. They take into account the fuel consumption rate and try to minimize the total traveling distance. They also propos two heuristics algorithms and show efficiency of developed heuristics. Mirzapour Al-e-hasem & Rekik (2013) investigate impact of considering green criteria in IRPs while total cost should be minimized and total Greenhouse Gas (GHG) emission produced by vehicles shouldn't be exceeded. Bertazzi *et al.* (2013) propose a dynamic stochastic IRP to minimize total costs. They use probabilistic information to predict the demand. Moreover, the authors solve the proposed stochastic IRP by using rollout approach.

Sazvar *et al.* (2014) propose a multi-objective mathematical model to show the effect of environmental criteria on the total cost in the pharmaceutical industry. In this problem, demand of customers is uncertain and scenario-based approach is used to handle the uncertainty. They consider the recycling cost of the expired products and the amount of GHG emissions generated by recycling the perished products. The authors assume that predefined percentage of stocked products would deteriorate in each period. They use the weighted sum method to solve the proposed model. Al Shamsi *et al.* (2014) propose a multi-objective mathematical model to find trade-off between the cost resulting from the GHG emissions and the total costs of inventory and routing problem. In this study, authors take into account perishable products and recycling of expired products. They consider the effect of the weight and the speed of vehicles on GHG emissions. Nolz *et al.* (2014) present a multi-objective IRP model to make a trade-off between cost and social issue. They minimize the public health risk considering the collection of pharmaceutical waste as social issue in IRPs. Hauge *et al.* (2014) consider the collection of the industrial waste from different sites and assume that full containers should be driven to dump sites. Treitl *et al.* (2014) consider

environmental issues in IRP in petrochemical industry. The authors convert amount of produced GHGH emission in distribution process to cost and try to minimize total cost. Soysal *et al.* (2015) investigate impact of considering environmental criteria in total costs of IRPs, especially for perishable products. To deal with environmental issues, they concern on fuel consumption of vehicles and convert its value to cost. Jabir *et al.* (2015) develop a bi-objective mathematical model that first objective function minimizes the costs while second objective function minimize the produced GHG emission by vehicles. The authors hybridize the ant colony optimization and variable neighborhood search algorithms and address an efficient heuristic to solve the proposed problem.

Zhalechian *et al.* (2016) propose a multi-objective non-linear mixed-integer mathematiccla model for IRPs by integration of location-allocation issues in a closed loop supplychain. The authors define three objective function, first objective minimizes the total costs. Second obejctive function considers minimization of enviromental issues which is measured by produced GHG emission of vehicles, fuel consumption and energy wasted when vehicles wait for receiving service. Third objective function maximizes social issues which is measured by the created job opportunities and maximization of the balanced economic development. The authors concern that the demand, costs and distance between nods are uncertain and they applied two-phase approach to handle uncertain parameter in the model. In the first phase, stochastic-possibilistic programming approach is used which is obtained by integration of chance-constrained programming and possibilistic programming. Then in the second phase, they apply a modified game theory approach. Finally to solve the model, the authors develope a meta-heuristic by combining self-adaptive genetic algorithm approach and variable neighborhood search algorithm. Soysal *et al.* (2016) take into account the produced GHG emission due to distribution of perishable products in IRPs. The authors consider uncertainty in the demand. They show applicability of propsoed model by applying a real case in food industry. Soysal (2016) integrates closloop supply chian in IRP for collection of wastes of prodcuts. The author considers demand uncertainty in the model. He applied the propsoed model for a real case where a distributer delivers a soft drink to retailers. Cheng *et al.* (2017) present a comprehensive model to consider environmental issue in IRPs. The authors concern on fuel consumption where it is measured based on load, distance, speed and vehicle characteristics. Iassinovskaia *et al.* (2017) propose a problem where a producer, produces returnable products and delivers them to customers. Each customer defines a specific time window that should be respected by distributer. Moreover, distributer is responsible of collection the empty returnable items. There exist two different storage area for delivered and empty products at customers. The authors proposed a specific heuristic to solve the proposed problem.

1.2.1.3 IRP considering service level

Yu *et al.* (2012) propose the mathematical model of inventory routing problems in a study of uncertainty in demand. They take into account that demand has to satisfy by limiting the probability of stock out. Mirzaei & Seifi (2015) propose a multi objective mathematical model to investigate impact of minimization of lost sales in total cost for distribution of perishable products. Singh *et al.* (2015) use IRPs in distribution of liquefied industrial gases to maximize service-level which is converted as cost. In this study, there exist three main issues. All orders should be satisfied, stock out should not be occurred and efficiency of the bulk gas distribution should be considered. The efficiency is measured by ratio of the total distribution costs and the total delivered product.

1.2.1.4 IRP for perishable products

Tarantilis & Kiranoudis (2002) formulate a multi depot in VRPs for distribution fresh meat to increase profit of company. The authors propose a search algorithm called as list-based threshold accepting algorithm. Custódio & Oliveira (2006) propos a mathematical model to minimize the total inventory and distribution costs in delivering of frozen food. In order to solve the proposed model, they use a heuristic, which is called stationary nested policy. Hsu *et al.* (2007) consider to distribution of perishable products in food industry by proposing a new mathematical model to minimize the total inventory and distribution costs. They concern that each retailer defines specific time window who is available in this interval time and should be respect in distribution planning. Moreover, the authors consider energy saving in the model that should be minimized. They convert energy concept as a cost in the objective function. They solve the proposed model using specific heuristic that called time-oriented nearest neighbor. Nagurney *et al.* (2011) focus on the distribution of human blood under a stochastic demand assumption. They involve a cost in the model related to the waste of perished blood.

Le *et al.* (2013) present a IRP framework for distribution of perishable product where total cost should be minimized. Moreover, they introduce a column generation-based algorithm to solve the proposed model and show its efficiency in obtaining the good result. Amorim & Almada-Lobo (2014) consider perishability of product in addition to economic aspect. The authors introduce a multi-objective mathematical model where the first objective minimizes the related costs while the second objective attempts to maximize the freshness of the delivered products. They solve the model by using ε -constraint for small sizes and adapting a multi-objective evolutionary algorithm for large instance problems. Coelho & Laporte (2014) study IRP for perishable products aiming to maximize profit by assuming that products have different ages. The supplier decides about the number of products with differing ages delivered to each

customer. In the proposed model, two inventory policies considered where the supplier could sell fresher first or older first. The authors solve the proposed model using branch-and-cut algorithm. Jia *et al.* (2014) propose a two-echelon supply chain by considering production step in IRPs to minimize the total costs. The authors take into account limited production capacity in supplier side where one supplier distribute one perishable product to retailers. They present a two-phase algorithm to solve the problem and show efficiency of their proposed algorithm.

Andersson *et al.* (2015) investigate IRP in liquefied natural gas field where decision maker is responsible for production part, routing and scheduling ships, and inventory of regasification terminals. Moreover, they consider there are limited number of berths for loading and unloading. They concern perishability concept in their study where constant rate of gas in tankers evaporates each day. The authors propose an algorithm based on branch-and-cut method to solve the proposed model. Ghiami *et al.* (2015) consider IRP for distribution liquefied natural gas where a constant rate of gas evaporates each day at the storage facilities and filling stations. Azadeh *et al.* (2017) integrate transshipment option in IRPs where supplier delivers one perishable product to customers. The authors consider that product, deteriorates at the exponential rate during the time at the warehouse. They propose a genetic algorithm to solve the problem. Hiassat *et al.* (2017) concern in location decisions in the IRPs to find the location of required warehouses in addition to classical decisions of IRPs.

1.2.2 Synthesis

Table 1.1 illustrates the classification of the presented papers in the IRP literature. Based on this literature review and Table 1.1, we observe that economic performance is historically the main objective that is considered by researchers. In the last few years, the research community has started to include environmental criteria, service level, time optimization, and social issue. As an example, the specificity of IRP in urban logistic, oblige the researchers and decision makers to take into account social and environmental criteria in IRPs modelling. But, except the investigation of Zhalechian *et al.* (2016) which include sustainability in IRPs, there is no other study, which model and take into account such issues in IRPs. It should be mentioned that such a few number of investigations dealing with sustainability, could be explained by the difficulty to model social considerations in a quantitative manner and to include them in the classical IRP framework.

Based on our literature review, recently researchers consider perishable products a lot in their investigations. For example, they attempt to maximize the freshness of the delivered products (Amorim & Almada-Lobo 2014) or to consider the

GHG emission and cost due to recycling the perished products (Sazvar et al. 2014). In fact, the researchers define a penalty cost or take into account produced GHG emission due to recycling the perishable products. There is no study to include a discount mechanism or more holding cost for perishable products in IRP modelling. These methods causes more sale of fresh products and decrease the expired products in the warehouse of retailers.

Another gap in literature deals with using of real-time information in IRPs. Based on our litterateur review, demand is the unique parameter that the researchers considered in dynamic optimization (Solyali et al. 2012; Bertazzi et al. 2013; Coelho et al. 2014; Roldán et al. 2016). In this way, researchers deal with only inventory side of IRP while traffic conditions in the routes is also another parameter which should be considered in dynamic optimization. In other word, there is no study to take into account demand variation and traffic condition as two key parameters to consider both inventory and routing aspects in dynamic optimization of IRP.

Beside explained issues, uncertainty is another criteria which is not a lot studied by researchers. Regarding the complexity of IRPs, most research assume the parameters as certain. In contrast to the multi-periods in IRPs, but researchers assume that there is a predefined demand for each product in each period. Only few researchers considered the uncertainties in costs, traveling time and *etc.*

As conclusion, we can say, there are four main research gaps in IRPs:

- Considering sustainability and service level in addition to the economic aspect of IRP.
- Considering a multi-objective mathematical modeling for perishable products.
- Taking into account the variation of parameters which have uncertain nature such as demand, transportation costs, traffic in the routes, etc.
- Considering a dynamic optimization for the IRP especially by integrating real time data about demand and traffic conditions in the route.

Table 1.1 Classification of literature about IRP

Author	Objective function	Data nature	Perishability	Sustainability			Service level	Dynamic	Solving method
				Cost	Environment	Social			
Bertazzi <i>et al.</i> (2002)	Single	Certain		✓					Heuristic
Bertazzi & Speranza (2002)	Single	Certain		✓					Heuristic
Tarantilis & Kiranoudis (2002)	Single	Certain	✓	✓					Heuristic
Gaur & Fisher (2004)	Single	Certain		✓					Heuristic
Custódio & Oliveira (2006)	Single	Certain	✓	✓					Heuristic
Archetti <i>et al.</i> (2007)	Single	Certain		✓					Branch-and-cut
Hsu <i>et al.</i> (2007)	Single	Uncertain	✓	✓					Heuristic
Bard & Nananukul (2008, 2010)	Single	Certain		✓					Heuristic
Hemmelmayr <i>et al.</i> (2008, 2010)	Single	Uncertain		✓					VNS
Savelsbergh and Song (2008)	Single	Certain		✓					Heuristic
Chen & Lin (2009)	Single	Uncertain		✓					PSO
Abdelmaguid <i>et al.</i> (2009)	Single	Certain		✓					Heuristic
Ahmadi Javid & Azad (2010)	Single	Uncertain		✓					TS & SA
Huang & Lin (2010)	Single	Uncertain		✓					ACO
Oppen <i>et al.</i> (2010)	Single	Certain		✓					Column generation
Benjamin & Beasley (2010)	Single	Certain		✓	✓				VNS & TS
Christiansen <i>et al.</i> (2011)	Single	Certain		✓					GA
Siswanto <i>et al.</i> (2011)	Single	Certain		✓					Heuristic
Popović <i>et al.</i> (2011)	Single	Uncertain		✓					Simulation
Moin <i>et al.</i> (2011)	Single	Certain		✓					GA
Nagurney <i>et al.</i> (2011)	Single	Uncertain	✓	✓					Exact
Zhong & Aghezzaf (2011)	Single	Certain		✓					Heuristic

Table 1.1 Classification of literature about IRP

Author	Objective function	Data nature	Perishability	Sustainability			Service level	Dynamic	Solving method
				Cost	Environment	Social			
Coelho <i>et al.</i> (2012a)	Single	Certain		✓					Branch-and-cut
Stalhane <i>et al.</i> (2012)	Single	Certain		✓					Heuristic
Yu <i>et al.</i> (2012)	Single	Uncertain		✓			✓		Heuristic
Aksen <i>et al.</i> (2012)	Single	Certain		✓	✓				Exact
Coelho <i>et al.</i> (2012b)	Single	Certain		✓					Heuristic
Solyali <i>et al.</i> (2012)	Single	Uncertain		✓				✓	Branch-and-cut
Erdog˘an & Miller-Hooks (2012)	Single	Certain		✓	✓				Heuristic
Ahmadi-Javid & Seddighi (2012)	Single	Certain		✓					ACO & SA
Mirzapour Al-e-hashem & Rekik (2013)	Single	Certain		✓	✓				Exact
Bertazzi <i>et al.</i> (2013)	Single	Uncertain		✓				✓	Heuristic
Coelho & Laporte (2013)	Single	Certain		✓					Branch-and-cut
Hewitt <i>et al.</i> (2013)	Single	Certain		✓					Branch-and-price
Le <i>et al.</i> (2013)	Single	Certain	✓	✓					Heuristic
Tavakkoli-Moghaddam <i>et al.</i> (2013)	Multi	Uncertain		✓					Weighted-sum
Coelho <i>et al.</i> (2014)	Single	Uncertain		✓				✓	Rolling algorithm
Amorim & Almada-Lobo (2014)	Multi	Certain	✓	✓					NSGA-II
Coelho & Laporte (2014)	Single	Certain	✓	✓					Branch-and-cut
Sazvar <i>et al.</i> (2014)	Multi	Uncertain	✓	✓	✓				Weighted sum
Al Shamsi <i>et al.</i> (2014)	Multi	Certain	✓	✓	✓	✓			Exact
Nolz <i>et al.</i> (2014)	Multi	Certain		✓			✓		ALNS
Hauge <i>et al.</i> (2014)	Single	Certain		✓	✓				Hybrid (CG&TS)
Treitl <i>et al.</i> (2014)	Single	Certain		✓	✓				Exact

Table 1.1 Classification of literature about IRP

Author	Objective function	Data nature	Perishability	Sustainability			Service level	Dynamic	Solving method
				Cost	Environment	Social			
Jia <i>et al.</i> (2014)	Single	Certain	✓	✓					TS & NS
Mirzaei & Seifi (2015)	Multi	Certain	✓	✓			✓		Hybrid (SA&TS)
Bertazzi <i>et al.</i> (2015)	Single	Uncertain		✓					Rollout algorithm
Soysal <i>et al.</i> (2015)	Single	Uncertain	✓	✓	✓				Simulation
Jabir <i>et al.</i> (2015)	Multi	Certain		✓	✓				Hybrid (ACO & VNS)
Brinkmann <i>et al.</i> (2015)	Single	Uncertain		✓					Heuristic
Shao <i>et al.</i> (2015)	Single	Certain		✓					Hybrid (rolling time, greedy randomized adaptive search & NS)
Andersson <i>et al.</i> (2015)	Single	Certain	✓	✓					Branch-and-cut
Agra <i>et al.</i> (2015)	Single	Uncertain		✓					Heuristic
Singh <i>et al.</i> (2015)	Single	Certain		✓			✓		Randomized local-search
Ghiami <i>et al.</i> (2015)	Single	Certain	✓	✓					Heuristic
Chitsaz <i>et al.</i> (2016)	Single	Certain		✓					Heuristic
Roldán <i>et al.</i> (2016)	Single	Uncertain		✓			✓		Exact
Zhalechian <i>et al.</i> (2016)	Multi	Uncertain		✓	✓	✓			Hybrid (SAGA & VNS)
Ghorbani & Akbari Jokar (2016)	Single	Certain		✓					Hybrid (IC & SA)
Soysal <i>et al.</i> (2016)	Single	Uncertain		✓	✓				Exact
Soysal (2016)	Single	Uncertain		✓	✓				Exact
Azadeh <i>et al.</i> (2017)	Single	Certain	✓	✓					GA
Cheng <i>et al.</i> (2017)	Single	Certain		✓	✓				Branch-and-cut
Iassinovskaia <i>et al.</i> (2017)	Single	Certain		✓	✓				Heuristic
Hiassat <i>et al.</i> (2017)	Single	Certain	✓	✓					GA

1.3 Problem statement and methodology

Our motivation in this thesis is to develop new methods which can apply and integrate accurately and realistically several important issues in IRP, which have not been well addressed and are needed for today's businesses. We first propose to integrate sustainability and service level considerations into IPPs for perishable products. In the second step, we develop a dynamic IRP model that takes advantage of real-time data collected.

The practical research questions that will be addressed in this research are:

- How to integrate the sustainable criteria in the IRP
- What is the impact of the sustainable criteria on IRP
- How to model the perishable products in the IRP
- What is the relationship between costs and service level in IRP
- What is the impact of dynamically optimizing the IRP

In the theory part, we contribute by:

- How to develop a resolution approach dealing with uncertain parameters in IRP
- How to model and take into account several objectives in the IRP

In order to reach these objectives and answer these research questions, our methodology will follow the following steps:

1. Identification of the indicators which measures the sustainability and service level issues in IRP.
2. Proposition of the three new IRP models integrating several considerations in terms of decision objective: service level, environmental and economic considerations in the first model; environmental, social and economic considerations in the second and a dynamic optimization of the IRP in the third model.
3. Proposition of effective resolution methods for each model.
4. Realization of numerical studies highlighting the applicability of the proposed models and deduction of managerial insights for decision makers.

We propose in the following next sections a summary of the three models developed in order to answer the research question.

1.4 Contribution and novelty

This thesis extends the previous research in the IRP by considering the sustainable issues, service level and dynamic optimization where products have the expiration date. In order to achieve these objectives, we developed three

frameworks of IRP. In this section, the contributions and innovations of each framework are presented.

1.4.1 First model

In the first model (Chapter 2), we contribute to the existing literatures in the developing a new multi-objective mathematical model and applying a resolution approach to control variation of uncertain parameters. In the following, the contributions of this model are detailed and presented.

- We integrate the service level in IRPs, and explore the linkage between conflict criteria such as the IRP transportation and inventory costs, the service level and the environment. We consider a service level measuring both the inventory control and the transportation performances. Therefore, we measure the service level with the joint rate of delays, the rate of backorder as well as the rate of backorder frequency.
- We model the vehicles with different technologies (electric and diesel) to obtain insights on the link between the technology under consideration and its GHG footprint. In fact, certain practitioners would be interested in studying the impact of using electrical energy in urban transportation for the distribution of perishable products. Assuming that this type of vehicle has a higher fixed and variable transportation cost than the alternative, it produces very low volumes of GHG emissions when compared with diesel vehicles.
- We model the products' perishability in IRPs using two methodologies; we model the non-freshness of products that are transferred from one period to another using a step-wise nonlinear unit holding cost that is equivalent to a price discount performed on these non-fresh products. Our IRP proposal also enables the modeling of the management of the reverse logistics of perished products that should be recycled. In addition, we assume that recycling these perished products has an impact on the economic performance of the IRP as well as on its GHG footprint.
- In contrast to most investigations in the IRP literature and for a better modeling of perishable products, we enable the holding cost function to behave as a nonlinear step function. Such modeling is motivated by extra inspection tasks that the products need before transferring them to the next period. Such modeling could also be interpreted as a price discount offered for non-fresh product in the forthcoming periods.
- Moreover, to be close to real IRP business cases, we assume that certain parameters such as demand, variable transportation costs and vehicle

speed are uncertain, and we model them with a fuzzy possibilistic distribution.

1.4.2 Second model

The second model (Chapter 3) takes into account integration of sustainable issues in IRP under uncertainty in some parameters. Economic and social issues are considered as objective while environmental criteria are represented as constraints. In this model, we contribute to the existing literatures in the proposing a new bi-objective mathematical model and a resolution approach to control variation of uncertain parameters. In the following, the contributions of this study are explained and presented.

- We model and include some social considerations in the IRP framework. Due to interaction between human and machine during different activities of distribution and inventory, considering social issues in IRPs are particularly important. For this aim, the social issue in the IRPs, risk of accident, vehicle noise and number of expired product are considered as social issues.
- We integrate the concept of reverse logistics in the model. Due to dealing with perishable products, enforce us to consider the picking up and recycling of these products after their expiration date.
- An all units quantity discounts function as a nonlinear multiple breakpoint function is integrated in the model to encourage the retailer to buy more products which causes increasing the profit of system.
- Since there are various uncertain parameters in the real world, some parameters such as demand, traffic speed, vehicle speed, and variable transportation cost are considered as uncertain parameters. In order to handle uncertain parameters in the model, a stochastic optimization model using a scenario-based stochastic approach is developed and adopted.

1.4.3 Third model

The main objective of third study (Chapter 4) is investigation the impact of considering dynamic optimization in efficiency of IRPs. We used the proposed framework in chapter 3 by omitting reverse logistics. We contribute to the existing literatures in the following issues:

- In contrast to previous studies that only considered the demand in dynamic optimization, we take into account information on the variation of demand and on traffic as two parameters for dynamic optimization.

- A re-optimization strategy is defined to study the effect of using real-time information in the proposed problem. The general idea of this strategy is to optimize the model and to find the initial solutions where the value of uncertain parameters is predicted. We then select the initial solution and re-optimize the problem at each period, based on real time information. The re-optimizing strategy enables us to satisfy all new demands based on updated demand. Moreover, based on updated information about traffic, the initial routing will be re-optimized.
- In addition to dynamic optimization by considering real time information, we consider uncertainty in some parameters in step of finding initial solution. For this purpose, we apply fuzzy possibilistic approach to predict the value of uncertain parameters.

1.5 Conclusion

In this chapter, a brief introduction of IRP, importance of taking into account real time information and conflict issues in IRPs are explained. Then, the previous studies of IRPs is reviewed and classified, to show the existing research gaps. Finally, the problem statement, and research contribution of the thesis are presented. The remainder of this thesis is organized as follows. Chapter 2 focuses on integration of service level and environmental criteria beside of economic aspect in IRP with uncertain parameters. Chapter 3 presents a bi-objective model for sustainable IRP and shows efficiency and power of introduced resolution approach to handle variation of uncertain parameters. Chapter 4 elaborates the impact of using real time information in efficacy of IRPs. As mentioned in precedent paragraphs, the proposed frameworks in this thesis, deals with perishable products. Finally, chapter 5 summarizes results and concludes with future research opportunities.

2

Multi-objective inventory routing problem: A stochastic model to consider profit, service level and green criteria

2 Multi-objective inventory routing problem: A stochastic model to consider profit, service level and green criteria

2.1 Motivation

As mentioned in chapter 1, increasing of competitive global marketplace makes intensive pressure for companies and oblige them to improve efficiency of their activities, as much as possible to increase satisfaction of their customers. While, high service levels is one of the key factors to strengthen customer satisfaction and loyalty. According to our literature review, service level is one of the issues, which is few considered by researchers in context of IRP, particularly for perishable products.

In this chapter, an attempt has been made to integrate service level in IRP by making trade-off between economic, environmental and service level aspects. The research presented in this chapter contributes to the existent literature in following ways.

- We integrate the service level in IRPs, and explore the linkage between conflictual criteria such as the IRP transportation and inventory costs, the service level and the environment. We consider a service level measuring both the inventory control and the transportation performances. Therefore, we measure the service level with the joint rate of delays, the rate of backorder as well as the rate of backorder frequency.
- We model the vehicles with different technologies (electric and diesel) to obtain insights on the link between the technology under consideration and its GHG footprint. In fact, certain practitioners would be interested in studying the impact of using electrical energy in urban transportation for the distribution of perishable products. Assuming that this type of vehicle has a higher fixed and variable transportation cost than the alternative, it produces very low volumes of GHG emissions when compared with diesel vehicles.
- We model the products' perishability in IRPs using two methodologies; we model the non-freshness of products that are transferred from one period to another using a step-wise nonlinear unit holding cost that is equivalent to a price discount performed on these non-fresh products. Our IRP proposal also enables the modeling of the management of the reverse logistics of perished products that should be recycled. In

addition, we assume that recycling these perished products has an impact on the economic performance of the IRP as well as on its GHG footprint.

- In contrast to most investigations in the IRP literature and for a better modeling of perishable products, we enable the holding cost function to behave as a nonlinear step function. Such modeling is motivated by extra inspection tasks that the products need before transferring them to the next period. Such modeling could also be interpreted as a price discount offered for non-fresh product in the forthcoming periods.

2.2 Problem formulation

The objective of this section is to describe our extended IRP framework and to model it as a multi-objective mathematical framework for perishable products that allows the service level and environmental considerations in addition to the economic performance to be considered.

The IRP under study in this research can be described as follows. We consider T selling periods where one supplier distributes F perishable products to M retailers. The distribution of products could be performed with three vehicle types of different sizes (small, medium and large) and different energy technologies (diesel and electric).

Most researchers have investigated the IRP by considering the Vendor Managed Inventory (VMI) concept where the vendor determines the product quantity and the delivery date based on the minimum and maximum levels defined jointly with the retailer. Such a concept is not easily applicable for perishable products due to the difficulty of defining the responsibility of each member of the supply chain with regard to the perished products. Therefore, as with (Pezeshki *et al.* 2013), we assume that the supply chain is coordinated by a contract that enables the decision maker to have access to all information about the inventory levels of products for the supplier and retailers, as well as information about the final customer requests. The decision maker is furthermore provided the opportunity to launch a negotiation between the supplier and the retailers regarding the quantity and delivery date. The final decisions must consider both the supplier's and the retailers' constraints to derive the best solution for the whole supply chain. The decision maker's objective is not only to maximize the expected profit of the supply chain but also to maximize the service level considerations and to consider the environmental footprint of the solution. Please notice that this explanation is considered for proposed framework in Chapter 3.

2.2.1 Economical issue: profit maximization

The economic performance of the IRP is measured by the profit function, which is equal to the sales revenue minus the related inventory and distribution costs, including holding, backorder, recycling, fixed and variable transportation, ordering, and loading and unloading costs.

To better model product perishability, we model the unit holding cost as a nonlinear step function depending on the stock remaining at the end of each period. Therefore, the higher the ending stock is, the higher the unit holding cost will be. The unit holding cost (h_{if}) associated with product f at retailer i depends on the inventory level (I_{ift}) at the end of period t , as modeled in equation (2-1).

$$h_{if} = \begin{cases} h_{if1} & \text{if } 0 \leq I_{ift} \leq i_1 \\ h_{if2} & \text{if } i_1 \leq I_{ift} \leq i_2 \\ \vdots & \\ h_{ifm} & \text{if } i_{m-1} \leq I_{ift} \end{cases} \quad (h_{if1} \leq h_{if2} \leq \dots \leq h_{ifm}) \quad (2-1)$$

This assumption is motivated by the following:

- For perishable products, the unsold items in a given period may need inspections and possibly treatments before their transfer to the next selling period. The cost associated with such a process is directly linked to the quantity needing the inspection. To push the decision maker to limit the quantity of unsold items, our assumption directly impacts such a scenario and indirectly leads to a decrease of the perished products. We show that the proposed holding cost function assumption impacts the trade-off between the economic, service level and environmental criteria.
- The holding cost in the inventory control area is mainly composed of three components: i) the investment (warehousing) needed to retain stocks; ii) the financial penalty of not investing in the value of the stock and iii) the obsolescence risk linked with holding a stock. In the presence of perishable items, the last component is important and can motivate the holding unit cost modeling proposed in Eq. 2-1. For a higher stock level remaining in a given period, the obsolescence risk is higher for the following period.

It is worth noting that:

- Our assumption is a generalization of the classical holding function assumption. Assuming that the unit holding cost is independent of the end of period stock level, the latter assumption is simply a particular case of our assumption.
- Our assumption is equivalent to the case where the holding unit cost is assumed to be fixed but where the retailers propose a discount price for non-fresh products that are transferred from one period to another. In

other words, the product non-freshness could either be modelled by higher holding costs or by a lower revenue for items remaining from previous periods. We will propose in Section 2.4.2, a particular case of Eq. 2-1 permitting to model the non-freshness cost as a price discount.

2.2.2 Service level

In addition to the classical economic objective described in the last section, we integrate a service level measure in our IRP. The service level defines a degree of satisfaction offered to the customer. Therefore, under an inventory and distribution context, the service level may include many possible measures among which we have chosen the following:

- The rate of delivery delay; a delay occurs if the vehicle visits a retailer after the allowed time window
- The rate of backorder
- The rate of the backorder frequency

The first service measure is associated with the distribution side of the IRP. Delays are one of the largest problems confronting food distribution in the UK. According to (McKinnon, Ge and Leuchars 2003), 29% of the retailers surveyed in the food supply chain in the UK had experienced delivery delays that were shown to directly impact their customer's satisfaction. We model the delay rate by considering the total number of delays that we divide by the total number of visits.

The second and third service level measures are linked to the inventory side of the IRP. For a given product, the backorder rate is modeled by the total quantity backordered divided by the total demand. The frequency backorder rate is modeled by the total number of backorders divided by the total number of selling periods.

In the presence of different measures for the service level, we use three weighting factors (β_d , β_B , β_r), whose sum is equal to one, to address the relative importance of each one when compared with the others. Due to the differences in the nature of the three service levels, we furthermore proceed to a normalization of the three measures.

2.2.3 Environmental issue

In addition to the economic and service level considerations described in the previous sections, we introduce an environmental criterion in our extended IRP. Currently, there is increasing pressure on companies, stemming from the governmental and non-governmental communities and, more generally, from public opinion, to encourage them to master and decrease their GHG footprint.

This reduction is not only to protect the environment but is also economically motivated, because new regulations provide for environmental penalties if this emission is higher than certain thresholds (Mirzapour Al-e-hasem & Rekik 2013). If products perish, we assume that they need to be collected and recycled. For comprehensiveness, in addition to the GHG emissions resulting from the distribution and the loading/unloading operations, we include those associated with the recycling of perished products.

2.2.4 Problem assumption

The assumptions are classified into two parts: general assumptions, which are shared with other proposed models in next chapters, and specific assumptions that are applicable for the model in each chapter. The general and specific assumptions are presented as follows:

General assumptions

- There is an urban logistics network in which various types of perishable products are distributed from one supplier to a set of retailers in each period.
- The Just-in-time (JIT) and cross-docking philosophies are considered on the supplier side, leading to a scenario with no inventory for the supplier and the assumption that the products delivered to the retailers are fresh.
- For each retailer, we consider that the inventory capacity and the initial inventory level for each product are known.
- Each product has a given shelf life (L_f), and we assume that products cannot be sold after the expiration date and should be recycled.
- There is a time window constraint defined by the earliest and the latest possible distribution time for each retailer. It is assumed that a delay occurs if the vehicle arrives after the latest possible time. If the vehicle arrives sooner than the earliest time window, it must wait.
- The unloading time within the retailers' warehouses is considered and is calculated based on the quantity of products delivered.

Specific assumptions

- The supplier uses a heterogeneous fleet of vehicles with different capacities, different technology (electric and diesel), different fixed and variable costs, and different GHG emissions levels per kilometer.
- The demand for each retailer is independent of the service level achieved in the IRP.

- The supplier and retailers have two types of equipment (gas and electric) for loading and unloading, with different costs and GHG emissions.

The objective of the proposed model is to determine the set of retailers and delivery sequences for each vehicle (by considering type and technology), as well as the quantities of products delivered to each retailer in each period over the planning horizon.

2.2.5 Notation

The following notations are used in the proposed model. In particular, the uncertain parameters are described with a tilde and are differentiated from the crisp parameters.

Sets	
M	set of retailers, index for retailer ($1, 2, \dots, M$)
M'	set of retailer and supplier, $M \cup \{0\}$
f	index for product ($1, 2, \dots, F$)
k	index for vehicle type ($1, 2, \dots, K$)
u	index for vehicle technology ($1, 2, \dots, U$)
d	index for loading equipment type ($1, 2, \dots, D$)
d'	index for unloading equipment type ($1, 2, \dots, D'$)
t, t'	index for period ($1, 2, \dots, T$)

Parameters	
I_{if0}	initial inventory level of product f at retailer i
h_{if}	inventory holding cost at retailer i per unit of product f per period
IC_{if}	maximum inventory capacity of retailer i for product f
Y_{if}	backordering cost of one unit of product f at retailer i
O_{if}	ordering cost of product f for retailer i
R_{ft}	revenue of whole system for one unit product f at period t
c_{ij}	distance between retailer i and j
\tilde{v}_{ku}	variable transportation cost per unit and per distance for vehicle type k with technology u
fc_{ku}	fixed transportation cost for vehicle type k with technology u per trip
cap_{ku}	capacity of vehicle type k with technology u
\tilde{d}_{ift}	quantity of product f send from retailer i at period t
L_f	shelf life of product f , which is a specific percentage of time horizon
sp_{ku}	required time to unload one unit product from vehicle k with technology u
$[a_i, b_i]$	earliest and latest authorized arrival time at retailer i
\tilde{s}_{ijku}	speed of vehicle type k with technology u in the route between i and j
LC_d	loading cost of one unit product through equipment type d
$UC_{d'}$	unloading cost of one unit product through equipment type d'
GL_d	GHG emission produced through equipment type d for loading 1kg of product
$GU_{d'}$	GHG emission produced through equipment type d' for unloading 1kg of product
MA_f	mass of one unit product f

GT_{ku}	GHG emission produced by vehicle type k with technology u in one unit of distance
GE	average of produced emission by recycling one unit of expired product
θ_f	recycling cost of one unit of expired product f
wt	maximum working time of tours
G	a large value number
$B = M , A = M \cdot T $	

Variables

x_{ijkut}	1 if retailer j is visited exactly after retailer i by vehicle type k and technology u at period t , otherwise 0
I_{ift}	inventory level of product f at retailer i at the end of period t
y_{kut}	number of vehicle type k with technology u at period t
$q_{ijkut}^{dd'} \ (t < t')$	quantity of product f received by retailer i through vehicle k with technology u at period t for being used at period t' , and which is loaded by equipment d and unloaded by equipment d'
$q_{ijkut}^{dd'} \ (t > t')$	quantity of product f received by retailer i through vehicle k with technology u at period t to satisfy the backordering quantity, and is loaded by equipment d and unloaded by equipment d'
B_{ift}	quantity of backordered product f of retailer i at the end of period t
EX_{ift}	quantity of expired products f in inventory of retailer i at the end of period t
n_{it}	1 if delay occurred in visiting retailer i at period t , otherwise 0
r_{it}	1 if backorder occurred in visiting retailer i at period t , otherwise 0
z_{ikut}	1 if retailer i is served at period t by vehicle k , technology u , otherwise 0
T_{ikut}	arrival time at retailer i by vehicle k with technology u at period t
C_{ift}	1 if product f is delivered to retailer i at period t , otherwise 0

2.2.6 Mathematical formulation

The mathematical model associated with the presented framework is provided in this section. Each equation in this model is detailed below.

$$\begin{aligned} \text{Max } f_1 = & \left[\sum_{i \in M, f, k, u} \sum_{d, d', t, t'} R_{f t} \cdot [q_{ijkut}^{dd'} - EX_{ift}] \right] - \sum_{i \in M} \sum_{f, t} h_{if} I_{ift} - \sum_{i \in M} \sum_{f, t} \gamma_{if} B_{ift} \\ & - \sum_{i \in M} \sum_{f, t} \theta_f EX_{ift} - \sum_{i \in M} \sum_{f, t} O_{if} C_{ift} - \sum_{k, u, t} f c_{ku} z_{0kut} - \sum_{(i, j) \in M} \sum_{k, u, t} \tilde{\gamma}_{kt} y_{kut} c_{ij} x_{ijkut} \\ & - \sum_{i \in M, f, k, u} \sum_{d, d', t, t'} L C_d q_{ijkut}^{dd'} - \sum_{i \in M, f, k, u} \sum_{d, d', t, t'} U C_{id'} q_{ijkut}^{dd'} \end{aligned} \quad (2-2)$$

$$\text{Min } f_2 = \beta_d \left(\frac{\sum_{i, t} n_{it}}{\sum_{i, k, u, t} z_{ikut}} \right) + \beta_B \left(\sum_{i \in M} \sum_{f, t} \frac{B_{if}}{d_{if}} \right) + \beta_r \left(\frac{\sum_{i, t} r_{it}}{\sum_{i, k, u, t} z_{ikut}} \right) \quad (2-3)$$

$$\begin{aligned} \text{Min } f_3 = & \sum_{(i, j) \in M} \sum_{k, u, t} GT_{ku} y_{kut} c_{ij} x_{ijkut} + \sum_{i \in M} \sum_{f, t} GE EX_{ift} \\ & + \sum_{i \in M, f, k, u} \sum_{d, d', t, t'} M A_f G L_d q_{ijkut}^{dd'} + \sum_{i \in M, f, k, u} \sum_{d, d', t, t'} M A_f G U_{id'} q_{ijkut}^{dd'} \end{aligned} \quad (2-4)$$

S.t.

$$I_{ift} - B_{ift} = I_{if(t-1)} - \tilde{d}_{ift} + \sum_{k,u,d,d',t'} q_{ifikut'}^{dd'} - EX_{ift} - B_{if(t-1)} \quad \forall i \in M, f, t \quad (2-5)$$

$$B_{ift} r_{it} \geq \sum_{k,u,d,d',t' > t'} q_{ifikut'}^{dd'} \quad \forall i \in M, f, t \quad (2-6)$$

$$I_{ift} \times B_{ift} = 0 \quad \forall i \in M, f, t \quad (2-7)$$

$$\sum_{k,u,d,d',t'} q_{ifikut'}^{dd'} \leq IC_{if} - I_{if(t-1)} \quad \forall i \in M, f, t \quad (2-8)$$

$$q_{ifikut'}^{dd'} \leq IC_{if} \cdot z_{ikut} \quad \forall i \in M, f, k, u, d, d', t, t' \quad (2-9)$$

$$\sum_{k,u,d,d' t' > (t+L_f)} q_{ifikut'}^{dd'} \leq EX_{ift} \quad \forall i \in M, f, t \quad (2-10)$$

$$\frac{C_{ift}}{G} \leq \sum_{k,u,d,d',t'} q_{ifikut'}^{dd'} \leq C_{if} G \quad \forall i \in M, f, t \quad (2-11)$$

$$T_{ikut} + \sum_{f,d,d',t'} q_{ifikut'}^{dd'} \cdot sp_{ku} + \frac{c_{ij}}{\bar{s}_{ijk}} \leq T_{jkut} + G(1 - x_{ijkut}) \quad \forall (i, j) \in M', k, u, t \quad (2-12)$$

$$a_i \leq \sum_{k \in K} \sum_{u \in U} T_{ikut} \leq (b_i + (wt - b_i) \cdot n_{it}) \quad \forall i \in M, t \quad (2-13)$$

$$\sum_{i \in M} \sum_{f,d,d',t'} q_{ifikut'}^{dd'} \leq cap_{ku} \cdot y_{kut} \cdot z_{0kut} \quad \forall k, u, t \quad (2-14)$$

$$\sum_{j \in M'} x_{ijkut} = \sum_{j \in M'} x_{jikut} = z_{ikut} \quad \forall i \in M', k, u, t \quad (2-15)$$

$$\sum_{u,k} z_{ikut} \leq 1 \quad \forall i \in M, t \quad (2-16)$$

$$\sum_{u,k,t} z_{ikut} \geq 1 \quad \forall i \in M \quad (2-17)$$

$$\sum_{i,k,u} x_{0ikut} \geq 1 \quad \forall t \quad (2-18)$$

$$\sum_{i,k,u} x_{i0kut} \geq 1 \quad \forall t \quad (2-19)$$

$$x_{ijkut}, n_{it}, r_{it}, z_{ikut}, C_{if} \in \{0, 1\} \quad \forall (i, j) \in M, k, u, t, i \neq j \quad (2-20)$$

$$q_{ifikut'}^{dd'}, I_{ift}, B_{ift}, EX_{ift}, y_{kut}, T_{ikut} \geq 0, \text{Integer} \quad \forall i \in M, f, k, u, d, d', t \quad (2-21)$$

Objective function (2-2) maximizes the profit which is equal to the sales revenue of products minus the costs including (in the order of writing in (2-2)), the holding cost, the backordering cost, the recycling of expired products costs, the ordering costs, the fixed and variable transportation costs, and the loading and unloading costs. The second objective function (2-3) optimizes the weighted

service level criteria by the minimization of the rate of delays that might occur when visiting the retailers, the rate of number of backordered products, and the backorder frequency rate. The third objective function (2-4) minimizes the quantity of GHG emissions resulting from the transportation, the loading/unloading the products and the GHG emissions due to the recycling of expired products.

Constraint (2-5) balances the inventory level between each two successive periods. Constraint (2-6) calculates the volume of backordered products. With this constraint, if the quantity of the backordered products is positive, then r_{it} should be equal to one, meaning that the supplier finds a retailer with a backorder situation when visiting him/her. Therefore, the frequency of backorders is calculated by using this equation. Equation (2-7) guarantees that the remaining stock (I_{ift}) and the backordered quantity (B_{ift}) cannot be simultaneously positive. Equations (2-8) and (2-9) guarantee that the retailers' capacity for each product is well respected. Constraint (2-10) calculates the number of expired products. Constraint (2-11) checks whether a retailer receives any product. Equation (2-12) determines the arrival time at the next retailer, which is calculated as the visiting time of the immediate previous retailer increased by the unloading duration of products and the traveling time between the two retailers visited. Equation (2-13) checks the time window constraint and calculates the number of delays. Constraint (2-14) guarantees that the capacity of each vehicle is well respected. Moreover, this constraint allow to define the quantity of vehicle for transportation of products. We assume that the measuring unit for all products is fix as the dimension of pallet. Please notice that the quantity of Stock Keeping Unit (SKU) of each product on pallet depends to its volume. However, knowing that the capacity of vehicle, loading, and unloading are determined by number of pallets, we only used this common unit (pallet) for all products. Equations (2-15) to (2-19) serve to determine routes and to eliminate sub-routes. Finally, (2-20) and (2-21) place bounds on the variables

2.2.7 Linearization

Due to the existence of nonlinear equations in the objective functions and of constraints, four linearization techniques are applied to convert the model to its equivalent linear form.

- *Linearization of the nonlinear holding cost function*

As noted above, the inventory holding cost (h_{if}), provided in equation (2-1) is non-linear. The linearization technique proposed by Sazvar *et al.* (2014) can be applied. Therefore, binary variables, p_{iftm} , and non-negative variables, I_{iftm} , are defined and the following constraints (2-22 to 2-24) are added.

$$I_{ift} = \sum_m I_{ifm} \quad \forall i \in M, f, t \quad (2-22)$$

$$i_m \cdot p_{ifm} \leq I_{ifm} \leq i_{m+1} \cdot p_{ifm} \quad \forall i \in M, f, t \quad (2-23)$$

$$\sum_m p_{ifm} = 1 \quad \forall i \in M, f, t \quad (2-24)$$

- *Linearization of the nonlinear variable resulting from the division of two variables*

The division of two variables, $(\frac{\sum_{i,t} n_{it}}{\sum_{i,k,u,t} z_{ikut}} & \frac{\sum_{i,t} r_{it}}{\sum_{i,k,u,t} z_{ikut}})$, as written in the second objective function (2-3), results in nonlinearity. Therefore, the relaxation technique proposed by McCormick (1976) could be applied. The technique can be explained briefly as follows:

$$If k = x_1 x_2 and x_1 \in [x_1^L, x_1^U], x_2 \in [x_2^L, x_2^U] \quad (2-25)$$

The four equations can then be added as new constraints:

$$k \geq x_1^L x_2 + x_2^L x_1 - x_1^L x_2^L \quad (2-26)$$

$$k \geq x_1^U x_2 + x_2^U x_1 - x_1^U x_2^U \quad (2-27)$$

$$k \leq x_1^L x_2 + x_2^U x_1 - x_1^L x_2^U \quad (2-28)$$

$$k \leq x_1^U x_2 + x_2^L x_1 - x_1^U x_2^L \quad (2-29)$$

To apply this technique in our case, we define two non-negative variables W and V . The lower and upper bounds are then defined as follows:

$$W = \sum_{i,t} n_{it} \cdot \frac{1}{\sum_{i,k,u,t} z_{ikut}} \quad V = \sum_{i,t} r_{it} \cdot \frac{1}{\sum_{i,k,u,t} z_{ikut}}$$

$$\sum_{i,t} n_{it} \in [0, A] \quad \sum_{i,t} r_{it} \in [0, A] \quad \sum_{i,k,u,t} \frac{1}{z_{ikut}} \in \left[\frac{1}{A}, \frac{1}{B} \right]$$

The reformulation of the second objective function (2-3) and the following new constraints are added to convert it into a linear form:

$$Min \quad f_2 = \beta_d(W) + \beta_B \left(\sum_{i \in M} \sum_{f,t} \frac{B_{ift}}{\tilde{d}_{ift}} \right) + \beta_r(V) \quad (2-30)$$

$$W \geq \left[\sum_{it} n_{it} / A \right] \quad (2-31)$$

$$W \geq \left[A / \sum_{i,k,u,t} z_{ikut} \right] + \left[\sum_{it} n_{it} / B \right] - \left[A / B \right] \quad (2-32)$$

$$W \leq \sum_{i,t} n_{it} / B \quad (2-33)$$

$$W \leq \left[A / \sum_{i,k,u,t} z_{ikut} \right] + \left[\sum_{it} n_{it} / A \right] - 1 \quad (2-34)$$

$$V \geq \left[\sum_{it} r_{it} / A \right] \quad (2-35)$$

$$V \geq \left[A / \sum_{i,k,u,t} z_{ikut} \right] + \left[\sum_{it} r_{it} / B \right] - [A/B] \quad (2-36)$$

$$V \leq \sum_{i,t} r_{it} / B \quad (2-37)$$

$$V \leq \left[A / \sum_{i,k,u,t} z_{ikut} \right] + \left[\sum_{it} r_{it} / A \right] - 1 \quad (2-38)$$

This equation remains nonlinear $\left[A / \sum_{i,k,u,t} z_{ikut} \right]$; however, this should be linearized.

Therefore, we replace this equation with a sum of binary variables (as illustrated in equation (2-39)), assuming that only one of the binary variables is non-zero (equation (2-40)). We can therefore rewrite the nonlinear equation as proposed in constraint (2-41).

$$\sum_{i,k,u,t} z_{ikut} = \sum_{i,k,u,t} \sum_{l=B}^A l \cdot z_{ikul} \quad (2-39)$$

$$\sum_{l=B}^A z_{ikul} = 1 \quad \forall i \in M, k, u, t \quad (2-40)$$

$$\frac{A}{\sum_{i,k,u,t} z_{ikut}} = \sum_{i,k,u,t} \sum_{l=B}^A A \cdot \frac{z_{ikut}}{l} \quad (2-41)$$

- Linearization of the nonlinear variable resulting from the multiplication of a binary with an integer variable

The multiplication of integer and binary variables, as defined in constraints (2-6) and (2-14), the results in non-linearity. The same occurs in the first and third objective functions. The nonlinear equations could be converted into linear equations by omitting the binary variable and considering the new equations (2-42) to (2-46).

$$B_{ift} \geq \sum_{k,u,d,d'} \sum_{t>t'} q_{ijkut'}^{dd'} \quad \forall i \in M, f, t \quad (2-42)$$

$$\frac{r_{it}}{G} \leq \sum_{f \in F} B_{ift} \leq G \cdot r_{it} \quad \forall i \in M, t \quad (2-43)$$

$$\sum_{i \in M} \sum_{f,d,d',t'} q_{ijkut'}^{dd'} \leq cap_{ku} \cdot y_{kut} \quad \forall k,u,t \quad (2-44)$$

$$\frac{z_{0kut}}{G} \leq y_{kut} \leq z_{0kut} \cdot G \quad \forall k,u,t \quad (2-45)$$

$$\frac{x_{ijkut}}{G} \leq y_{kut} \leq x_{ijkut} \cdot G \quad \forall i,k,u,t \quad (2-46)$$

- Linearization of the nonlinear variable resulting from the multiplication of two integer variables

Due to the multiplication of the two integer variables (I_{ift}) and (B_{ift}) in constraint (2-7), a new binary variable F_{ift} and two new constraints (2-48) and (2-49) replace the previous one as follows:

$$F_{ift} = \begin{cases} 1 & I_{ift} = 0 \\ 0 & B_{ift} = 0 \end{cases} \quad \forall i, f, t \quad (2-47)$$

$$B_{ift} \leq G \times F_{ift} \quad \forall i, f, t \quad (2-48)$$

$$I_{ift} \leq G \times (1 - F_{ift}) \quad \forall i, f, t \quad (2-49)$$

2.3 Resolution approach

To solve our extended IRP model, the following two steps are applied:

- First, we proceed with the conversion of the original model into an equivalent auxiliary crisp model by applying fuzzy possibilistic approach.
- Second, due to the NP-hardness of the IRP (Shukla *et al.* 2013; Coelho *et al.* 2012), we apply the NSGA-II proposed by Deb *et al.* (2002) to solve the equivalent auxiliary crisp model and to derive the optimal Pareto.

We notice that the choice of the NSGA-II method is motivated by the fact that it has been proved as an efficient meta-heuristic for IRPs (Amorim & Almada-Lobo 2014). In addition to efficiency, the procedure of this algorithm does not allow a previously found Pareto optimal solution to be deleted. In addition, the run time of the algorithm is generally acceptable.

2.3.1 The equivalent auxiliary crisp model

The IRP literature (Abdul Rahim *et al.* 2014; Bertazzi *et al.* 2013; Chen and Lin 2009) shows that IRPs encounter a high degree of uncertainty in the retailers' demand. Moreover, variations in the energy price, the weather conditions, and the traffic status have a significant impact on transportation costs(Cui & Sheng 2012) and lead to a high degree of uncertainty of these costs even in the short term. For applicability, the IRP should be designed in a manner that is able to consider the uncertainty of certain parameters; otherwise its solution leads to a high risk for the enterprise(Chen and Lin 2009; Abdul Rahim, Zhong, Aghezzaf, & Aouam, 2014).

Motivated by the above explanation, we assume that the demand, the variable transportation cost and the vehicle speed are subject to uncertainty and are modeled with fuzzy distributions. First, we define for each uncertain variable s the pattern set of a triangular fuzzy number (s^p, s^m, s^o) where s^p defines the most pessimistic value, s^m defines the most likely value, and s^o defines the optimistic value of s . Then, we use the principle of the fuzzy possibilistic approach by Pishvaae & Torabi (2010) to transform the extended IRP model to the equivalent multi-objective crisp model. Such a conversion leads to the following formulation:

$$\begin{aligned} \text{Max } f_1 = & \left[\sum_{i \in M, f, k, u} \sum_{d, d', t, t'} R_{if} \cdot \left[q_{ifkut'}^{dd'} - EX_{ift} \right] \right] - \sum_{i \in M} \sum_{f, t, m} h_{ifm} I_{iftm} - \sum_{i \in M} \sum_{f, t} \gamma_{if} B_{ift} \\ & - \sum_{i \in M} \sum_{f, t} \theta_f EX_{ift} - \sum_{i \in M} \sum_{f, t} O_{if} C_{ift} - \sum_{k, u, t} f_{ku} z_{0ku} - \sum_{(i, j) \in M'} \sum_{k, u, t} \left(\frac{v_{ku}^p + 2v_{ku}^m + v_{ku}^o}{4} \right) y_{ku} c_{ij} \\ & - \sum_{i \in M, f, k, u} \sum_{d, d', t, t'} LC_d q_{ifkut'}^{dd'} - \sum_{i \in M, f, k, u} \sum_{d, d', t, t'} UC_{id'} q_{ifkut'}^{dd'} \end{aligned} \quad (2-50)$$

$$\text{Min } f_2 = \beta_d(W) + \beta_B \left(\sum_{i \in M} \sum_{f, t} 4 \cdot \frac{B_{ift}}{d_{ift}^p + 2d_{ift}^m + d_{ift}^o} \right) + \beta_r(V) \quad (2-51)$$

$$\begin{aligned} \text{Min } f_3 = & \sum_{(i, j) \in M'} \sum_{k, u, t} GT_{ku} y_{ku} c_{ij} + \sum_{i \in M} \sum_{f, t} GE EX_{ift} \\ & + \sum_{i \in M, f, k, u} \sum_{d, d', t, t'} MA_f GL_d q_{ifkut'}^{dd'} + \sum_{i \in M, f, k, u} \sum_{d, d', t, t'} MA_f GU_{id'} q_{ifkut'}^{dd'} \end{aligned} \quad (2-52)$$

S.t.

$$I_{ift} - B_{ift} \leq I_{if(t-1)} + \sum_{k, u, d, d', t'} q_{ifkut'}^{dd'} - \left[\left(\frac{\alpha}{2} \right) \times \frac{d_{ift}^m + d_{ift}^o}{2} + \left(1 - \frac{\alpha}{2} \right) \times \frac{d_{ift}^p + d_{ift}^m}{2} \right] \quad \forall i \in M, f, t \quad (2-53)$$

$$-EX_{ift} - B_{if(t-1)}$$

$$I_{ift} - B_{ift} \geq I_{if(t-1)} + \sum_{k, u, d, d', t'} q_{ifkut'}^{dd'} - \left[\left(1 - \frac{\alpha}{2} \right) \times \frac{d_{ift}^m + d_{ift}^o}{2} + \left(\frac{\alpha}{2} \right) \times \frac{d_{ift}^p + d_{ift}^m}{2} \right] \quad \forall i \in M, f, t \quad (2-54)$$

$$-EX_{ift} - B_{if(t-1)}$$

$$B_{ift} \geq \sum_{k,u,d,d'} \sum_{t>t'} q_{ifikut'}^{dd'} \quad \forall i \in M, f, t \quad (2-55)$$

$$\frac{r_{it}}{G} \leq \sum_{f \in F} B_{ift} \leq G \cdot r_{it} \quad \forall i \in M, t \quad (2-56)$$

$$B_{ift} \leq G \times F_{ift} \quad \forall i \in M, f, t \quad (2-57)$$

$$I_{ift} \leq G \times (1 - F_{ift}) \quad \forall i \in M, f, t \quad (2-58)$$

$$\sum_{k,u,d,d',t'} q_{ifikut'}^{dd'} \leq IC_{if} - I_{if(t-1)} \quad \forall i \in M, f, t \quad (2-59)$$

$$q_{ifikut'}^{dd'} \leq IC_{if} \cdot z_{ikut} \quad \forall i \in M, f, k, u, d, d', t, t' \quad (2-60)$$

$$\sum_{k,u,d,d',t'} \sum_{t' > (t+L_f)} q_{ifikut'}^{dd'} \leq EX_{ift} \quad \forall i \in M, f, t \quad (2-61)$$

$$\frac{C_{ift}}{G} \leq \sum_{k,u,d,d',t'} q_{ifikut'}^{dd'} \leq C_{ift} G \quad \forall i \in M, f, k, u, t \quad (2-62)$$

$$T_{jkut} + G(1 - x_{ijkut}) \geq T_{ikut} + \sum_{f,d,d',t'} q_{ifikut'}^{dd'} \cdot sp_{ku} \\ + \left[\frac{c_{ij}}{\left(\alpha \times \left(\frac{s_{ijku}^m + s_{ijku}^o}{2} \right) + (1 - \alpha) \times \left(\frac{s_{ijku}^p + s_{ijku}^m}{2} \right) \right)} \right] \quad \forall (i,j) \in M', k, u, t \quad (2-63)$$

$$a_i \leq \sum_{k \in K} \sum_{u \in U} T_{ikau} \leq (b_i + (wt - b_i) \cdot n_{it}) \quad \forall i \in M, t \quad (2-64)$$

$$\sum_{i \in M} \sum_{f,d,d',t'} q_{ifikut'}^{dd'} \leq cap_{ku} \cdot y_{kut} \quad \forall k, u, t \quad (2-65)$$

$$\frac{z_{0kut}}{G} \leq y_{kut} \leq z_{0kut} G \quad \forall k, u, t \quad (2-66)$$

$$\frac{x_{ijkut}}{G} \leq y_{kut} \leq x_{ijkut} G \quad \forall i, k, u, t \quad (2-67)$$

$$\sum_{j \in M'} x_{ijkut} = \sum_{j \in M'} x_{jikut} = z_{ikut} \quad \forall i \in M', k, u, t \quad (2-68)$$

$$\sum_{u,k} z_{ikut} \leq 1 \quad \forall i \in M, t \quad (2-69)$$

$$\sum_{u,k,t} z_{ikut} \geq 1 \quad \forall i \in M \quad (2-70)$$

$$\sum_{i,k,u} x_{0ikut} \geq 1 \quad \forall t \quad (2-71)$$

$$\sum_{i,k,u} x_{i0kut} \geq 1 \quad \forall t \quad (2-72)$$

$$I_{ifm} = \sum_m I_{ifm} \quad \forall i \in M, f, t \quad (2-73)$$

$$i_m \cdot p_{ifm} \leq I_{ifm} \leq i_{m+1} \cdot p_{ifm} \quad \forall i \in M, f, t \quad (2-74)$$

$$\sum_m p_{ifm} = 1 \quad \forall i \in M, f, t \quad (2-75)$$

$$W \geq \left[\sum_{it} n_{it} / A \right] \quad (2-76)$$

$$W \geq \left[\sum_{i,k,u,t} \sum_{l=B}^A A \cdot z_{ikut} / l \right] + \left[\sum_{it} n_{it} / B \right] - [A/B] \quad (2-77)$$

$$W \leq \sum_{i,t} n_{it} / B \quad (2-78)$$

$$W \leq \left[\sum_{i,k,u,t} \sum_{l=B}^A A \cdot z_{ikut} / l \right] + \left[\sum_{it} n_{it} / A \right] - 1 \quad (2-79)$$

$$V \geq \left[\sum_{it} r_{it} / A \right] \quad (2-80)$$

$$V \geq \left[\sum_{i,k,u,t} \sum_{l=B}^A A \cdot z_{ikut} / l \right] + \left[\sum_{it} r_{it} / B \right] - [A/B] \quad (2-81)$$

$$V \leq \sum_{i,t} r_{it} / B \quad (2-82)$$

$$V \leq \left[\sum_{i,k,u,t} \sum_{l=B}^A A \cdot z_{ikut} / l \right] + \left[\sum_{it} r_{it} / A \right] - 1 \quad (2-83)$$

$$\sum_{i,k,u,t} z_{ikut} = \sum_{i,k,u,t} \sum_{l=B}^A l \cdot z_{ikutl} \quad (2-84)$$

$$\sum_{l=B}^A z_{ikutl} = 1 \quad \forall i \in M, k, u, t \quad (2-85)$$

$$x_{ijkut}, n_{it}, r_{it}, z_{ikut}, C_{if}, F_{if}, p_{ifm}, z_{ikutl} \in \{0,1\} \quad \forall (i,j) \in M, k, u, t, i \neq j \quad (2-86)$$

$$q_{ijkut}^{dd'}, I_{if}, B_{if}, EX_{if}, y_{kut}, T_{ikut}, W, V, I_{ifm} \geq 0, Integer \quad \forall i \in M, f, k, u, d, d', t \quad (2-87)$$

2.3.2 Non-Dominated Sorting Genetic Algorithm II (NSGA-II)

In a single objective optimization, the aim is to find the best global minimum or maximum solution, whereas in the real world, managers require decisions based on various and occasionally conflicting objective functions. In such a case, there is not one feasible solution, while all the objective functions are simultaneously optimal. Instead of one optimal solution, there is a set of optimal solutions that proposes the minimum objective conflict. Such a set of solutions is called the

optimal Pareto. There are various methods to address multi-objective problems. Some of these methods convert the multi-objective into a single objective model by using methods such as the objective weighting, the distance functions and the Min-Max formulation (Srinivas & Deb 1994). With such methods, the results will be obtained in a single point solution while managers need to select a solution among the various alternatives during the decision process by making compromises. The other methods attempt to find a set of optimal solutions (optimal Pareto) that cannot be overridden by other solutions.

Deb *et al.* (2002) propose a meta-heuristic, referred to as the Non-dominated Sorting Genetic Algorithm II (NSGA-II), to solve multi-objective problems. This algorithm begins with an initial population that is randomly generated; in each iteration, a new set of solutions is created from existing ones by applying specific crossover and mutation operators. In the crossover operator, two parents are selected, and then two new children are generated and obtained by integrating the parents' characteristics. In the mutation operator, one member is chosen and is changed in certain respects. Thereafter, the new solutions and current solutions are merged together in each iteration to make a new population.

The members of the new population are compared with each other by considering the rank and the crowding distance. To rank the members of a population, the concept of domination is used. Members of the population that are not dominated by other members belong to the front with a rank equal to 1. For instance, members that are dominated only by the individuals in the first front are assigned to the second front. Consequently, members of a same rank cannot dominate each other, leading to the conclusion that neither is better in all objective functions. In addition, the crowding distance determines the diversity in the population where a higher one is preferred. The distance measures the Euclidian distance between each member in a given front and its neighbors in the same front. The high value of this measure shows the wider diversity in the population. The value of the crowding distance for each member can be calculated using equation (2-88) where Z is the objective function, I_j is the value of the crowding distance for the j^{th} outcome, $f_{j,n}$ presents the value of the j^{th} outcome, the n^{th} objective function, and finally, $f_{\max,n}$ and $f_{\min,n}$ show the value of the maximum and minimum of the n^{th} objective function, respectively. Furthermore, the value of the crowding distance for boundary members (members with maximum and minimum values for the objective function) is infinite. This procedure continues until the stopping criterion is achieved (Niakan *et al.* 2015).

$$I_j = \sum_{n=1}^{\sigma} \frac{f_{j+1}^n - f_{j-1}^n}{f_{\max}^n - f_{\min}^n} \quad (2-88)$$

2.4 Experimental results

In this section, we first show the applicability of our extended IRP framework from a numerical perspective. We then provide certain managerial insights resulting from a numerical analysis. Therefore, fifteen different instance problems (Table 2.1) are considered with different problem sizes (number of products and retailers), configuration types (vehicle types and technology) and horizon length (number of selling periods).

Table 2.1 Size of instance problems

Problem No.	Retailer	Product	Vehicle type	Vehicle technology	Loading /Unloading equipment type	Period
1	2	2	3	2	2	2
2	3	1	3	2	2	3
3	5	2	3	2	2	2
4	10	7	3	2	2	3
5	13	6	3	2	2	4
6	15	4	3	2	2	3
7	15	5	3	2	2	4
8	16	12	3	2	2	7
9	18	8	3	2	2	5
10	19	7	3	2	2	5
11	20	10	3	2	2	6
12	22	9	3	2	2	5
13	22	15	3	2	2	7
14	25	12	3	2	2	7
15	25	15	3	2	2	8

The fuzzy parameters need the definition of three values (most likely, pessimistic and optimistic). The most likely value, s^m , is first generated by using a uniform distribution (the uniform distributions illustrated in Table 2.2). Then, the method introduced by Lai and Hwang (1992) is used to generate the remaining optimistic and pessimistic values. Therefore, two random variables d_1 and d_2 are uniformly generated $(d_1, d_2) \sim Uniform(0.2, 0.8)$, then the optimistic value s^o and the pessimistic one s^p are derived as follows:

$$s^o = (1+d_1)s^m$$

$$s^p = (1-d_2)s^m$$

Table 2.2 Random value of parameters

Parameter	Value/Uniform distribution	Parameter	Value/Uniform distribution
I_{if0}	$\sim U[0,3]$	\tilde{d}_{ijt}	$\sim U[1,6]$
IC_{if}	$\sim U[1,2] \times \max\{\tilde{d}_{ijt}\}$	L_f (Period)	$\sim U[0.05,0.25] \times T ^{**}$
$\gamma_f(\epsilon)$	$\sim U[10,20]$	MA_f (Kg)	$\sim U[50,300]$
$O_{if}(\epsilon)$	$\sim U[40,60]$	a_i	0
$\theta_f(\epsilon)$	$\sim U[5,30]$	b_i (Hour)	$\sim U[0.5,8]$
R_{ft} (ϵ)	$\sim U[100,200]$	GE (kg/unit)	3.7
c_{ij}^* (Km)	$\sim U[5,35]$		

* The distance between two points is calculated by “minimum length path”

** $|T|$ = Number of periods in studied horizon

Furthermore, the information associated with the fleet of vehicles (capacity, fixed cost, variable cost, speed in routes, unloading speed and GHG emissions) and the loading/unloading equipment (cost and GHG emissions) are provided in Table 2.3 and Table 2.4, respectively. It is noteworthy that the GHG emissions of each vehicle is calculated according to the Greenhouse Gas (GHG) Protocol developed by the World Resources Institute and the World Business Council on Sustainable Development (WBCSD). The emissions for electricity produced from a renewable energy source, such as wind or solar, are set equal to zero.

Table 2.3 Parameters of vehicle

Vehicle type	Vehicle Tech.	Value of vehicle parameters					
		cap_{ku} (Pallet)	fc_{ku} (ϵ)	\tilde{v}_{ku} (ϵ)	SP_{ku} (hour/pallet)	\tilde{s}_{ijkku} (km/h)	GHG (kg/Km)
<i>Small</i>	<i>Diesel</i>	75	30	$\sim U[10,15]$	0.03	$\sim U[30,34]$	0.374
	<i>Electric</i>		60	$\sim U[15,20]$	0.03	$\sim U[35,38]$	0
<i>Medium</i>	<i>Diesel</i>	150	80	$\sim U[20,25]$	0.03	$\sim U[30,34]$	0.603
	<i>Electric</i>		160	$\sim U[30,35]$	0.03	$\sim U[35,38]$	0
<i>Large</i>	<i>Diesel</i>	250	150	$\sim U[30,35]$	0.03	$\sim U[30,34]$	0.870
	<i>Electric</i>		300	$\sim U[50,55]$	0.03	$\sim U[35,38]$	0

Table 2.4 Parameters of loading/unloading equipment

Equipment	Equipment type	load/unloading equipment	
		Load/Unload cost (ϵ)	GHG Emission (kg/ one kg of pallet)
<i>Load and Unload</i>	<i>Electric</i>	2.5	0
	<i>Gas</i>	2	0.003

It is notable that all the IRP frameworks in Chapters 2, 3 and 4; are coded using MATLAB 2014 on a personal computer Core i7, 2.27 GHZ with 12.0 GB RAM.

2.4.1 Parameter setting

It is obvious that selecting the value of NSGA-II parameters has a considerable impact on the performance of the resolution algorithm. The Taguchi method is applied to tune these parameters. The Taguchi method proposes two main categories of factors: controllable, and noise. The noise factors are out of control and their elimination is often impossible. The method attempts to find the optimal level of controllable factors by minimizing the effect of noise factors (Chatsirirungruang 2009).

To use the Taguchi method in our case, the Spacing Metric (SM) is considered to evaluate the optimal results. The value of SM is calculated using equation (2-89) where d_i measures the Euclidian distance between consecutive solutions, \bar{d} is the average of all d_i , and n denotes the number of members in the final solutions. It is noteworthy that a lower value of SM corresponds to a better performance of the algorithm.

$$SM = \frac{\sum_{i=1}^{n-1} |\bar{d} - d_i|}{(n-1)\bar{d}} \quad (2-89)$$

In this study, four critical parameters of the proposed resolution algorithm ($Npop$: number of population; $MaxIt$: maximum iteration; CrR : Crossover Rate; and MuR : Mutation Rate) are considered, and three levels for each factor are determined (Table 2.5). Additionally, Table 2.6 presents the combination of experiments and the answers obtained to tune the parameters. According to Figure 2.1, the best levels of the parameters are selected as follows: second level of $Npop$ (100), second level of $MaxIt$ (120), third level of CrR (0.7), and first level of MuR (0.2). It is noteworthy that the Taguchi method is applied in the Minitab software.

Table 2.5 Parameters setting

Factors	Proposed level		
	1	2	3
$Npop$	80	100	120
$MaxIt$	100	120	150
CrR	0.5	0.6	0.7
MuR	0.2	0.3	0.4

Table 2.6 Parameter configuration and values obtained in Taguchi design experiments

Expe.	Coded levels				Uncoded levels				Response
	Npop	MaxIt	CrR	MuR	Npop	MaxIt	CrR	MuR	
1	1	1	1	1	80	100	0.5	0.2	0.981
2	1	2	2	2	80	120	0.6	0.3	0.857
3	1	3	3	3	80	150	0.7	0.4	0.823
4	2	1	2	3	100	100	0.6	0.4	0.932
5	2	2	3	1	100	120	0.7	0.2	0.539
6	2	3	1	2	100	150	0.5	0.3	0.838
7	3	1	3	2	120	100	0.7	0.3	0.798
8	3	2	1	3	120	120	0.5	0.4	1.098
9	3	3	2	1	120	150	0.6	0.2	0.786

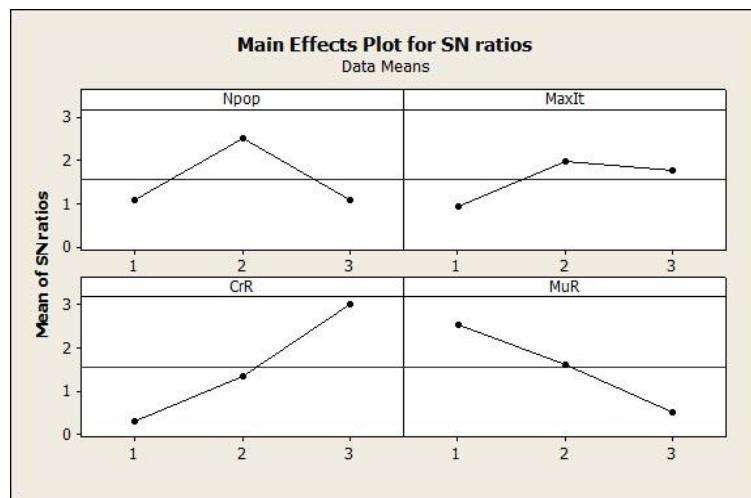


Figure 2.1 Signal to noise ratio for each level of the parameters

2.4.2 Computational results

Different algorithms and techniques exist to check the feasibility of a multi-objective optimization problem such as the objective weighting, the distance functions and the Min-Max technique (Sazvar et al. 2014). To validate the feasibility of our proposed model, we use the weighted sum technique as a compromise programming method.

Being the most widely used technique, we use the weighted sum technique to check the feasibility of our optimization. We are aware of the main disadvantage of such a technique (optimal solutions in non-convex regions are not detected as reported in (Kim & de Weck 2006)), but its use is only for feasibility checking and not for deriving optimal solutions.

With this technique, the problem is solved by considering each objective function separately in both the maximization and the minimization for finding extreme points of each objective function. Finally, a new single objective that strives to minimize the weighted sum over the normalized and non-dimensional objective function is solved. To solve such a problem, we use the “GAMS v22.2” optimization software using solver CPLEX v10.1.

To proof the applicability of our IRP, certain experiments are presented in the remainder of this section. The crisp model is solved by the NSGA-II algorithm, which is tuned for this problem. Consequently, a set of solutions referred to as the Pareto frontier is obtained. The Pareto set of this problem contains three important points or solutions with an optimum level for each objective function. We denote as solution A the optimum value associated with the profit objective (Z_1), solution B as the optimum value of the service level (Z_2), and solution C as the optimum value of the GHG emissions (Z_3).

In the following, we propose to detail the results associated with problems 3, 7, 11 and 15, which are representative of different sizes of the problem. All the problem instances previously presented are solved; the uncertainty level α is set equal to 0.6, and the best solutions are reported in Table 2.7. It should be noted that, due to the normalization of the second objective function, the results of the latter are between zero and one. The Pareto frontier of each problem is illustrated in Figure 2.2. Please notice that we illustrate the service level in Figure 2.2 as (1- Z_2) since Z_2 measures delays and backorders.

We notice that providing the obtained optimal Pareto frontier to practitioners is a better means to increase their capability to select a solution among the Pareto set by considering their own managerial judgment on the preference and priority to accord for each objective function.

Table 2.7 The best value of each objective in final Pareto

Problem No.	OF	The best solutions			CPU time (s)
		Solution A	Solution B	Solution C	
3	Z_1	1,618.50	815.00	758.00	28.54
	Z_2	0.09	1.00	0.87	
	Z_3	41.53	76.03	7.51	
7	Z_1	9,346.00	4,727.00	3,814.00	309.31
	Z_2	0.00	1.00	0.75	
	Z_3	1,687.50	1,730.40	338.40	
11	Z_1	32,162.00	15,107.00	12,114.00	947.02
	Z_2	0.00	1.00	0.69	
	Z_3	8,244.46	8,987.22	1,980.93	
15	Z_1	103,167.00	54,325.00	43,406.00	1,962.73
	Z_2	0.00	1.00	0.53	
	Z_3	14,377.22	15,852.25	4,530.53	

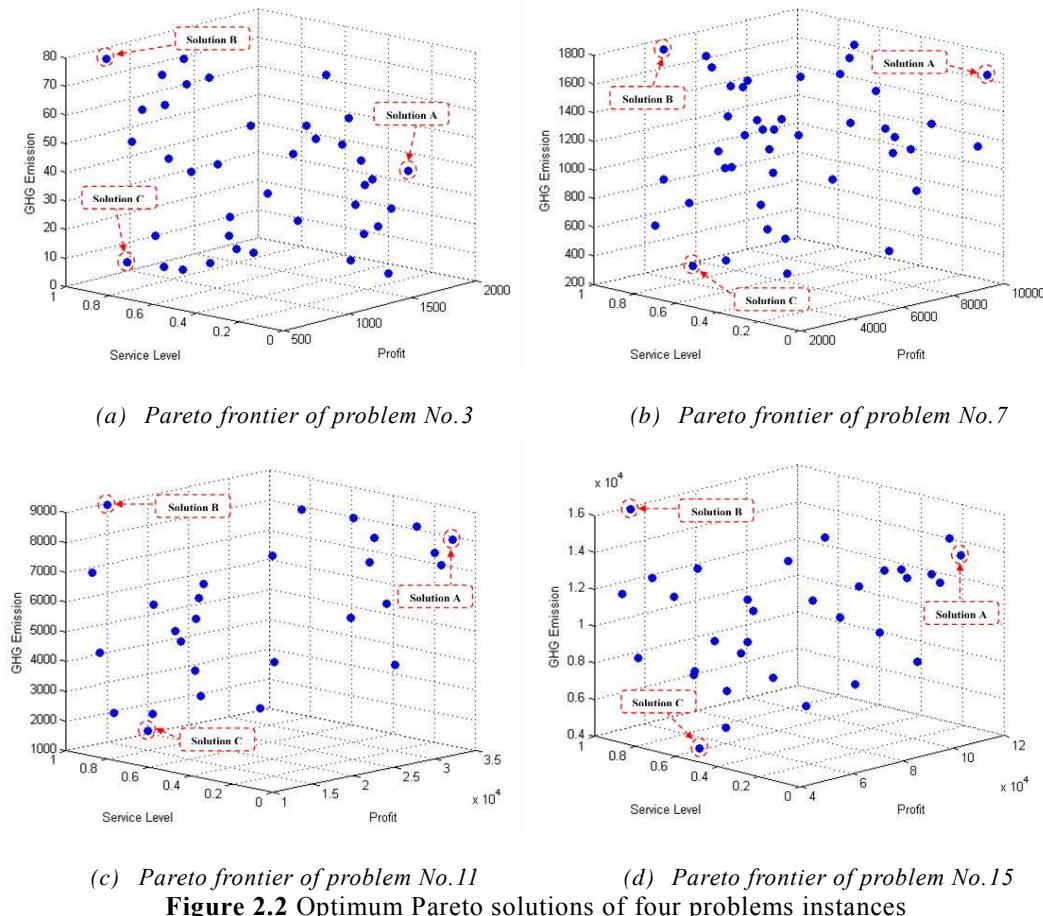


Figure 2.2 Optimum Pareto solutions of four problems instances

The analysis of the two best solutions A (Z1) and B (Z2) associated with problem No.11 shows that the manager can achieve the highest service level but the impact on the economic performance would be a profit decrease of 53%. Such a result permits the measurement of the impact of exogenously targeting a given service level without coordinating with the logistics component, i.e., the inventory and transportation costs. Indeed, target service levels are, in general, a corporate strategy or a marketing decision; when they are exogenously chosen, the impact on the logistics cost could be important.

Our framework enables practitioners to link the profit with the achieved service level and to help them to judgmentally select the best tradeoff. Such an analysis is common in Inventory Management but was never developed with IRPs to the best of our knowledge. For instance, we analyze the Pareto frontier of problem No. 11 obtained to deduce the set of solutions where a small variation of the profit has a significant impact on the service level. Table 2.8 illustrates the profit loss as a function of the service level improvement for problem No. 11. According to Table 2.8, in the set of solutions 7, 8, 15, 16, 24 and 25, the service level can be improved by approximately 25% to 27% with less than a 7% decrease

in the profit. This set of solutions is valuable for companies that are under pressure in a competitive marketplace where the achieved service level is an important customer satisfaction criterion. We refer to this set of solutions as the “solutions with a high priority”.

In contrast to this set of solutions, there is another set where a small improvement of the service level needs a significant impact on the profit. This set of solutions needs to be avoided. According to Table 2.8, in solutions 10, 11, 13 and 14 the service level can be improved by less than 3%, while the profit needs to be reduced by approximately 15 to 20%. We refer to these solutions as the “solutions with low priority”. Figure 2.3 shows the optimal Pareto frontier for problem No.11, considering the high and low priority of solutions.

Table 2.8 Lost profit against service level improvement (Problem No.11)

No. Solution	%lost profit	%service level improvement	No. Solution	%lost profit	%service level improvement
1 (Solution A)			15		
2			16	6.54	25.49
3			17		
4	10.94	11.00	18		
5			19 (Solution B)		
6			20	17.66	7.82
7			21		
8	1.97	26.54	22		
9	6.82	4.21	23		
10	15.74	3.11	24		
11			25	2.61	26.36
12	2.04	1.94	26		
13	20.02	2.62	27	5.01	4.61
14			28 (Solution C)		

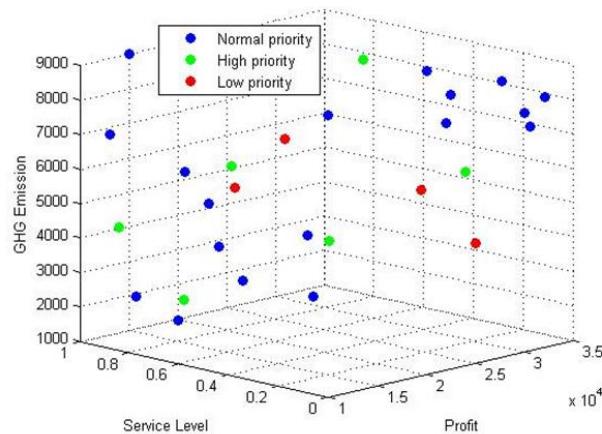


Figure 2.3 Classification of solutions (Problem No.11)

Please notice that the above analysis assumes that the demand distribution is independent of the achieved service level. In the long-term, it is obvious that improving the service level may also increase the demand and improve the revenue component of the profit function. The above solution could also be used to analyze the impact of the service level improvement or decease the green footprint of the IRP solution.

As previously noted, three important solutions, corresponding to the extreme solutions optimizing each objective function, could be considered by the decision maker. In addition to these three solutions, one could consider a fourth one referred to as the compromise solution. Therefore, we need to define the ideal solution, which is at the interface between the three extreme solutions and that provides the best values for Z_1 , Z_2 and Z_3 (Figure 2.4). The compromise solution may be interesting for managers who attempt to find the solution, which is closer to the ideal point. The latter cannot be achieved in practice (Marler & Arora 2004).

To find the compromise solution, we first need to normalize the objective functions and to convert their values to a number between 0 and 1. Such a normalization is needed because the objective functions are expressed with different units. Then, as a second step, the Euclidean Distance (ED) between each solution and the ideal point is calculated using equation (2-90). Finally, the solution leading to the lower Euclidean Distance from the ideal point is selected as the compromise solution.

$$ED_i = \sqrt{(f_1^i - f_1^{ideal})^2 + (f_2^i - f_2^{ideal})^2 + (f_3^i - f_3^{ideal})^2} \quad (2-90)$$

Figure 2.4 illustrates the compromise solution in the Pareto frontier associated with problem No.11. As reported in Table 2.9, solution number 17 is the compromise. This solution shows a profit of 16,061.00, a service level of 0.71, and an environmental criterion of 5092.12. This solution corresponds to the closest solution to the ideal point and could be chosen by the manager. The comparison between the compromise and the best solutions shows that the values of profit, service level and GHG emissions are decreased by 50%, 29% and 61%, respectively, when compared with the best values.

Table 2.9 Compromise solution against best solutions in the final Pareto

Problem No.	OF	Compromise solution(No.17)	The best solutions		
			Solution A	Solution B	Solution C
11	Z_1	16,061.00	32,162.00	15,107.00	12,114.00
	Z_2	0.71	0.00	1.00	0.69
	Z_3	5,092.12	8,244.46	8,987.22	1,980.93

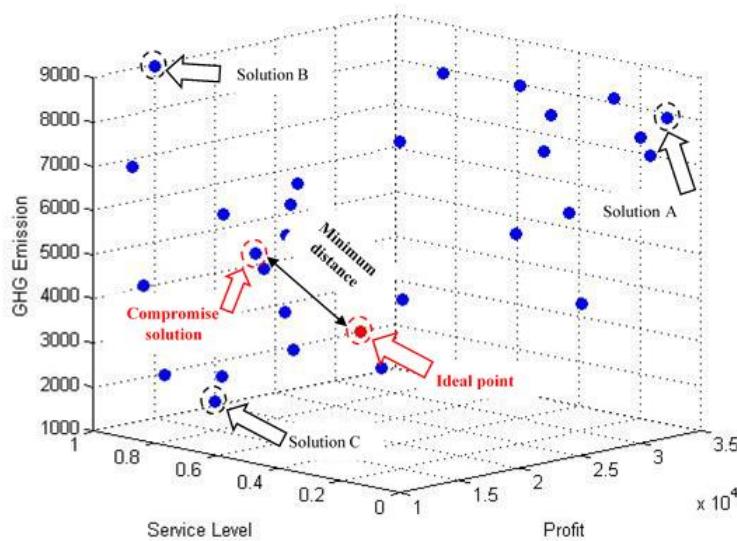


Figure 2.4 Compromise and ideal point (Problem No.11)

As noted in Section 2.2.1, the stepwise holding cost is used to model the products' non-freshness if they are transferred from one period to another; this is equivalent to a situation with a fixed holding cost where non-fresh products are offered at a discount selling price. In the following analysis, we investigate the impact of the product non-freshness on the optimal solution. Therefore, we consider a particular case of the holding function presented in equation (2-1). The unit holding cost for each product is assumed to be equal to the fixed component, h_{if}^{fix} plus a second component that we hereafter call the "variable holding cost" written as a percentage, λ_{if} , of the unit revenue:

$$h_{if} = h_{if}^{fix} + (\lambda_{if} R_{ft}) \quad (2-91)$$

Thus, the problem is equivalent to a situation where only the fixed component h_{if}^{fix} is charged for each item remaining in the stock but where these items are offered a discount λ_{if} on the unit revenue when transferred and consumed in the next period. As encouraged in Section 2.2.1, the product non-freshness could be included in the system as an additional holding cost, because the remaining items should be inspected before being transferred to the next period. The non-freshness could also be included as a discount price leading to a lower unit revenue of the non-fresh products. That is, the revenue for non-fresh product is not R_{ft} but is replaced by $(1-\lambda_{if})R_{ft}$.

We explore the latter scenario in the following numerical analysis where we rewrite the profit as the revenue (including the discount offered for non-fresh products) minus the logistics IRP cost (where only the fixed holding cost is represented).

The results of Problem No. 11 for different values of the revenue discount percentage λ_{if} are presented in Table 2.10:

Table 2.10 The best value of each objective in different value of λ_{if}

Value of λ_{if}	The best value of each objective function					
	Profit			Service Level	Green	
	Revenue	Cost*	Variable holding cost			
0.0	187,305.00	150,544.00	0.00	36,761.00	0.89	1,910.84
0.01	187,492.00	150,618.00	140.00	36,734.00	0.89	1,923.29
0.02	187,508.00	150,734.00	190.00	36,584.00	0.90	1,934.05
0.03	187,574.00	144,006.00	7,222.00	36,319.00	0.90	1,938.40
0.04	187,672.00	144,126.00	7,542.00	36,004.00	0.90	1,956.19
0.05	187,703.00	144,180.00	7,606.00	35,917.00	0.91	1,959.32
0.2	188,854.00	144,858.00	8,587.00	35,409.00	0.93	2,002.96
0.4	188,959.00	146,021.00	10,048.00	32,890.00	0.97	2,105.92
0.6	192,608.00	150,306.00	12,305.00	29,997.00	1.00	2,281.07

*: total cost where the variable holding cost are excluded

**: profit= (Revenue-Cost-Variable holding cost)

It is apparent that discounting non-fresh products is a means to increase the service level; however, the profitability of the system is negatively impacted. We recall that discounting is a penalty for holding non-fresh product. Discounting is a means to eliminate these non-fresh products that are not generating extra demand. If the discount percentage is higher, the system avoids having non-fresh products; consequently, lower quantities are delivered, and vehicle tours are performed more often. Therefore, the stockout probability could be lower (the service level is consequently higher), and the green footprint is higher.

It is important to notice in Table 2.10 that the Cost (exclusive of the variable holding cost) as well as the (Revenue-the variable holding cost) are non-monotonous with the revenue discount percentage λ_{if} .

We investigate the latter issue by considering two situations with different values of the unit fixed cost h_{if}^{fix} and the unit revenue R_{if} (cf. Table 2.11):

Table 2.11 Value of fix holding cost and revenue

Situation	Uniform distribution	
	Unit Fixed holding cost	Unit Revenue
Situation 1	~U[5,10]	~U[100,200]
Situation 2	~U[10,15]	~U[50,100]

The evolution of the cost (exclusive of the variable holding component) illustrated in Figure 2.5 and the evolution of the revenue (inclusive of the non-freshness cost, i.e., inclusive of the variable holding component) illustrated in Figure 2.6 show a threshold value of the discount percentage.

The logistics IRP cost is superior on the right side after the threshold. From a logistic perspective, if non-fresh products have no logistics cost, the discount option is welcome, because it permits better management of the joint inventory and distribution decisions. However, for increasing λ_{if} , the system will avoid

holding non-fresh products to avoid penalizing the profitability. Therefore, the logistics need to deliver lower quantities and make tours more often; this, in turn, increases the IRP logistics costs. The revenue (inclusive of the non-freshness cost) is superior on the left side of the threshold; the margin optimization avoids offering the discount option for non-fresh products, which increases the sales revenue. However, on the other side, the logistics costs increase considerably.

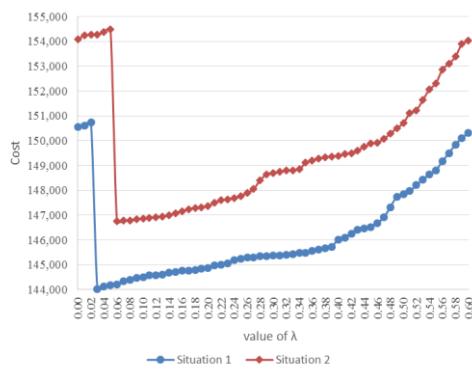


Figure 2.5 Variation of the Cost (exclusive of the variable holding cost) with λ (Problem No.11)

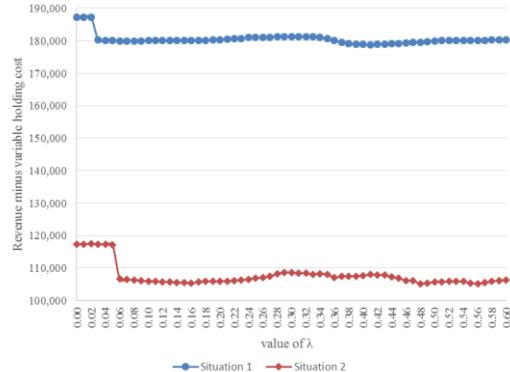


Figure 2.6 Variation of ‘discounted’ revenue (Revenue – variable holding cost) with λ (Problem No.11)

With regard to the linkage between the profit, service level and the green IRP footprint, the following figure illustrate the evolution of the best “profit” and “green” solutions with different values of the service level (Figure 2.7).

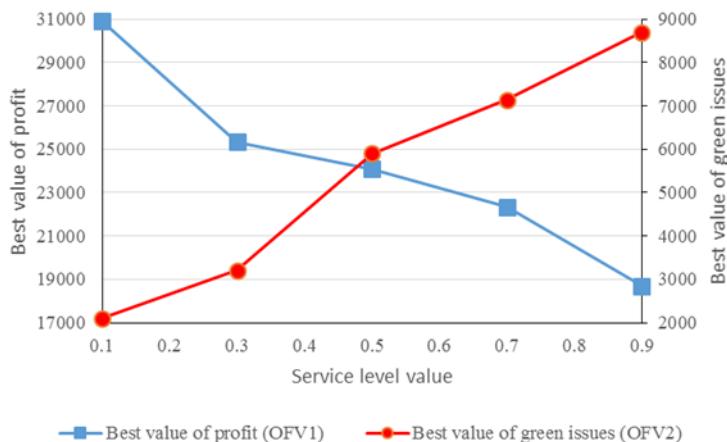


Figure 2.7 Variation of best value of profit and green issues against the variation of the fixed value of service level (Problem No.11)

As intuitively expected, the higher the service level is, the lower the profit is. This result is mainly due to the increase of the logistics and inventory costs; in

addition, the higher GHG emissions is due to the need to perform more tours and more loading and unloading tasks.

In the following, we end our numerical analysis by studying the impact of the uncertainty degree on the three IRP objective functions. Therefore, we increase the value of the uncertainty level α and investigate the impact on the results on Problem No.11. (cf. Table 2.12). The profit is decreasing with α , while the GHG emissions are increasing with it. When the system is subject to more uncertainty, more inventory is needed; consequently more trips are made, and more products may need to be recycled. We note that the invariant service level in Solution B is due not to the invariance of the service level with uncertainty but to the normalization of the service level measure that assigns the value 1 for the best solution.

Table 2.12 Sensitivity analysis based on α - uncertain level (Problem No.11)

α -level	OF	The best solutions			CPU time (s)
		Solution A	Solution B	Solution C	
0.6	Z ₁	32,162.00	15,107.00	12,114.00	947.02
	Z ₂	0.00	1.00	0.69	
	Z ₃	8,244.46	8,987.22	1,980.93	
0.7	Z ₁	31,383.00	14,672.00	13,464.00	1,037.29
	Z ₂	0.00	1.00	0.73	
	Z ₃	8,360.39	8,361.40	2,164.03	
0.8	Z ₁	30,124.00	15,993.00	13,874.00	982.13
	Z ₂	0.00	1.00	0.67	
	Z ₃	8,203.07	9,026.91	2,245.96	
0.9	Z ₁	29,765.00	15,346.00	11,392.00	910.21
	Z ₂	0.00	1.00	0.54	
	Z ₃	8,037.61	8,875.26	2,182.41	
1	Z ₁	29,291.00	13,809.00	14,387.00	936.72
	Z ₂	0.00	1.00	0.59	
	Z ₃	7,628.92	9,077.82	2,491.18	

2.5 Conclusion

This chapter presents a new study of the Inventory Routing Problem by considering the service level and the GHG emissions in the distribution of perishable products. We proposed a new multi-objective mathematical model in which the first objective function maximizes the profit function. The second objective function maximizes the service level by minimizing the rate of delays and the rate of the number and frequency of backorders. The third objective function minimizes the GHG emissions produced by vehicles, loading/unloading equipment, and expired products. In this framework, we considered perishable products by defining a specific expiration date and investigated the impact of using electric vehicles and loading/unloading equipment in urban transportation.

Moreover, to increase the effectiveness of the proposed model in addressing uncertainty, certain parameters such as demand, variable transportation costs and vehicle speed were modeled as uncertain parameters. A fuzzy possibilistic approach was adopted to convert the original model to an equivalent auxiliary crisp model, and NSGA-II as a multi-objective evolutionary algorithm was designed and tuned to obtain the optimal Pareto frontier. Finally, analyses were conducted to demonstrate the strength of the proposed algorithm, and certain managerial insights were described. In particular:

- We showed the ease of application of the proposed framework and the manner in which the results could be used to derive the best tradeoff between the three objective functions. Indeed, the results could be interpreted differently, based on the judgmental weight that the decision maker could assign to each objective.
- We explored the linkage between the profit/service level and the green footprint under an IRP framework. Such a linkage was recently explored in the inventory context, but none of the IRP investigations considered it to the best of our knowledge. In companies, target service levels are generally a corporate strategy or marketing matter. Inventory holding and distribution costs are logistics matters. These two matters are, in some firms, decided separately. The green footprint is an ethical / sustainability / legislation (in some countries) matter. Our proposal permits us to first model an IRP with these conflicting objectives and to propose tradeoff mechanisms. For managers, it is possible to check the impact of x% increase of the service level on the logistics costs as well as the green footprint.
- In an internally nonintegrated company, the framework permits us to analyze the penalty of not coordinating service level choices with logistics operations. The results provided in Table 10 are an excellent illustration of the managerial implications with regard to the link between service levels and logistics costs in the IRP.
- We explored the cost of product non-freshness and its impact on the performance. The product non-freshness could either be paid by the logistics side as an additional holding cost motivated by the need to inspect products before transferring them to the next period. The non-freshness could also be modelled as a lower margin for non-fresh items enabled by a price discount offered for these products.

3

A bi-objective model for the sustainable inventory routing problem: products perishability and reverse logistics considerations

3 A bi-objective model for the sustainable inventory routing problem: products perishability and reverse logistics considerations

3.1 Motivation

New regulations, laws and standards have furthermore been adopted in recent years and must be taken into account in the IRP modeling and optimization. Examples include the occupational safety and health administration (NIOSH 2014), the European Parliament regulation about the vehicle noise (European Parlem 2012) and the social responsibility guidance provided in the ISO 26000 standard (ISO 2010). Supply chain managers need to reconsider the modeling of joint inventory and distribution problems by including these new regulations in the framework.

On the other hand, there is increasing pressure on companies from the governmental and non-governmental communities and more generally from public opinion to persuade them to include sustainable considerations in their activities. According to Cruz & Wakolbinger (2008), some leading corporations such as Shell, McDonalds, Nike and Disney acquired a negative reputation with a profit impact because of certain media reports.

Despite the increase of studies dealing with the sustainable issues and their importance, based on the literature review (Chapter 1), IRP investigations have not considered this issue a lot. Few numbers of investigations dealing with social IRP modelling can be explained by the complexity and difficulty of modeling these social issues in a quantitative manner and of including them in a classical IRP framework. However, we think that some new regulations and law (ISO, 2010; GRI, 2011; NIOSH, 2014 and European Parlem, 2012) could be modelled and included in the IRP framework as will be illustrated in the following section. Therefore, in this chapter, we present a new bi-objective mathematical model to study possibility of integration of sustainable issues in IRPs. The research presented in this chapter contributes to the existent literature in following ways. We develop a new bi-objective mathematical model by:

- Modeling and including some social considerations in the IRP framework. Due to human-machine interaction during various distribution and inventory activities, considering social issues in IRPs is particularly important. For this reason, the risks of accidents, vehicle noise and number of expired products are considered as social issues in

the IRP. Moreover, environmental criteria are taken into account as constraints.

- Considering that perishable products make IRPs more complex by introducing criteria such as managing expiration date, gathering the expired products, pollution, etc.. In this situation, decision makers must find the best trade-off between the inventory level, backorders and expired products. These issues require them to take the expiration date of products into account. Moreover, the picking up and recycling of these products after their expiration date also have to be considered. For this purpose, the concept of reverse logistics is applied in the proposed model.
- In order to increase the profitability of the system, we assume the possibility of a quantity discount function to encourage the retailer to buy more products. We consider the all units quantity discounts function as a nonlinear multiple breakpoint function. In this situation, more demand generates more and more discount. Since dealing with the nonlinear function creates complexity in the model, many IRP models have been taken into account in the linear functions.

Handling and controlling uncertain parameters:

- Since there are various uncertain parameters in the real world, some parameters such as demand, Average Traffic Speed (ATS), Average Vehicle Speed (AVS), and variable transportation costs are considered as uncertain parameters. In order to handle uncertain parameters in the model, a stochastic optimization model using a scenario-based stochastic approach is developed and adopted.

3.2 Problem formulation

The aim of this section is to present a bi-objective mathematical model by taking into account sustainability considerations in IRP for perishable items. As mentioned earlier, the first objective function deals with the profit maximization while the second one looks at some social considerations.

The IRP under study in this research can be described as follows. We consider T selling periods where one supplier distributes F perishable products to M retailers. The products could be distributed with three types of vehicle (small, medium and large) and we assume that two route types (urban route and ring road) could be used to travel between the M retailers.

3.2.1 Economic issue: profit maximization

For the economic side of the IRP, we consider the profit function as revenue minus the related inventory and distribution costs, including holding, backorder, fixed and variable transportation, ordering, and the penalty cost paid if the delivery to the retailer occurs outside the allowed time windows.

As one of the negotiation levers, we also consider a quantity discount mechanism, where the unit margin of each product is a function of the quantity delivered to the retailer. We assume that the supplier's quantity discount proposal can permit a simultaneous improvement of the performance of all members of the supply chain. Depending on the delivered quantity (d_{ift}) of product f to retailer i during period t , the unit margin of the d_{ift} is changing by being multiplied by the factor $1-\lambda_{(d_{ift})}$ where $\lambda_{(d_{ift})}$ is an increasing factor with d_{ift} . The parameter π_i presents the following slope (Figure 3.1):

$$\lambda_{(d_{ift})} = \begin{cases} \lambda_1 + \pi_1(d_{ift} - d_1) & \text{if } d_1 \leq d_{ift} \leq d_2 \\ \lambda_2 + \pi_2(d_{ift} - d_2) & \text{if } d_2 \leq d_{ift} \leq d_3 \\ \vdots \\ \lambda_{(n-1)} + \pi_{(n-1)}(d_{ift} - d_{n-1}) & \text{if } d_{n-1} \leq d_{ift} \leq d_n \end{cases} \quad (3-1)$$

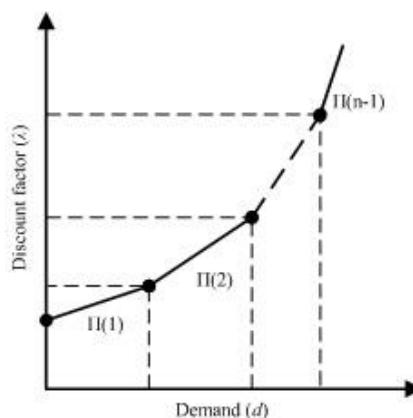


Figure 3.1 Multiple breakpoint quantity discount function

The choice of the quantity discount mechanism is motivated by the following remarks:

- In the inventory literature, it is shown that the quantity discount contract allows for better coordination of the supply chain.
- Our framework with the quantity discount mechanism is a more generalized way to model the IRP since the case with no quantity discount is a particular case of our model.
- The quantity discount mechanism affects the trade-off that we will show between the economic and social objectives.

3.2.2 Social issue

Apart from the economic objective described in the last section, we examine some social considerations in our IRP. The modeling of social considerations is not straightforward and we have tried to build our modeling approach based on some reporting frameworks such as ISO 26000 (ISO 2010), the occupational safety and health administration report (NIOSH 2014), and the Global Reporting Initiative (GRI 2011).

According to these reports, we could model three social considerations within the scope of IRP for perishable items:

- The accident rate during the forward and reverse logistics of products
- The vehicle noise emission
- The number of expired products, The fact that higher numbers of expired products generate more reverse logistics which cause more accidents and more noise, because of the utilization of vehicles for forward and reverse logistics.

The first social issue concerns the accident rate value associated with a vehicle routing solution. When dealing with distribution, all possible routes should be used, where each one could be associated with an accident rate. This rate is a function of many criteria, including the nature of the route, the speed limit on this route, the type of most of the vehicles using it, and the statistical accident data associated with it.

In order to model this first social issue, in our supply chain network we considered different types of routes characterized by two parameters: i) the Average Traffic Speed (ATS) on each route and ii) the Average Vehicle Speed (AVS) for each route. The first speed measure depends on several route factors, including the type of route, the weather, and the weekday, whereas the second speed measure depends on the vehicle driver's attitude on this route. This in turn depends on some demographic characteristics of the driver (age, sex, exposure, etc.), his/her driving skills and certain psychological factors (risk tolerance, sensation seeking, etc.) as well as temporary states (mood, fatigue, illness, etc.). Intuitively, we can expect the accident rate to increase with AVS and to decrease with ATS (Quimby, A., Maycock, G., Palmer, C., Buttress 1999).

Quimby et al. (1999) provide an excellent analysis resulting from a questionnaire survey based on a multivariate regression technique in order to explore the relationship between accident frequency (the number of accidents reported in a three-year period) and a range of explanatory variables (age, sex, speed, etc.). Of these explanatory variables, we mainly use the link between the accident rate and the predicted speed in our IPR framework:

$$\text{Rate of accident} = 0.215 \times \left(\frac{\text{AVS}}{\text{ATS}} \right)^{7.8} \quad (3-2)$$

More analytical formulations of the accident rate could be used based on the investigations of Kloeden, C.N., McLean, A.J., Glonek, (2002) and Baruya A, (1998).

We could intuitively expect a trade-off between travel speed and route choice, and consequently the accident rate, and other constraints of the IRP such as delivering to customers within the time windows to avoid delay penalties. A second expected trade-off could be between the route selection and the vehicle's fuel consumption, and consequently the CO₂ emission associated with the selected route.

The second social issue concerns the vehicle's noise emission. Traffic noise is a widespread problem that affects over 44% of European Union citizens and constitutes a serious health risk (European Parlem, 2012). For analytical noise emission modeling, we use the investigation of Y Oshino, S Kono, T Iwase, H Ohnishi, T Sone (2000) where the authors link the noise emission with the vehicle type, modeled by parameter α , and the average vehicle speed on the route:

$$\text{Vehicle noise emission} = \alpha + \left[30 \times \left(\log_{10}^{\text{AVS}_{ijkl}} \right) \right] \quad (3-3)$$

Finally, the third social issue concerns the number of expired products which cause more reverse logistics and, indirectly, more accidents and noise. We consider products with a limited shelf life and assume that expired products should be collected and recycled. Hence, this IRP deals with both forward and reverse logistics in order to model the delivery of fresh products and the collection of expired ones. The expired products are collected by a fleet of vehicles different from the ones used in the forward logistics, mainly for two reasons: i) expired products do not need the particular and costly care given to fresh products (refrigerated vehicles for instance), and ii) fresh and expired products should not be mixed because of possible contamination.

In the presence of different criteria for the social issues (accident rate and produced vehicle noise emission during the forward and reverse logistics, as well as the number of expired products), we use five weighting factors ($\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$), whose sum is equal to one, in order to handle the relative importance of each one when compared with the others. Due to the difference in the nature of the five social criteria, we furthermore proceed to a normalization of the five measures.

3.2.3 Environmental issue

In addition to the economic and social considerations described in the previous sections, we also consider an environmental criterion in our IRP. In particular,

we consider the GHG emission produced by the transportation of products (forward and reverse). As mentioned in (Mirzapour Al-e-hashem & Rekik 2013), companies are nowadays obliged to master and decrease their GHG footprint not only to protect the environment but also because some new regulations apply environmental penalties if these emissions exceed certain thresholds. We model the GHG environmental issue as a constraint where the total GHG emission resulting from distribution and the recycling of expired products should not be higher than a maximum allowed threshold in each selling period.

3.2.4 Problem assumption

In addition to the general assumptions presented in chapter 2, the specific assumptions of this model are presented as follows:

- The supplier uses a heterogeneous fleet of vehicles with different capacities, different fixed and variable costs, and different GHG emission levels per kilometer.
- For each retailer there is a satisfying demand rate that determines the minimum percentage of fresh products at a retailer's warehouses.

The main aim of the proposed model is to determine the set of retailers and delivery sequences for each vehicle (forward and reverse), as well as the quantities of products delivered to each retailer in each period over the planning horizon.

3.2.5 Notation

In order to analytically model the supply chain described above, in addition to used notation in Chapter 2, we use the following notations and their associated descriptions:

<i>Sets</i>	
r	index for route type ($1, 2, \dots, R$)
<i>Parameters</i>	
c_{ijr}	distance between retailer/supplier i, j by route r
$\lambda_{(dift)}$	discount factor based on quantity of demand
v_{kr}	variable transportation cost per unit nad per distance for vehicle type k in route r
f_{ck}	fixed transportation cost for vehicle type k
vr_{kr}	variable reverse transportation cost per unit and per distance for vehicle type k in route r
fcr_k	fixed reverse transportation cost for vehicle type k
cap_k	capacity of vehicle type k
g_{if}	rate of minimum demand should be satisfied at each period for retailer i and product f
sp_k	required time to unload one unit product from vehicle k
DP_i	penalty cost per unit of time due to visiting the retailer i after latest possible arriving time
ATS_{ijrt}	average traffic speed in the route r between retailer/supplier i and j at

	period t
AVS_{ijkrt}	average speed of vehicle type k in route r between retailer/supplier i and j at period t
a_k	constant parameter related to vehicle type k
GHG_k	produced GHG emission by vehicle type k in one unit distance
$GHG_{t, total}$	maximum allowed produced GHG emission at period t
<hr/>	
<i>Variables</i>	
x_{ijkrt}	1 if retailer j is visited exactly after retailer i by vehicle type k using route r at period t , otherwise 0
x'_{ijkrt}	1 if retailer j is visited exactly after retailer i by vehicle type k using route r at period t for revers logistics of expired products, otherwise 0
I_{ift}	inventory level of product f in retailer i at the end of period t
y_{kt}	number of vehicle type k at period t
y'_{kt}	number of vehicle type k at period t for revers logistics of the expired products
$q_{iktt'; t < t'}$	quantity of received product by retailer i through vehicle k at period t for being used at period t'
$q_{iktt'; t > t'}$	quantity of received product by retailer i through vehicle k at period t to satisfy the backordering quantity
φ_{it}	1 if there is expired product in inventory of retailer i at period t , otherwise 0
DT_{irt}	delay in visiting retailer i due to using route r at period t
z_{ikrt}	1 if retailer i is served at period t by vehicle k and route r , otherwise 0
z'_{ikrt}	1 if retailer i is visited at period t by vehicle k , route r for revers logistics of expired products, otherwise 0
T_{ikrt}	arriving time to retailer i by vehicle k and rout r at period t
C_{ift}	1 if product f is delivered to retailer i at period t , otherwise 0

3.2.6 Mathematical formulation

In the following, we provide first the mathematical formulation of our IRP proposal and then a detailed description of each component.

$$\begin{aligned} \text{Max } f_1 = & \left[\sum_{i \in M} \sum_{f, k, t, t'} \left[(1 - \lambda_{(d_{if})}) R_{if} \right] \left[q_{ijkrt'} - EX_{if} \right] \right] - \sum_{i \in M} \sum_{f, t} h_{if} I_{if} - \sum_{i \in M} \sum_{f, t} \gamma_{if} B_{if} \\ & - \sum_{i \in M} \sum_{r, t} D P_i D T_{irt} - \sum_{i \in M} \sum_{f, t} O_{if} C_{if} - \sum_{k, r, t} f c_k z_{0krt} - \sum_{(i,j) \in M' k, r, t} v_{kr} y_{kt} C_{ijr} x_{ijkrt} \\ & - \sum_{k, r, t} f c r_k z_{0krt}' - \sum_{(i,j) \in M' k, r, t} v r_{kr} y_{kt}' C_{ijr} x_{ijkrt}' \end{aligned} \quad (3-4)$$

$$\begin{aligned} \text{Min } f_2 = & \beta_1 \left(0.215 \times \left(\sum_{(i,j) \in M' k, r, t} x_{ijkrt} y_{kt} \left(\frac{AVS_{ijkrt}}{ATS_{ijkrt}} \right)^{7.8} \right) \right) \\ & + \beta_2 \left(0.215 \times \left(\sum_{(i,j) \in M' k, r, t} x_{ijkrt}' y_{kt}' \left(\frac{AVS_{ijkrt}}{ATS_{ijkrt}} \right)^{7.8} \right) \right) \\ & + \beta_3 \left(\sum_{(i,j) \in M' k, r, t} \left((\alpha_k + [30 \times (\log_{10}^{AVS_{ijkrt}})]) \cdot y_{kt} x_{ijkrt} \right) \right) \\ & + \beta_4 \left(\sum_{(i,j) \in M' k, r, t} \left((\alpha_k + [30 \times (\log_{10}^{AVS_{ijkrt}})]) \cdot y_{kt}' x_{ijkrt}' \right) \right) + \beta_5 \left(\sum_{i \in M} \sum_{f, t} EX_{if} \right) \end{aligned} \quad (3-5)$$

S.t.

$$I_{if} - B_{if} = I_{if(t-1)} - d_{if} + \sum_{k, t'} q_{ijkrt'} - EX_{if} - B_{if(t-1)} \quad \forall i \in M, f, t \quad (3-6)$$

$$B_{if} \geq \sum_k \sum_{t > t'} q_{ijkrt'} \quad \forall i \in M, f, t \quad (3-7)$$

$$I_{if} \times B_{if} = 0 \quad \forall i \in M, f, t \quad (3-8)$$

$$\sum_{k, t'} q_{ijkrt'} \leq IC_{if} - I_{if(t-1)} \quad \forall i \in M, f, t \quad (3-9)$$

$$q_{ijkrt'} \leq IC_{if} z_{ikrt} \quad \forall i \in M, f, k, r, t, t' \quad (3-10)$$

$$\sum_k \sum_{t' > (t+L_f)} q_{ijkrt'} \leq EX_{if} \quad \forall i \in M, f, t \quad (3-11)$$

$$\frac{\varphi_{it}}{G} \leq \sum_f EX_{if} \leq \varphi_{it} G \quad \forall i \in M, t \quad (3-12)$$

$$\frac{C_{if}}{G} \leq \sum_{k, t'} q_{ijkrt'} \leq C_{if} G \quad \forall i \in M, f, t \quad (3-13)$$

$$g_{if} d_{if} \leq \sum_k q_{ijkrt'} \quad \forall i \in M, f, t, t' = t \quad (3-14)$$

$$T_{ikrt} + \sum_{f, t'} q_{ijkrt'} s p_k + \left(\frac{c_{ijr}}{AVS_{ijkrt}} \right) \leq T_{jkr} + G(1 - x_{ijkrt}) \quad \forall (i, j) \in M', k, r, t \quad (3-15)$$

$$a_i \leq \sum_k T_{ikrt} \leq (b_i + DT_{irt}) \quad \forall i \in M, r, t \quad (3-16)$$

$$GHG_{total}^t \geq \sum_{(i,j) \in M'} \sum_{f,k,r} GHG_k \cdot c_{ijr} \cdot x_{ijkrt} \cdot y_{kt} + \sum_{(i,j) \in M'} \sum_{f,k,r} GHG_k \cdot c_{ijr} \cdot x'_{ijkrt} \cdot y'_{kt} + \sum_{i \in M} \sum_{f,t} GE \cdot EX_{ift} \quad \forall t \quad (3-17)$$

$$\sum_{i \in M} \sum_{f,t} q_{ifkt} \leq cap_k \cdot y_{kt} \cdot z_{0krt} \quad \forall k, r, t \quad (3-18)$$

$$\sum_{i \in M} \sum_f EX_{ift} \leq cap_k \cdot y'_{kt} \cdot \varphi_{it} \cdot z'_{0krt} \quad \forall k, r, t \quad (3-19)$$

$$\sum_r x_{ijkrt} = 1 \quad \forall (i, j) \in M', k, t \quad (3-20)$$

$$\sum_r x'_{ijkrt} = 1 \quad \forall (i, j) \in M', k, t \quad (3-21)$$

$$\sum_{j \in M'} \sum_r x_{ijkrt} = \sum_{j \in M'} \sum_r x_{jikrt} = z_{ikrt} \quad \forall i \in M', k, t \quad (3-22)$$

$$\sum_{r,k} z_{ikrt} \leq 1 \quad \forall i \in M, t \quad (3-23)$$

$$\sum_{i,k,r} x_{0ikrt} \geq 1 \quad \forall t \quad (3-24)$$

$$\sum_{i,k,r} x_{i0krt} \geq 1 \quad \forall t \quad (3-25)$$

$$\sum_{j \in M'} \sum_r x'_{0jkrt} = \sum_{j \in M'} \sum_r x'_{j0krt} = z'_{0krt} \quad \forall k, t \quad (3-26)$$

$$\varphi_{it} \cdot \sum_{r,k} z'_{ikrt} \leq 1 \quad \forall i \in M, t \quad (3-27)$$

$$\varphi_{it} \cdot \sum_{i,k,r} x'_{0ikrt} \geq 1 \quad \forall t \quad (3-28)$$

$$\varphi_{it} \cdot \sum_{i,k,r} x'_{i0krt} \geq 1 \quad \forall t \quad (3-29)$$

$$x_{ijkrt}, x'_{ijkrt}, z_{ikrt}, z'_{ikrt}, \varphi_{it}, C_{ift} \in \{0,1\} \quad \forall (i, j) \in M, f, k, r, t, i \neq j \quad (3-30)$$

$$q_{ifkt}, I_{ift}, B_{ift}, EX_{ift}, y_{kt}, y'_{kt}, T_{ikrt}, DT_{ikrt} \geq 0, \text{Integer} \quad \forall i \in M, f, k, r, t \quad (3-31)$$

The first objective function (3-4) maximizes the profit which is equal to the sales revenue of products decreased by the costs including (in the order of writing in (3-4)), the holding cost, the backordering cost, the ordering cost, and the fixed and variable transportation costs for both forward and reverse logistics. The second objective function (3-5) optimizes the weighted social criterion by the minimization of the accident rate and total produced vehicle noise emission during the forward and reverse logistics, as well as the number of expired products. Constraint (3-6) balances the inventory level between each two successive periods. Constraint (3-7) calculates the number of backordered products. Equation (3-8) guarantees that the remaining stock (I_{ift}) and the

backordered quantity (B_{ift}) cannot be positive simultaneously. Equations (3-9) and (3-10) guarantee that the retailer's capacity for each product is respected. Constraint (3-11) calculates the number of expired products. Constraint (3-12) checks if a retailer has any expired product in the inventory. Constraint (3-13) checks if a retailer receives any product. Constraint (3-14) ensures that a minimum of fresh products are delivered to each retailer. Equation (3-15) determines the arrival time at the next retailer, which is calculated as the visiting time of the immediate previous retailer, increased by the unloading time of products and the traveling time between the two retailers. Equation (3-16) checks the time window constraint and calculates the delay. Constraint (3-17) checks that the GHG emission is lower than the maximum allowed threshold in each period. Constraints (3-18) and (3-19) guarantee that the capacity of each vehicle is respected during the forward and reverse logistics. Moreover, this constraint allow to define the quantity of vehicle for transportation of products. We assume that the measuring unit for all products is fix as the dimension of pallet. Please notice that the quantity of SKU of each product on pallet depends to its volume. However, knowing that the capacity of vehicle, loading, and unloading are determined by number of pallets, we only used this common unit (pallet) for all products. Constraints (3-20) and (3-21) check that only one route is selected between each two retailers. Equations (3-22) to (3-29) serve to determine routes and to eliminate sub-routes during the forward and reverse logistics. Finally, (3-30) and (3-31) impose bounds on the variables.

3.2.7 Linearization

Due to the existence of nonlinear equations in the objective functions and of some constraints, three linearization methods are applied to convert the model to its equivalent linear form.

- *Linearization of the nonlinear quantity discount function*

Because of the quantity discount mechanism, the discount factor $\lambda_{(dif)}$ is nonlinear. The linearization technique proposed by Mirzapour Al-e-hashem, Baboli, & Sazvar (2013) could be applied. For this purpose, d_{ift} is converted to $n-1$ independent parameters denoted as d_{ift}^n . Consequently, d_{ift} and equation (3-1) are replaced by equations (3-32) and (3-33):

$$d_{ift} = \sum_{n'=1}^{n-1} d_{ift}^{n'} \quad (3-32)$$

$$\lambda_{(d_{ift})} = \begin{cases} (\lambda_1 - \pi_1 d_1) + \pi_1 d_{ift}^1 & \text{if } d_1 \leq d_{ift}^1 \leq d_2 \\ (\lambda_2 - \pi_2 d_2) + \pi_2 d_{ift}^2 & \text{if } d_2 \leq d_{ift}^2 \leq d_3 \\ \vdots \\ (\lambda_{(n-1)} - \pi_{(n-1)} d_{(n-1)}) + \pi_{(n-1)} d_{ift}^{(n-1)} & \text{if } d_{n-1} \leq d_{ift}^{n-1} \leq d_n \end{cases} \quad (3-33)$$

As shown in (Mirzapour Al-e-hashem et al. 2013) and according to equations (3-32) and (3-33), the quantity discount mechanism could be linearized by using the expression provided in (3-33) for the discount factor $\lambda_{(d_{ift})}$ in the first objective function and also by adding the following three new constraints. A binary variable (η) is also introduced to determine in which interval of discount function the amount of demand is located.

$$\sum_{i,f,t} \sum_{n'=1}^{n-1} [(\lambda_{n'} - \pi_{n'} d_{n'}) + \pi_{n'} d_{ift}^{n'}] \quad (3-34)$$

S.t.

$$d_{n-1} \eta_{n-1} \leq d_{ift}^{n-1} \leq d_n \eta_{n-1} \quad \forall i, f, t, n \quad (3-35)$$

$$d_{ift} = \sum_{n'=1}^{n-1} d_{ift}^{n'} \quad \forall i, f, t \quad (3-36)$$

$$\sum_{n'=1}^{n-1} \eta_{n'} = 1 \quad (3-37)$$

- Linearization of the nonlinear variable resulting from the multiplication of a binary with an integer variable

Due to the multiplication of a binary and an integer variable, some constraints ((3-17) to (3-19) and (3-27) to (3-29) as well first and second objective functions) are nonlinear. The nonlinear equations could be converted into linear ones by omitting the binary variable and considering the new equations (3-38) to (3-45).

$$\frac{x_{ijkrt}}{G} \leq y_{kt} \leq x_{ijkrt} G \quad \forall (i, j) \in M, k, r, t \quad (3-38)$$

$$\frac{x'_{ijkrt}}{G} \leq y'_{kt} \leq x'_{ijkrt} G \quad \forall (i, j) \in M, k, r, t \quad (3-39)$$

$$\frac{z_{0krt}}{G} \leq y_{kt} \leq z_{0krt} G \quad \forall k, r, t \quad (3-40)$$

$$\frac{z'_{0krt}}{G} \leq y'_{kt} \leq z'_{0krt} G \quad \forall k, r, t \quad (3-41)$$

$$\frac{\varphi_{it}}{G} \leq y'_{kt} \leq \varphi_{it}G \quad \forall i, k, t \quad (3-42)$$

$$\frac{\varphi_{it}}{G} \leq z'_{ikrt} \leq \varphi_{it}G \quad \forall i \in M, k, r, t \quad (3-43)$$

$$\frac{\varphi_{it}}{G} \leq x'_{i0krt} \leq \varphi_{it}G \quad \forall i \in M, k, r, t \quad (3-44)$$

$$\frac{\varphi_{it}}{G} \leq x'_{0ikrt} \leq \varphi_{it}G \quad \forall i \in M, k, r, t \quad (3-45)$$

- *Linearization of the nonlinear variable resulting from the multiplication of two integer variables*

Due to the multiplication of the two integer variables (I_{ift}) and (B_{ift}) in constraint (3-8) a new binary variable χ_{ift} provide in (3-46) and the addition of two new constraints (3-47) and (3-48):

$$\chi_{ift} = \begin{cases} 1 & I_{ift} = 0 \\ 0 & B_{ift} = 0 \end{cases} \quad \forall i, f, t \quad (3-46)$$

$$B_{ift} \leq G \times \chi_{ift} \quad \forall i, f, t \quad (3-47)$$

$$I_{ift} \leq G \times (1 - \chi_{ift}) \quad \forall i, f, t \quad (3-48)$$

3.3 Resolution approach

The mathematical formulation presented in the last section and the associated linearization actions assume a deterministic setting of our IRP. In this section we propose a stochastic counterpart of the previous formulation to deal with its stochastic setting using a scenario-based stochastic approach. In the next step, due to NP-hard nature of IRPs (Shukla, Tiwari, & Ceglarek, 2013; Liu & Lee, 2011), the MOSA method is applied to solve the stochastic counterpart of the proposed model and to obtain the optimal Pareto. The main contribution of this section is to show the efficiency of a scenario-based approach to handle uncertain parameters in this problem. For this reason, we used the MOSA method, which previously proved its efficiency in IRP.

3.3.1 Stochastic optimization model

As it is described in Chapter 2, IRPs face a high degree of uncertainty in parameters such as different costs, demand, speed of vehicle in the routes and etc.. In this section, we propose an extension of the mathematical formulation described above, to consider stochastic modeling of the demand, the variable transportation cost, the average vehicle speed, and the average traffic speed. For

for this purpose, a scenario-based stochastic approach is proposed to take into account the uncertainty pertaining to these IRP parameters.

We first recall the principle of the scenario-based stochastic approach and then apply this principle to our IRP formulation. Consider equation (3-49) as a mathematical model where $(c, a$ and $b)$ are the problem parameters and where $x \in \mathbb{R}^n$ is a feasible decision vector.

$$\min f = c_e x$$

s.t.

$$\begin{aligned} a_i x &\geq b_i \quad \forall i = 1, \dots, s \\ a_i x &= b_i \quad \forall i = s+1, \dots, h \\ x &\geq 0 \end{aligned} \tag{3-49}$$

Let us now consider Γ as the set of possible scenarios, and denote α as a specific scenario and μ_α as the probability associated with the scenario α . The expected objective function f could be obtained by summing all the scenarios in Γ (Birge & Louveaux, 1997 and Pishvaee, Jolai, & Razmi, 2009). The deterministic model presented in (3-49) can be converted into a scenario-based formulation as illustrated in (3-50):

$$\min f = \sum_{\alpha} \mu_{\alpha} c_{e\alpha} x_{\alpha}$$

s.t.

$$\begin{aligned} a_{i\alpha} x_{\alpha} &\geq b_{i\alpha} \quad \forall i = 1, \dots, s, \alpha \in \Gamma \\ a_{i\alpha} x_{\alpha} &= b_{i\alpha} \quad \forall i = s+1, \dots, h, \alpha \in \Gamma \\ x_{\alpha} &\geq 0 \end{aligned} \tag{3-50}$$

Applying the described scenario-based principle to our deterministic IRP enables us to extend it to deal with the uncertainty of demand, variable transportation costs, and average traffic and vehicle speed.

$$\begin{aligned} \text{Max } f_1 = & \left[\sum_{\alpha \in \Gamma, i \in M} \sum_{n=1}^{n-1} \sum_{f, k, t} \mu_{\alpha} \cdot \left[(1 - \lambda_{n'} + \pi_n d_n^{\alpha} - \pi_n d_{ijt}^{n\alpha}) \cdot R_{jt} \right] \cdot \left[q_{ijkt}^{\alpha} - EX_{ijt}^{\alpha} \right] \right] \\ & - \sum_{\alpha \in \Gamma, i \in M} \sum_{f, t} \mu_{\alpha} \cdot h_{if} \cdot I_{ijt}^{\alpha} - \sum_{\alpha \in \Gamma, i \in M} \sum_{f, t} \mu_{\alpha} \cdot \gamma_{if} \cdot B_{ijt}^{\alpha} - \sum_{\alpha \in \Gamma, i \in M} \sum_{r, t} \mu_{\alpha} \cdot Dp_i \cdot DT_{int}^{\alpha} \\ & - \sum_{i \in M} \sum_{f, t} O_{if} \cdot C_{ijt} - \sum_{\alpha \in \Gamma} \sum_{k, r, t} \mu_{\alpha} \cdot f_{C_k} \cdot z_{0krt}^{\alpha} - \sum_{\alpha \in \Gamma} \sum_{(i,j) \in M'} \sum_{k, r, t} \mu_{\alpha} \cdot v_{kr}^{\alpha} \cdot y_{kt}^{\alpha} \cdot c_{ijr} \\ & - \sum_{\alpha \in \Gamma} \sum_{k, r, t} \mu_{\alpha} \cdot f_{Cr_k} \cdot z_{0krt}^{\alpha} - \sum_{\alpha \in \Gamma} \sum_{(i,j) \in M'} \sum_{k, r, t} \mu_{\alpha} \cdot v_{kr}^{\alpha} \cdot y_{kt}^{\alpha} \cdot c_{ijr} \end{aligned} \tag{3-51}$$

$$\begin{aligned}
 \text{Min } f_2 = & \beta_1 \left(0.215 \times \left(\sum_{(i,j) \in M'} \sum_{\alpha \in \Gamma, k, r, t} \mu_\alpha \cdot y_{k\alpha}^{\alpha} \cdot \left(\frac{AVS_{ijk\alpha}}{ATS_{ijk\alpha}} \right)^{7.8} \right) \right) \\
 & + \beta_2 \left(0.215 \times \left(\sum_{(i,j) \in M'} \sum_{\alpha \in \Gamma, k, r, t} \mu_\alpha \cdot y'_{k\alpha}^{\alpha} \cdot \left(\frac{AVS_{ijk\alpha}}{ATS_{ijk\alpha}} \right)^{7.8} \right) \right) \\
 & + \beta_5 \left(\sum_{i \in M} \sum_{\alpha \in \Gamma, f, t} \mu_\alpha \cdot EX_{if\alpha}^{\alpha} \right) + \beta_3 \left(\sum_{(i,j) \in M'} \sum_{\alpha \in \Gamma, k, r, t} \mu_\alpha \cdot \left(\left(\alpha_k + \left[30 \times \left(\log_{10}^{AVS_{ijk\alpha}} \right) \right] \right) \cdot y_{k\alpha}^{\alpha} \right) \right) \\
 & + \beta_4 \left(\sum_{(i,j) \in M'} \sum_{\alpha \in \Gamma, k, r, t} \mu_\alpha \cdot \left(\left(\alpha_k + \left[30 \times \left(\log_{10}^{AVS_{ijk\alpha}} \right) \right] \right) \cdot y'_{k\alpha}^{\alpha} \right) \right)
 \end{aligned} \tag{3-52}$$

S.t.

$$I_{if\alpha}^{\alpha} - B_{if\alpha}^{\alpha} = I_{if(t-1)}^{\alpha} - d_{if\alpha}^{\alpha} + \sum_{k,t'} q_{ijk\alpha}^{\alpha} - EX_{if\alpha}^{\alpha} - B_{if(t-1)}^{\alpha} \quad \forall \alpha \in \Gamma, i \in M, f, t \tag{3-53}$$

$$d_{n-1}^{\alpha} \eta_{n-1}^{\alpha} \leq d_{if\alpha}^{n-1,\alpha} \leq d_n^{\alpha} \eta_{n-1}^{\alpha} \quad \forall \alpha \in \Gamma, i, f, t, n \tag{3-54}$$

$$d_{if\alpha}^{\alpha} = \sum_{n'=1}^{n-1} d_{if\alpha}^{n',\alpha} \quad \forall \alpha \in \Gamma, i, f, t \tag{3-55}$$

$$\sum_{n'=1}^{n-1} \eta_{n'}^{\alpha} = 1 \quad \forall \alpha \in \Gamma \tag{3-56}$$

$$B_{if\alpha}^{\alpha} \geq \sum_k \sum_{t>t'} q_{ijk\alpha}^{\alpha} \quad \forall \alpha \in \Gamma, i \in M, f, t \tag{3-57}$$

$$B_{if\alpha}^{\alpha} \leq G \times \chi_{if\alpha}^{\alpha} \quad \forall \alpha \in \Gamma, i \in M, f, t \tag{3-58}$$

$$I_{if\alpha}^{\alpha} \leq G \times (1 - \chi_{if\alpha}^{\alpha}) \quad \forall \alpha \in \Gamma, i \in M, f, t \tag{3-59}$$

$$\sum_{k,t'} q_{ijk\alpha}^{\alpha} \leq IC_{if\alpha} - I_{if(t-1)}^{\alpha} \quad \forall \alpha \in \Gamma, i \in M, f, t \tag{3-60}$$

$$q_{ijk\alpha}^{\alpha} \leq IC_{if\alpha} \cdot z_{ik\alpha}^{\alpha} \quad \forall \alpha \in \Gamma, i \in M, f, k, r, t, t' \tag{3-61}$$

$$\sum_k \sum_{t>(t+L_f)} q_{ijk\alpha}^{\alpha} \leq EX_{if\alpha}^{\alpha} \quad \forall \alpha \in \Gamma, i \in M, f, t \tag{3-62}$$

$$\frac{\varphi_{it}^{\alpha}}{G} \leq \sum_f EX_{if\alpha}^{\alpha} \leq \varphi_{it}^{\alpha} \cdot G \quad \forall \alpha \in \Gamma, i \in M, t \tag{3-63}$$

$$\frac{C_{if\alpha}}{G} \leq \sum_{k,t'} q_{ijk\alpha}^{\alpha} \leq C_{if\alpha} \cdot G \quad \forall \alpha \in \Gamma, i \in M, f, t \tag{3-64}$$

$$q_{if\alpha} \cdot d_{if\alpha}^{\alpha} \leq \sum_k q_{ijk\alpha}^{\alpha} \quad \forall \alpha \in \Gamma, i \in M, f, t, t' = t \tag{3-65}$$

$$T_{ik\alpha}^{\alpha} + \sum_{f,t'} q_{ijk\alpha}^{\alpha} \cdot sp_k + \left(\frac{c_{ijr}}{AVS_{ijk\alpha}} \right) \leq T_{jk\alpha}^{\alpha} + G(1 - x_{ijk\alpha}^{\alpha}) \quad \forall \alpha \in \Gamma, \forall (i,j) \in M', k, r, t \tag{3-66}$$

$$a_i \leq \sum_k T_{ik\alpha}^{\alpha} \leq (b_i + DT_{ir\alpha}^{\alpha}) \quad \forall \alpha \in \Gamma, i \in M, r, t \tag{3-67}$$

$$GHG_{total}^t \geq \sum_{(i,j) \in M'} \sum_{f,k,r} GHG_k \cdot c_{ijr} \cdot y_{ijkrt}^\alpha + \sum_{(i,j) \in M'} \sum_{f,k,r} GHG_k \cdot c_{ijr} \cdot y_{ijkrt}'^\alpha + \sum_{i \in M} \sum_{f,t} GE \cdot EX_{ift}^\alpha \quad \forall \alpha \in \Gamma, t \quad (3-68)$$

$$\sum_{i \in M} \sum_{f,t} q_{ijkrt}'^\alpha \leq cap_k y_{kt}^\alpha \quad \forall \alpha \in \Gamma, k, t \quad (3-69)$$

$$\frac{z_{0krt}^\alpha}{G} \leq y_{kt}^\alpha \leq z_{0krt}^\alpha G \quad \forall \alpha \in \Gamma, k, r, t \quad (3-70)$$

$$\sum_{i \in M} \sum_f EX_{ift}^\alpha \leq cap_k y_{kt}^\alpha \quad \forall \alpha \in \Gamma, k, t \quad (3-71)$$

$$\frac{z_{0krt}'^\alpha}{G} \leq y_{kt}^\alpha \leq z_{0krt}'^\alpha G \quad \forall \alpha \in \Gamma, k, r, t \quad (3-72)$$

$$\frac{\varphi_{it}^\alpha}{G} \leq y_{kt}^\alpha \leq \varphi_{it}^\alpha G \quad \forall \alpha \in \Gamma, i, k, t \quad (3-73)$$

$$\sum_r x_{ijkrt}^\alpha = 1 \quad \forall \alpha \in \Gamma, (i, j) \in M', k, t \quad (3-74)$$

$$\sum_r x_{ijkrt}'^\alpha = 1 \quad \forall \alpha \in \Gamma, (i, j) \in M', k, t \quad (3-75)$$

$$\sum_{j \in M'} \sum_r x_{ijkrt} = \sum_{j \in M'} \sum_r x_{jikrt} = z_{ikrt} \quad \forall \alpha \in \Gamma, i \in M', k, t \quad (3-76)$$

$$\sum_{j \in M'} \sum_r x_{0jkrt}'^\alpha = \sum_{j \in M'} \sum_r x_{j0krt}^\alpha = z_{0krt}'^\alpha \quad \forall \alpha \in \Gamma, k, t \quad (3-77)$$

$$\sum_{r,k} z_{ikrt}^\alpha \leq 1 \quad \forall \alpha \in \Gamma, i \in M, t \quad (3-78)$$

$$\sum_{i,k,r} x_{0ikrt}^\alpha \geq 1 \quad \forall \alpha \in \Gamma, t \quad (3-79)$$

$$\sum_{i,k,r} x_{i0krt}^\alpha \geq 1 \quad \forall \alpha \in \Gamma, t \quad (3-80)$$

$$\sum_{r,k} z_{ikrt}^\alpha \leq 1 \quad \forall \alpha \in \Gamma, i \in M, t \quad (3-81)$$

$$\sum_{i,k,r} x_{0ikrt}'^\alpha \geq 1 \quad \forall \alpha \in \Gamma, t \quad (3-82)$$

$$\sum_{i,k,r} x_{i0krt}'^\alpha \geq 1 \quad \forall \alpha \in \Gamma, t \quad (3-83)$$

$$\frac{\varphi_{it}^\alpha}{G} \leq x_{i0krt}^\alpha \leq \varphi_{it}^\alpha G \quad \forall \alpha \in \Gamma, i \in M, k, r, t \quad (3-84)$$

$$\frac{\varphi_{it}^\alpha}{G} \leq x_{0ikrt}'^\alpha \leq \varphi_{it}^\alpha G \quad \forall \alpha \in \Gamma, i \in M, k, r, t \quad (3-85)$$

$$\frac{\varphi_{it}^\alpha}{G} \leq z'_{ikrt}^\alpha \leq \varphi_{it}^\alpha G \quad \forall \alpha \in \Gamma, i \in M, k, r, t \quad (3-86)$$

$$\frac{x_{ijkrt}^\alpha}{G} \leq y_{kt}^\alpha \leq x_{ijkrt}^\alpha G \quad \forall \alpha \in \Gamma, (i, j) \in M, k, r, t \quad (3-87)$$

$$\frac{x'_{ijkrt}}{G} \leq y'_{kt}^\alpha \leq x'_{ijkrt} G \quad \forall \alpha \in \Gamma, (i, j) \in M, k, r, t \quad (3-88)$$

$$x_{ijkrt}^\alpha, x'_{ijkrt}, z_{ikrt}^\alpha, z'_{ikrt}, \varphi_{it}^\alpha, \chi_{ijt}^\alpha, \eta_n^\alpha \in \{0, 1\} \quad \forall \alpha \in \Gamma, (i, j) \in M, f, k, r, t, i \neq j \quad (3-89)$$

$$q_{ijkrt}^\alpha, I_{ijt}^\alpha, B_{ijt}^\alpha, EX_{ijt}^\alpha, y_{kt}^\alpha, y'_{kt}^\alpha, T_{ikrt}^\alpha, DT_{irt}^\alpha, d_{ijt}^{n'\alpha} \geq 0, \text{ Integer} \quad \forall \alpha \in \Gamma, i \in M, f, k, r, t \quad (3-90)$$

3.3.2 Multi-Objective Simulated Annealing (MOSA)

The aim of this section is to provide the resolution approach we use to deal with the two objectives of our IRP. Several resolution approaches exist to optimize multi-objective problems, including the conversion of the multi-objective problem into a single objective one by using techniques such as objective weighting, distance functions and Min-Max formulation (Srinivas & Deb 1994). In such a resolution approach, the final result is a single point solution while the decision maker might need to select a solution among many possible alternatives providing different trade-offs between the different objectives. To tackle such an issue, the second set of resolution approaches attempts to find a set of optimal solutions (optimal Pareto) which cannot be dominated by other solutions and which could be more useful in decision making. The decision maker could choose the best solution from the proposed set, based on her/his point of view on the trade-off between the different objectives.

Smith, Everson, & Fieldsend (2004) proposed a meta-heuristic, entitled the Multi-Objective Simulated Annealing (MOSA), to solve multi-objective problems. The algorithm principle is to accept worse solutions with predefined probability in order to avoid being trapped in a local optimum. Simulated Annealing (SA) is inspired from annealing in solids (Metropolis et al. 1953) and was first applied in optimization by Kirkpatrick, Gelatt, & Vecchi (1983). These authors (Kirkpatrick et al. 1983) showed how the principle could be applied in optimization problems where the value of the objective function corresponded in energy to the states of the solids. This algorithm starts with a random initial solution and in each iteration, a new solution is created from the neighborhood of the current solution by some specific mutation strategies. Afterwards, the new solution is compared with the current one and the domination is checked. In case of no domination, the new solution is added to the representative solutions and the search procedure continues with the new iteration. In case of domination, the new worst solution is added to the representative solution with a predefined small

probability. The search procedure continues until the stopping criterion is reached (Mohammadi et al. 2014). Due to the fact that this algorithm is based on annealing in solids, in each iteration an annealing schedule is defined to decrease the temperature of the algorithm (Niakan et al. 2016).

For this purpose, we add equations (3-91) to (3-95) to calculate the initial and final temperature, the accepting probability of the worse solution and the update of the temperature in each iteration. We use equation (3-91) to decrease the algorithm temperature in each iteration where T_{it} is the temperature in each iteration and ω defines the cooling rate. Equation (3-92) calculates the initial temperature T_0 where f_1 and f_2 address the objective functions values of the initial solution. In order to calculate the stopping criterion, we use equation (3-93) to calculate the value of the final temperature T_z where θ defines the power value to obtain the final temperature. Finally, equations (3-94) and (3-95) are used to calculate the accepting probability of the worst solution where f_{1N} and f_{2N} present the objective functions values of the new solution and ρ is the accepting probability. It is noteworthy that reaching the final temperature is selected as a finishing criterion.

$$T_{it} = \omega \times T_{it-1} \quad (3-91)$$

$$T_0 = f_1 + f_2 \quad (3-92)$$

$$T_z = 10^{-\theta} \times T_0 \quad (3-93)$$

$$\rho = e^{-\frac{\Delta f}{T_{it}}} \quad (3-94)$$

$$\Delta f = \left| \frac{(f_{1N} - f_1)}{f_{1N}} + \frac{(f_{2N} - f_2)}{f_{2N}} \right| \quad (3-95)$$

3.4 Experimental results

The aim of this section is twofold. We first show the applicability of our IRP framework from a numerical point of view. We then provide some managerial insights resulting from our numerical analysis. We consider different numerical problems with different problem sizes (presented in Chapter 2, Table 2.1). The parameters are generated randomly according to a uniform distribution, as illustrated in Tables 2.2 and 2.3 in Chapter 2. In addition to presented uniform distribution in Chapter 2, value of holding cost (h_{if} (€)) and delay cost (DP_i (€)) are generated based on $U \sim [10, 20]$ as uniform distribution.

Moreover, the constant parameter related to each type of vehicle (α_k) is extracted from the investigation of Y Oshino, S Kono, T Iwase, H Ohnishi, T Sone (2000).

Table 3.1 Value of vehicle noise emission parameter

Vehicle type	α_k
<i>Small</i>	47.6
<i>Medium</i>	51.5
<i>Large</i>	54.4

In Table 3.2, we present the four scenarios under study concerning the demand uncertainty with the probability associated with each scenario. Table 3.3, presents the uncertainty parameters for each scenario, regarding the transportation per type of vehicle (variable transportation cost, average traffic and vehicle speed). It is noteworthy that the probability of each scenario illustrates its importance. We assume four scenarios, where we consider the worst case, the best case and two most probabilistic cases.

Table 3.2 Probability of scenarios and demand information

Scenario No.	Probability of scenario	Demand
1	0.40	$\sim U[1,4]$
2	0.15	$\sim U[7,12]$
3	0.25	$\sim U[3,7]$
4	0.20	$\sim U[5,10]$

Table 3.3 Parameters of vehicle and route in different scenarios

Scen. No.	Vehicle Parameter	Vehicle Type (urban route)			Vehicle Type (ring road)		
		Small	Medium	Large	Small	Medium	Large
1	v_{kr} (€)	~U[15,20]	~U[30,35]	~U[50,55]	~U[10,15]	~U[20,25]	~U[30,35]
	vr_{kr} (€)	~U[4,8]	~U[5,15]	~U[10,20]	~U[3,5]	~U[8,11]	~U[10,15]
	AVS_{ijklrt} (km/h)	~U[60,65]	~U[55,65]	~U[50,60]	~U[75,85]	~U[70,80]	~U[70,75]
	ATS_{ijklrt} (km/h)	~U[55,65]	~U[55,65]	~U[55,65]	~U[70,85]	~U[70,85]	~U[70,85]
2	v_{kr} (€)	~U[12,16]	~U[25,30]	~U[40,45]	~U[9,13]	~U[15,20]	~U[25,30]
	vr_{kr} (€)	~U[2,5]	~U[7,13]	~U[15,25]	~U[1,4]	~U[3,10]	~U[10,20]
	AVS_{ijklrt} (km/h)	~U[60,70]	~U[60,70]	~U[55,65]	~U[75,80]	~U[70,75]	~U[65,70]
	ATS_{ijklrt} (km/h)	~U[55,70]	~U[55,70]	~U[55,70]	~U[65,80]	~U[65,80]	~U[65,80]
3	v_{kr} (€)	~U[18,25]	~U[20,25]	~U[45,55]	~U[5,15]	~U[10,25]	~U[30,40]
	vr_{kr} (€)	~U[6,10]	~U[8,11]	~U[10,15]	~U[4,7]	~U[6,9]	~U[9,13]
	AVS_{ijklrt} (km/h)	~U[55,60]	~U[50,60]	~U[50,55]	~U[80,90]	~U[75,80]	~U[70,78]
	ATS_{ijklrt} (km/h)	~U[50,60]	~U[50,60]	~U[50,60]	~U[75,90]	~U[75,90]	~U[75,90]
4	v_{kr} (€)	~U[25,30]	~U[25,45]	~U[52,57]	~U[20,25]	~U[25,30]	~U[35,45]
	vr_{kr} (€)	~U[7,11]	~U[10,15]	~U[15,20]	~U[2,7]	~U[5,8]	~U[7,16]
	AVS_{ijklrt} (km/h)	~U[50,55]	~U[45,50]	~U[45,50]	~U[65,70]	~U[60,65]	~U[57,63]
	ATS_{ijklrt} (km/h)	~U[45,55]	~U[45,55]	~U[45,55]	~U[60,70]	~U[60,70]	~U[60,70]

3.4.1 Parameter setting

Selecting the value of the MOSA parameters has an important impact on the performance of the resolution algorithm. For this reason, we applied the Taguchi method to tune the related parameters. Taguchi proposes two main categories of factors: controllable, and noise. The noise factors are out of control and their elimination is often impossible. The method attempts to find the optimal level of controllable factors by minimizing the effect of noise factors (Chatsirirungruang 2009). In order to use the Taguchi method in this study, the spacing metric is selected as a response for evaluation of the optimal results. The value of SM is calculated by equation (3-96) where d_i measures the Euclidian distance between consecutive solutions, \bar{d} is the average of all d_i , and n denotes the number of members in the final solutions.

$$SM = \frac{\sum_{i=1}^{n-1} |\bar{d} - d_i|}{(n-1)\bar{d}} \quad (3-96)$$

In this study, two critical parameters of the proposed algorithm (ω : cooling rate, θ : power value to calculate final temperature) are considered and three levels for each factor are determined (Table 3.4). Additionally, Table 3.5 presents the combination of experiments and the answers obtained to tune the parameters. According to Figure 3.2, the best levels of the parameters are selected as follows: second level of cooling rate (0.6) and third level of θ (9). It is noteworthy that the Taguchi method is applied on Minitab software.

Table 3.4 Parameters setting

Factors	Proposed level		
	1	2	3
ω	0.4	0.6	0.8
θ	5	7	9

Table 3.5 Parameter configuration and values obtained in Taguchi design experiments

Experiments	Coded levels		Uncoded levels		Response
	ω	θ	ω	θ	
1	1	1	0.4	5	0.890
2	1	2	0.4	7	1.007
3	1	3	0.4	9	0.865
4	2	1	0.6	5	0.931
5	2	2	0.6	7	0.891
6	2	3	0.6	9	0.849
7	3	1	0.8	5	0.942
8	3	2	0.8	7	0.861
9	3	3	0.8	9	0.992

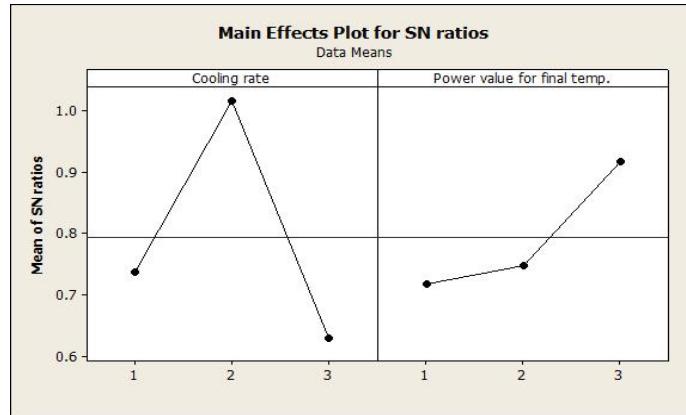


Figure 3.2 Signal to noise ratio for each level of the parameters

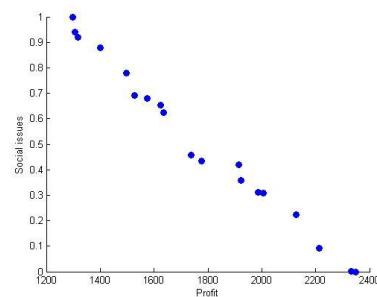
3.4.2 Computational results

In order to show the applicability of our IRP, some experiments are presented in this section. The problems are solved by the MOSA algorithm, which is tuned for this problem. Finally, a set of solutions called the Pareto frontier is obtained. The Pareto set of bi-objective problems contains two important points or solutions with an optimum level for each objective function. In this problem, solution A is an optimum value of profit objective (Z_1) and solution B is the optimum value of the social issues (Z_2).

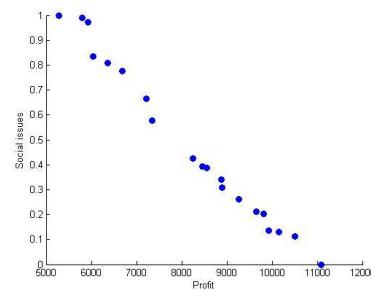
In the following, the results associated with problems 3, 7, 11 and 15, which are representative of different sizes and are solved in the stochastic model, are presented in Table 3.6. Note that because the value of the second objective function is normalized, its reported value in Table 3.6 is zero or one. Moreover, since the value of the second objective function (Z_2) presents barriers relating to social issues, in this section the value of social issues ($1-Z_2$) is presented. Figure 3.3 illustrates the obtained Pareto solutions for the four problem instances. Providing the obtained optimal Pareto frontier is a better way to increase the decision maker's ability to select a solution among the Pareto by considering his/her own judgment on the priority of each objective function.

Table 3.6 The best value of each objective in the final Pareto

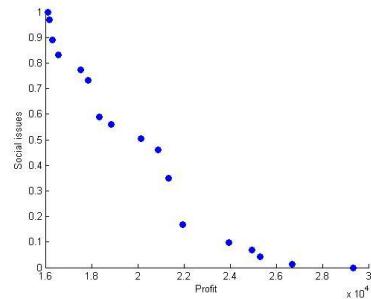
Problem No.	OF	The best solutions		CPU time (s)
		Solution A	Solution B	
3	Z_1	2,349.00	1,297.00	90.47
	Z_2	0.00	1.00	
7	Z_1	11,094.00	5,286.00	521.49
	Z_2	0.00	1.00	
11	Z_1	29,348.00	16,104.00	973.51
	Z_2	0.00	1.00	
15	Z_1	140,721.00	62,701.00	1737.42
	Z_2	0.00	1.00	



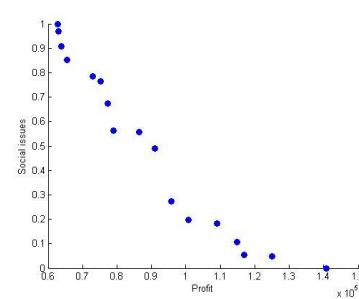
(a) Pareto frontier of problem No. 3



(b) Pareto frontier of problem No. 7



(c) Pareto frontier of problem No. 11



(d) Pareto frontier of problem No. 15

Figure 3.3 Optimum Pareto solutions of four instances problems

The analysis of the two best solutions A (Z_1) and B (Z_2), associated with problem No.11 shows that a manager can reach the best level in the social criterion by scarifying 45% of the profit. However, a 45% profit reduction is a steep slope, and a manager cannot make a big change in the profits of a system. Our framework enables one to link the achieved profit with the realized social issues and to help the decision maker to judgmentally select the best tradeoff. For instance, we analyze the obtained Pareto frontier of problem No. 11 in order to deduce the set of solutions where a small variation of the profit has a significant

impact on the social issue. Table 3.7 illustrates the loss in profit as a function of the social issue improvement for problem No. 11. According to this table, in the set of solutions 6, 7, 10, 11 and 12, the social issue can be improved by approximately 19% to 31% with less than 5% decrease in the profit. This set of solutions is valuable solutions for companies that are faced with pressure from governmental and non-governmental agencies to consider social issues, and that want to postpone their corrective actions in order to improve social criteria. We refer to this set of solutions as the “solutions with priority 1”.

In contrast to this set of solutions, there is another set where a small improvement of the social issues needs a significant impact on profits. This set of solutions needs to be avoided. According to Table 3.7, in solutions 13, 14, 15, 16 and 17 the social issues can be improved by less than 5% while the profit needs to be reduced by approximately 18%. We refer to these solutions as the “solutions with priority 3“.

There are also other sets of solutions (1,2,3,4,5,8 and 10) which show that slopes of lost profits and social improvement are appropriate relative to each other. In this set of solutions, the value of social issues can be improved by 7% to 13% by reducing profits by a maximum of 8%. We refer to this set of solutions as the “solutions with priority 2”. Figure 3.4 shows the optimal Pareto frontier for problem No.11, considering high and low priority of solutions.

Table 3.7 Lost profit against social improvement (Problem No.11)

No. Solution	%lost profit	%social improvement	No. Solution	%lost profit	%social improvement
1(SolutionA)			10		
2			11	4.82	31.11
3	8.13	12.53	12		
4			13		
5			14		
6	2.66	19.51	15	18.34	4.02
7			16		
8	6.32	7.01	17(Solution B)		
9					

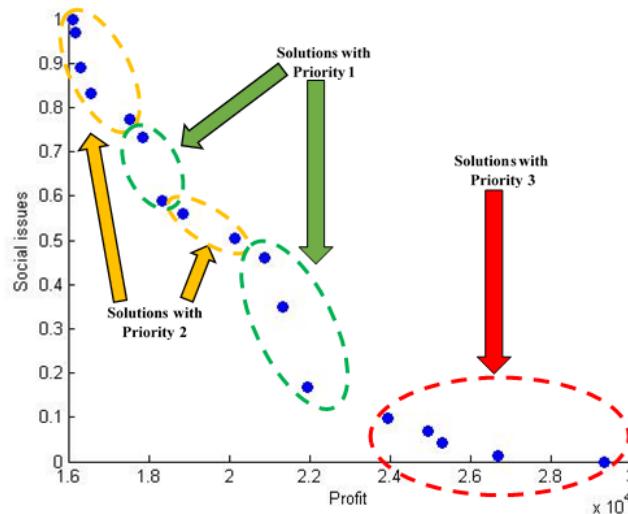


Figure 3.4 Classification of solutions considering amount of variation of each solution (Problem No.11)

As explained in Chapter 2, Section 2.4.2, in addition to best solutions, another one could consider which referred as the compromise solution. For this purpose, we need to define the ideal solution, which is at the intersection between the two extreme solutions and provides the best values for Z_1 and Z_2 (Figure 3.5).

In order to find the compromise solution, we need first to normalize the objective functions and to convert their values to a number between 0 and 1. Such normalization is needed because the two objective functions are expressed with different units. Then, as a second step, the Euclidean distance between each solution and the ideal point is calculated, based on equation (2-90). Finally, the solution leading to the lower Euclidean Distance from the ideal point is selected as the compromise solution.

Table 3.8 reports the value of each objective function, the normalized value, and the Euclidean distance of each solution from the ideal point for problem No.11, while Figure 3.5 illustrates the compromise solution in the obtained Pareto frontier for problem No.11. As reported in Table 3.8, the solution No. 10 is the compromise. It has a profit of 20,898 and a social criterion of 0.539. It corresponds to the closest solution to the ideal point and could be chosen by the decision maker.

Table 3.8 Euclidean distance of objective functions and ideal point (Problem No. 11)

Solution No.	OFV		Normalized OFV		Euclidean distance
	Profit	Social	Profit	Social	
1	16,104	1.000	0.000	1.000	1.0000
2	16,169	0.970	0.005	0.970	0.9956
3	16,308	0.891	0.015	0.891	0.9907
4	16,580	0.833	0.036	0.833	0.9785
5	17,530	0.774	0.108	0.774	0.9206
6	17,842	0.733	0.131	0.733	0.9088
7	18,329	0.590	0.168	0.590	0.9274
8	18,858	0.560	0.208	0.560	0.9061
9	20,132	0.505	0.304	0.505	0.8537
10	20,898	0.461	0.362	0.461	0.8355
11	21,334	0.348	0.395	0.348	0.8894
12	21,956	0.168	0.442	0.168	1.0021
13	23,966	0.098	0.594	0.098	0.9895
14	24,948	0.069	0.668	0.069	0.9890
15	25,299	0.042	0.694	0.042	1.0053
16	26,679	0.013	0.798	0.013	1.0076
17	29,348	0.000	1.000	0.000	1.0000

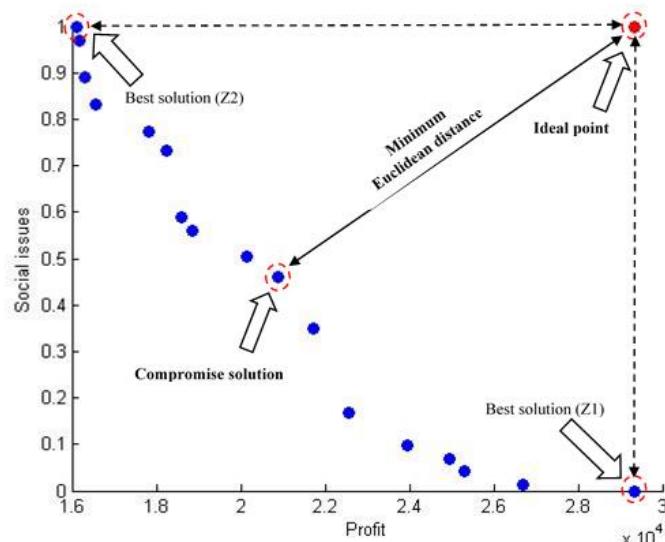


Figure 3.5 Compromise and ideal point (Problem No.11)

In the following, we assessed the performance of the proposed stochastic model. For this purpose, we solved both the deterministic and the stochastic models with the proposed MOSA algorithm. The solutions of the two models were assessed under each scenario by allowing the models to update their decision variables on the quantities of products delivered to each retailer. It should be mentioned that

the routing variables cannot be changed. This strategy is used to enable the models to satisfy the demands in each scenario and therefore to avoid infeasibility when the capacities and number of vehicles are sufficient to satisfy the demand. The above description of the performance of the deterministic and stochastic models under each scenario is reported in Tables 3.9 and 3.10.

The results show that the stochastic model determined the number of vehicles and the routing in a way that could satisfy all the scenarios. More vehicles were therefore used compared to the deterministic model. The lower profit of the stochastic model compared with the deterministic model also confirms this idea (Tables 3.9 and 3.10). In other words, the stochastic model obtained solutions that are immunized against (feasible for) all of the scenarios, and it can handle uncertainty in a desirable way with a reasonable increase in total cost (decrease in profit) compared with the deterministic model. It is obvious from Tables 3.9 and 3.10 that the deterministic model obtained more efficient solutions for nominal data (scenario 1); however, it results in infeasible solutions for all the other scenarios except for scenario 3 of problem No. 7 and the last scenario of problem No. 3. We can thus conclude that the deterministic model is unable to handle data uncertainty.

The value of the objective functions in Tables 3.9 and 3.10 shows that the amount of profit in the stochastic model is lower compared with the deterministic model. The reason has already been discussed in this section. The difference of the optimal objective function value under nominal data between the stochastic and the deterministic models is the price that is paid to avoid infeasibility or to ensure feasibility under all scenarios.

Table 3.9 Computational results under scenarios with best Z1

Problem No.	Scenario No.	Deterministic		Stochastic	
		Z1	Z2	Z1	Z2
3	1	2,905	0.000	2,478	0.231
	2	Infeasible	Infeasible	2,592	0.000
	3	Infeasible	Infeasible	2,531	0.171
	4	2,739	0.029	2,375	0.044
7	1	16,735	0.000	9,189	0.412
	2	Infeasible	Infeasible	13,351	0.302
	3	19,082	0.169	10,021	0.120
	4	Infeasible	Infeasible	14,872	0.000
11	1	33,605	0.000	20,391	0.029
	2	Infeasible	Infeasible	17,804	0.210
	3	Infeasible	Infeasible	24,527	0.139
	4	Infeasible	Infeasible	30,748	0.063
15	1	173,927	0.000	156,967	0.338
	2	Infeasible	Infeasible	127,019	0.623
	3	Infeasible	Infeasible	149,958	0.531
	4	Infeasible	Infeasible	167,341	0.000

Table 3.10 Computational results under scenarios with best Z2

Problem No.	Scenario No.	Deterministic		Stochastic	
		Z1	Z2	Z1	Z2
3	1	1,593	1.000	1,138	0.752
	2	Infeasible	Infeasible	1,452	1.000
	3	Infeasible	Infeasible	1,980	0.870
	4	1,086	0.727	891	0.557
7	1	7,892	1.000	8,451	0.793
	2	Infeasible	Infeasible	9,284	0.659
	3	3,552	0.759	6,804	0.901
	4	Infeasible	Infeasible	3,629	0.582
11	1	16,832	1.000	16,194	0.829
	2	Infeasible	Infeasible	10,582	1.000
	3	Infeasible	Infeasible	14,804	0.978
	4	Infeasible	Infeasible	19,351	0.748
15	1	57,345	1.000	79,724	0.702
	2	Infeasible	Infeasible	68,026	0.872
	3	Infeasible	Infeasible	88,397	1.000
	4	Infeasible	Infeasible	102,732	0.552

As mentioned above, the price of robustness is an important issue, and managers could choose to pay this price to reduce the risk of infeasibility in various situations. Figure 3.6 shows Pareto solutions of problem No. 11 for deterministic and stochastic models. In this figure, the presented risk is demonstrated and the value of this risk is 13% for profit (Z1) and 11% for social issues (Z2). This means if decision makers ignore 13% of best profits and 11% of social issues in a deterministic situation, they could obtain a robust solution that is feasible in different scenarios.

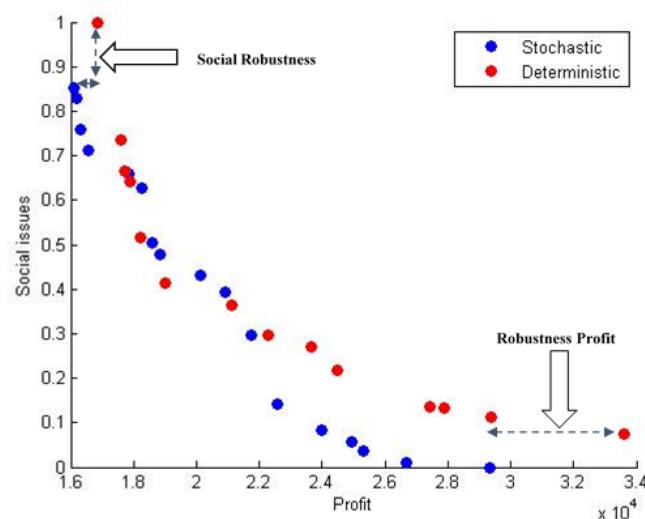


Figure 3.6 Robustness risk in the obtained optimal Pareto frontier (Problem No. 11)

In the following, we perform a sensitivity analysis for problem No.11 under the stochastic case. This analysis is related to the impact of variable transportation costs on the first and second objective functions. It shows that a decrease in the variable transportation cost in the urban routes leads to an increase in the value of the social criterion and in the profit.

As noted above, the variable transportation cost on urban routes is higher than the cost on ring roads, while the vehicle speed on ring roads is higher than on urban routes. Therefore, by decreasing the variable transportation cost on urban routes, the model attempts to use these routes instead of ring roads. Using urban routes with a lower transportation cost leads to an increase of the profit and to a decrease of the accident rate and vehicle noise emissions (increasing social criterion). This trend shows that if decision makers could decrease by 10% the variable transportation cost of urban routes, they would be able to improve the social criterion by 11% and the profit by 12% (Figure 3.7). The X-axis of Figure 3.7 presents the increasing variation of the variable transportation cost, in steps of 10%.

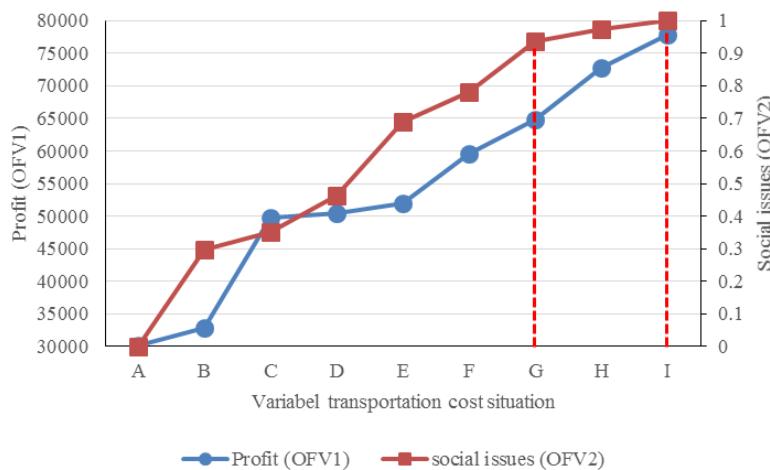


Figure 3.7 Value of first and second objective function against variation of transportation cost on urban routes (Problem No.11)

As shown in Figure 3.7, decreasing variable transportation costs on urban routes cause improvement in the value of social and profits, simultaneously. By considering Figure 3.7, we see that for situations A to G, the social and profit slopes are rather steep since the route selection is changed at these points. However, the slope of the social function is not very sensitive to transportation costs after point G, where profits could be increased by about 20% when social criteria are increased by less than 6%. This situation is due to the difference between transportation costs on urban routes and ring roads after point G disappears. In this case, the selection of each type of route does not have a significant effect on the value of social criteria. In other words, decreasing

transportation costs has a meaningful impact in improvement of social issues insofar as there is a gap between the costs of various routes.

3.5 Conclusion

This study examines a new sustainable inventory routing problem for distribution of perishable products, a subject that is largely overlooked in the literature on IRP. In this context, a bi-objective mathematical model is developed. The first objective of this model is to maximize the profit calculated by the sales revenue minus various inventory and distribution costs. A non-linear quantity discount function is also integrated into the calculation of profits to encourage customers to increase their orders. The second objective is to maximize the social issues measured by the rates of accidents, vehicle noise emissions and numbers of expired products, indirectly affecting the number of trips. Reverse logistics are also involved in the proposed model because of the need to collect the expired products from retailers and to return them to the supplier.

To cope with the uncertainty in the presented sustainable IRP, this paper proposes a scenario-based stochastic optimization model to develop and obtain the stochastic counterpart of the model. Some examples inspired from real cases have been generated and solved to support the design of a specific multi-objective simulated annealing. The results show the advantage of the proposed approach in handling the uncertain parameters and robustness of the solutions obtained, in comparison with the deterministic model. Despite the deterministic model, the stochastic model could reach appropriate solutions for all different scenarios. Finally, in order to find the trade-off between economic and social issues, and based on an analysis of the results, some managerial insights have been proposed.

4

Dynamic stochastic inventory routing problem for perishable products considering sustainable issues

4 Dynamic stochastic inventory routing problem for perishable products considering sustainable issues

4.1 Motivation

Decision makers these days need to rely on real-time information to make key business decisions in IRPs. The wrong or old information causes different problems such as shifts in demand, traffic caused by sudden accidents with vehicles, etc. The sharing of updated and reliable logistic information can meaningfully improve the efficiency of IRPs. In this chapter, we are going to investigate impact of using real-time information in the inventory routing problems.

Based on our litterateur review in Chapter 1, demand is the unique parameter that the researchers considered in dynamic optimization. In this way, we can deal with only inventory side of IRP while volume of traffic in the routes is also another parameter which has direct effect in routing and should be considered in dynamic optimization. We cannot predict the real condition of traffic beforehand and we need to update our routing based on real time information. For this reason, in this chapter, we take into account demand variation and traffic condition as two key parameters in dynamic optimization while have direct effect on both inventory and routing aspects of IRP.

This paper contributes to the existing literatures in the following issues.

- In contrast to previous studies that only considered the demand in dynamic optimization, we take into account information on the variation of demand and on traffic as two parameters for dynamic optimization.
- A re-optimization strategy is defined to study the effect of using real-time information in the proposed problem. The general idea of this strategy is to optimize the model and to find the initial solutions where the value of uncertain parameters is predicted. We then select the initial solution and re-optimize the problem at each period, based on real time information. The re-optimizing strategy enables us to satisfy all new demands based on updated demand. Moreover, based on updated information about traffic, the initial routing will be re-optimized.
- In addition to dynamic optimization considering real-time information, we consider uncertainty in some parameters in finding the initial

solution. For this purpose, we apply a fuzzy possibilistic approach to predict the value of uncertain parameters.

- Because of the particular nature of IRP in urban logistics, it is important to take into account other criteria such as social and environmental criteria. For this purpose, we develop a bi-objective mathematical model, where the first objective function is to maximize profits, and the second one is to maximize social issues. In this problem the risk of accidents and vehicle noise emissions are considered as two social criteria.
- Finally, we take into account the products' perishability in IRPs. Despite the fact that perishability adds more complexity to the model, the significant role of this type of product should not be overlooked. We assume that expired products should be recycled, which generates an additional cost and an additional GHG emission that should be taken into account in the environmental criteria.

It is necessary to point out that we distinguish between uncertainty and dynamics. In the first step of the proposed algorithm, we consider uncertainty in demand and traffic conditions , modeled by the average speed of a vehicle, to predict their value and find an initial solution. Then, at each period, we re-optimize the problem by considering updated information (real-time information) related to the variation of demand after starting the first routing, and to the last condition of traffic on the routes. In fact, dynamic aspect in this study can be interpreted by re-optimizing the problem in each period, and by taking into account real-time information. Considering the dynamic aspect helps managers to reduce their prediction error when seeking an initial solution.

4.2 Problem formulation

In this chapter, we use the proposed mathematical model in Chapter 3. To simplify the problem, we omit reverse logistics and quantity discount function. In the model, The first objective function maximizes profit of system while second objective function attempts to maximize social issues by minimizing barriers of social issues. The profit is calculated by selling revenue of products decreased by the costs including the holding cost, the backordering cost, the ordering cost, the fixed and variable transportation costs. Besides, the social issues are measured by the accident rate and total produced vehicle noise emission.

The IRP under study in this research can be described as follows. We consider T selling periods where one supplier distributes F perishable products to M retailers. The products could be distributed with three types of vehicle (small,

medium and large) and we assume that two route types (urban route and ring road) could be used to travel between the M retailers.

Due to existing various nonlinear equations in the proposed mathematical model, some linearization methods are applied to obtain its equivalent linear form, as it is explained in Chapter 3, section 3.2.7.

4.3 Resolution approach

To solve the extended IRP model, as a first step, we transfer the original model into an equivalent auxiliary crisp model by applying fuzzy possibilistic approach (Pishvaee & Torabi 2010). We assume that the variable transportation cost, the average vehicle speed and demand are subject to uncertainty and are fuzzy. We define for each uncertain variable s , the pattern set of a triangular fuzzy number (s^p, s^m, s^o) where s^p presents the most pessimistic value, s^m addresses the most likely value, and s^o defines the optimistic value of s . It should be mentioned that in Chapter 2 is shown the efficiency and power of this resolution approach in controlling uncertain parameters in IRPs.

Then, as a second step, in order to solve the equivalent auxiliary crisp model, we apply the NSGA-II proposed by Deb *et al.* (2002) which is previously its efficiency proved in IRP, to solve the proposed model. We selected NSGA-II to have confidence on getting good results while it has been proved as an efficient meta-heuristic for IRPs (Amorim & Almada-Lobo 2014).

4.4 Dynamic strategy

In this section, we introduce the dynamic strategy and algorithm that is defined and applied in this study. In the first step of the proposed algorithm, we optimize the stochastic problem and find the initial solution. In next step, at each period, we re-optimize the problem by considering updated information related to the last condition of traffic on the routes and the variation of demand after the beginning of the first route. The dynamic algorithm contains two main steps: the classification of retailers and re-optimization, which are detailed below and are demonstrated in Figure 4.1.

- Classification of retailers**

In the first step, we classify the retailers in the initial solution. We use Updating Time (UT) at each period for classification, where updating time can be defined by the decision maker. Since each tour in the initial solution contains different retailers, the classification of retailers can be done by the defined tours, which can be classified in three groups. The tours that serve the assigned retailers are complete (finished tours), have not started (not started tours), and are underway

(tours underway). The method of classification is based on comparison between UT and vehicle arriving/leaving time to retailers.

- *Finished tours:* In this group of tours, the vehicle has served all the retailers and has returned to the warehouse. The new demand by these retailers will be satisfied with another vehicle. Equation (4-1) is used to identify which tours are in this category. Based on this equation, the vehicle has left the last retailer of the tour, before updating time.

$$\text{Finished tours: } \max (T_{ikrt} + \sum_{f,t'} q_{ifkt'} \cdot sp_k) < UT \quad (4-1)$$

- *Not started tours:* In this group of tours, considering the initial solution and updating time, the vehicle is scheduled to leave the warehouse and serve the retailers after updating time. In this case, tours will be reorganized based on updated traffic information and a new demand will be satisfied with another vehicle, if necessary. Equation (4-2) is used to identify which tours are in this category.

$$\text{Not started tours: } UT < \min (T_{ikrt}) - \left(\frac{c_{0ir}}{\text{AVS}_{0ikrt}} \right) \quad (4-2)$$

- *Tours underway:* In this group of tours, the vehicle has left the warehouse after updating time while the last retailer has not been served. This means that, at the moment of updating, the vehicle is en route. In this case, the new routing should be defined based on updated traffic conditions, to serve the remaining retailers.

• Re-optimization

After classification of retailers, we need the new distribution plans:

- The new routing plan for vehicles which are on route
- The new distribution plan to satisfy the new demand of retailer

For this purpose, we deal with two new optimization problems to find the new and updated solution.

The one part of re-optimization is related to retailers which are classified in the third category. In fact, the objective of this optimization is to find the best sequence and route type to visit the remaining retailers. In this problem, the vehicle delivers a specific quantity of products to retailers, considering updated traffic conditions (equations (4-3) to (4-12)). In order to find a quick answer during the re-optimization process, we transform our bi-objective model into a mono-objective one, and we transform the second objective into a constraint.

$$\text{Min } f_1 = \sum_{i,j,r} v_r c_{ijr} x_{ijr} + \sum_{i,r} DP_i \cdot DT_{ir} \quad (4-3)$$

S.t.

$$T_{ir} + \sum_f q_{if} \cdot sp + \left[\frac{c_{ijr}}{AVS_{ijr}} \right] \leq T_{jr} + G(1 - x_{ijr}) \quad \forall i, j, r \quad (4-4)$$

$$a_i \leq \sum_k T_{ikr} \leq (b_i + G \cdot DT_{ir}) \quad \forall i, r \quad (4-5)$$

$$\beta_1 \left(0.215 \times \left(\sum_{i,j,r} x_{ijr} \cdot \left(\frac{AVS_{ijr}}{ATS_{ijr}} \right)^{7.8} \right) \right) + \beta_2 \left(\sum_{i,j,r} \left((\alpha + \left[30 \times \left(\log_{10}^{AVS_{ijr}} \right) \right]) \cdot x_{ijr} \right) \right) \leq TS_2 \quad (4-6)$$

$$\sum_r x_{ijr} = 1 \quad \forall i, j \quad (4-7)$$

$$\sum_{j,r} x_{ijr} = \sum_{j,r} x_{jir} = z_{ir} \quad \forall i \quad (4-8)$$

$$\sum_r z_{ir} \leq 1 \quad \forall i \quad (4-9)$$

$$\sum_{i,r} x_{i0r} \geq 1 \quad (4-10)$$

$$x_{ijr}, z_{ir} \in \{0, 1\} \quad \forall i, j, f, r, i \neq j \quad (4-11)$$

$$T_{ir}, DT_{ir} \geq 0, \text{ Integer} \quad \forall i, f, r \quad (4-12)$$

Another part of re-optimization is related to satisfying the retailers' new demand. In this problem. In this problem (equations (4-13) to (4-24)), the supplier uses a fleet of vehicles to deliver the retailers' new order.

$$\text{Max } f_1 = \sum_{i,f,k} R_f \cdot q_{ijk} - \sum_{k,r} fc_k z_{0kr} - \sum_{i,j,k,r} v_{kr} y_k c_{ijr} x_{ijk} - \sum_{i,f} O_{if} C_{if} \quad (4-13)$$

S.t.

$$\sum_{i,f} q_{ijk} \leq cap_k y_k z_{0kr} \quad \forall k, r \quad (4-14)$$

$$T_{ikr} + \sum_f q_{ijk} \cdot sp_k + \left[\frac{c_{ijr}}{AVS_{ijk}} \right] \leq T_{jkr} + G(1 - x_{ijk}) \quad \forall i, j, k, r \quad (4-15)$$

$$\frac{C_{if}}{G} \leq \sum_k q_{ijk} \leq C_{if} G \quad \forall i, f \quad (4-16)$$

$$\beta_1 \left(0.215 \times \left(\sum_{i,j,k,r} x_{ijk} \cdot y_k \cdot \left(\frac{AVS_{ijk}}{ATS_{ijr}} \right)^{7.8} \right) \right) + \beta_2 \left(\sum_{i,j,k,r} \left((\alpha_k + \left[30 \times \log_{10}^{AVS_{ijk}} \right]) \cdot y_k \cdot x_{ijk} \right) \right) \leq TS_1 \quad (4-17)$$

$$\sum_r x_{ijk} = 1 \quad \forall i, j, k \quad (4-18)$$

$$\sum_{j,r} x_{ijk} = \sum_{j,r} x_{jik} = z_{ikr} \quad \forall i, k \quad (4-19)$$

$$\sum_{r,k} z_{ikr} \leq 1 \quad \forall i \quad (4-20)$$

$$\sum_{i,k,r} x_{0ikr} \geq 1 \quad (4-21)$$

$$\sum_{i,k,r} x_{i0kr} \geq 1 \quad (4-22)$$

$$x_{ijk}, z_{ikr}, C_{if} \in \{0, 1\} \quad \forall i, j, f, k, r, i \neq j \quad (4-23)$$

$$q_{ijk}, y_k, T_{ikr} \geq 0, \text{ Integer} \quad \forall i, f, k, r \quad (4-24)$$

Figure 4.1 illustrates several steps of the re-optimization process by the proposed dynamic algorithm.

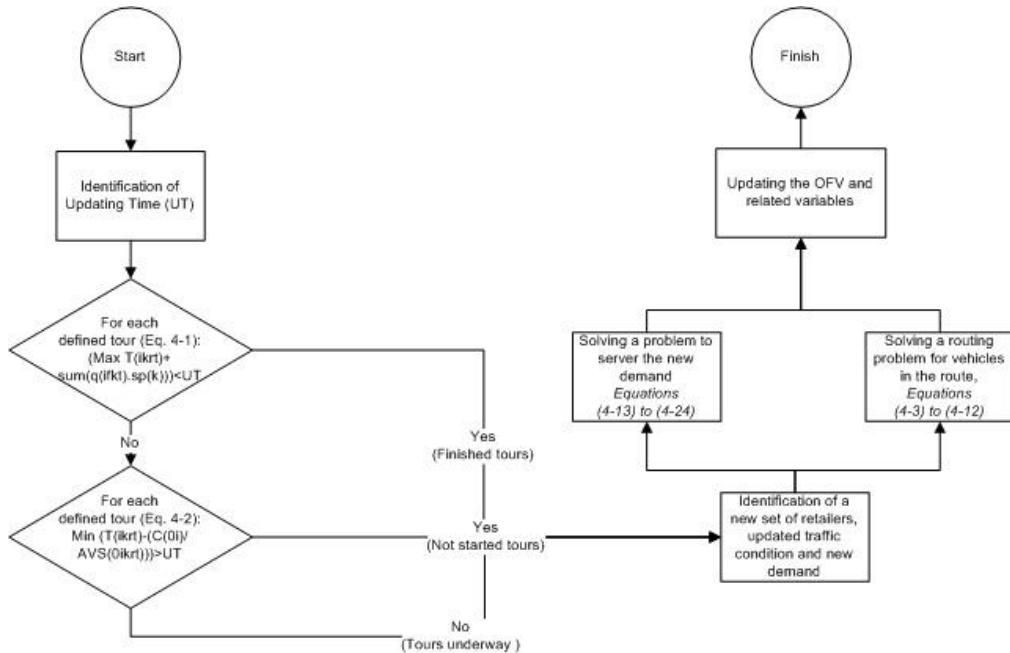


Figure 4.1 Dynamic algorithm

4.5 Experimental results

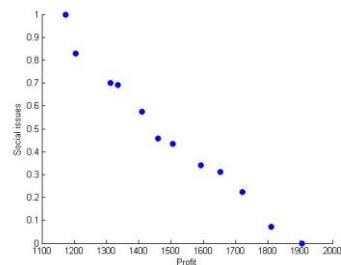
In this section, we show the applicability of proposed dynamic stochastic IRP framework from a numerical point of view. For this purpose, we use the instance problems, which are generated in Chapters 2 and 3.

After verification of feasibility, some experiments are presented to prove the applicability of the proposed dynamic stochastic IRP. We first solve the problem without considering the re-optimization algorithm. As a result, a set of solutions referred to as the Pareto frontier is obtained. We denote as solution "A" the optimum value associated with the profit objective (Z_1) and solution "B" as the optimum value of the social issues (Z_2). The results associated with problems 3, 7, 11 and 15, which are representative of different sizes, are presented in Table 4.1. Since the value of the second objective function (Z_2) presents barriers relating to social issues, the value of social issues ($1-Z_2$) is presented in this section. Figure 4.2 illustrates the obtained Pareto solutions for the four problem instances.

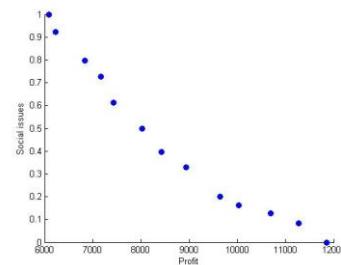
The analysis of the two best solutions A (Z_1) and B (Z_2), associated with problem No.11 shows that a manager can reach the best level in the social criterion by sacrificing 33% of the profit. However, a 33% profit reduction is a steep slope, and a manager cannot make a big change in the profits of a system. In fact, we did this analysis to show the trade-off between profit and social criteria, and the impact of social issues on IRPs.

Table 4.1 The best value of each objective in static situation

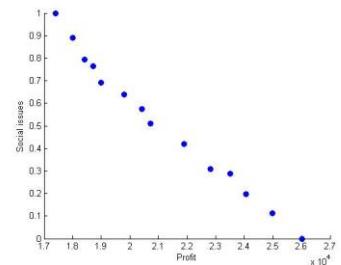
Problem No.	OF	The best solutions		CPU time (s)
		Solution A	Solution B	
3	Z ₁	1,905.00	1,173.00	48.43
	Z ₂	0.00	1.00	
7	Z ₁	11,852.00	6,084.00	379.01
	Z ₂	0.00	1.00	
11	Z ₁	26,018.00	17,403.00	842.35
	Z ₂	0.00	1.00	
15	Z ₁	143,196.00	74,379.00	1408.46
	Z ₂	0.00	1.00	



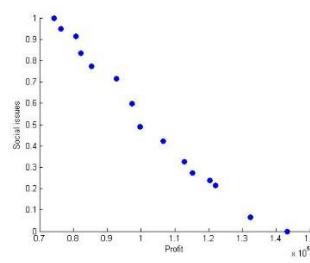
(a) Pareto frontier of problem No. 3



(b) Pareto frontier of problem No. 7



(c) Pareto frontier of problem No. 11



(d) Pareto frontier of problem No. 15

Figure 4.2 Optimum Pareto solutions of four instances problem in static situation

After solving the static problem or first optimization, we select solution A (best profit) as an initial solution and apply the described dynamic algorithm. The results are reported in 4.2 and 4.3.

Table 4.2 Computational results under static and dynamic models (best profit)

Prob. No.	Static model		Dynamic model		$\Delta\%$		CPU time (s)
	Z1	Z2	Z1	Z2	% profit improvement	% Lost social	
3	1,905.00	0.11	2,049	0.00	7.56	9.69	87.42
7	11,852	0.15	12,674	0.00	6.93	14.23	590.88
11	26,018	0.19	29,209	0.00	12.26	11.79	1105.58
15	143,196	0.22	161,915	0.00	13.07	16.37	1797.49

In the Table 4.2, value of profit and social issue are compared for both static and dynamic models. As shown in this table, for example for problem No.11, the decision maker deals with 12.26% improvement in the profit by taking into account the dynamic strategy. Moreover, we define a performance measurement for dynamic strategy based on new demands that could be considered as backordered in the static model and are satisfied in the dynamic model. This index is measured using equation (4-25) where d_{ift} is the quantity of predictive demand in the static model and nd_{ift} is the quantity of new demand.

$$\text{Dynamic index} = \frac{\sum_{i,f,t} nd_{ift}}{\sum_{i,f,t} (d_{ift} + nd_{ift})} \quad (4-25)$$

Table 4.3, illustrates the value of predictive and new demands as well as the dynamic index. As shown in this table, for problem No. 11, by considering the dynamic strategy, the decision maker is able to satisfy the 19.79% new demand, which was backordered in the static model. To conclude, Tables 4.2 and 4.3, show that the dynamic strategy increases the decision maker's ability to avoid 19.79% of backordered products and to have a better fill rate while system profit improves by 12.26%.

The results show that a dynamic management is more efficient than the static one. The decision maker is able to avoid large backorders, which has a direct effect on the fill rate and customer satisfaction.

Table 4.3 Value of dynamic index

Problem No.	Predictive demand (Static)	New demand (Dynamic)	Dynamic index
3	97	29	23.01%
7	520	251	32.55%
11	5,295	1,307	19.79%
15	10,637	3,249	23.40%

Another important point concerns the impact of traffic conditions in dynamic strategy. Figure 4.3 depicts the configuration of two selected tours from one period of problem No.11 in two different scenarios. The first situation is related to the initial solution (static model) and the second scenario shows the configuration of tours obtained when a dynamic strategy is applied considering the updated traffic conditions.

This figure shows that applying a dynamic strategy considering traffic conditions causes significant changes in the configuration of the retailers still to be visited. In scenario (i), after updating time, a medium-size vehicle serves retailer number 3 and then 4, and finally returns to the warehouse. The new configuration created by applying updated traffic conditions results in another routing plan. In this case, after serving retailer 2, retailer 4 should be visited using a type-2 route, then retailer 3 by a type-1 route, before returning to the warehouse by a type-2 route.

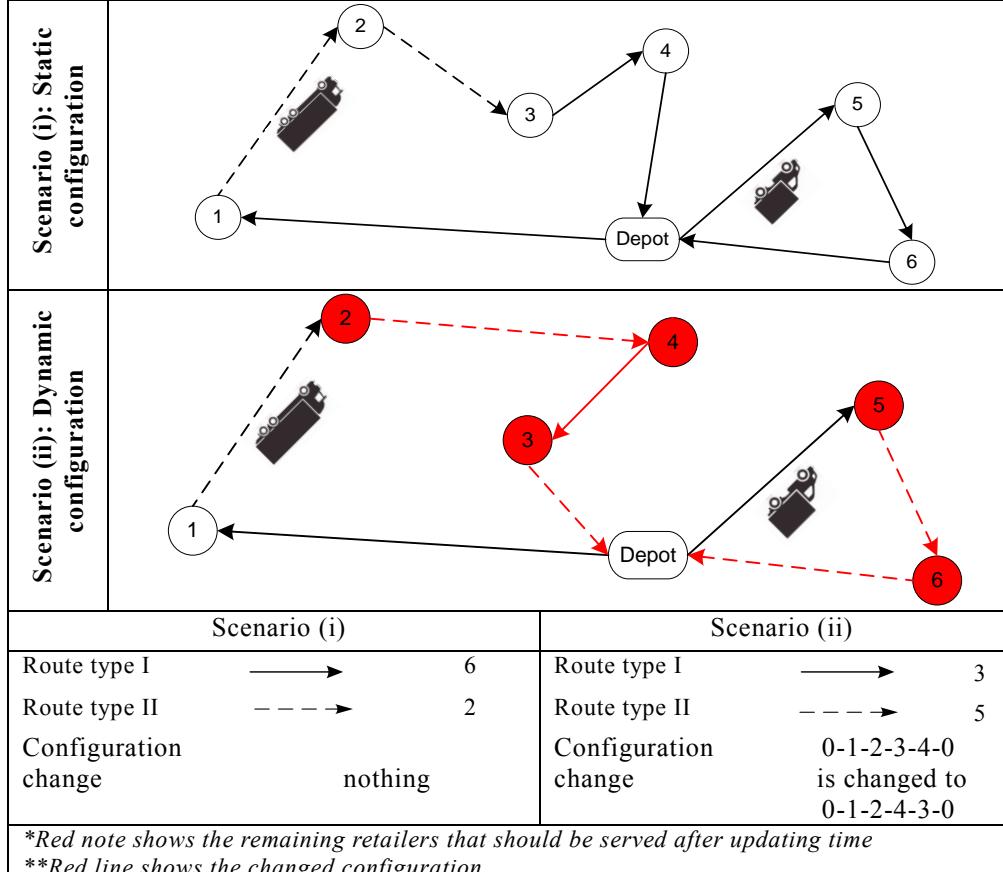


Figure 4.3 Schematic of configuration for two static and dynamic situations (One period of problem No.11)

This figure shows that taking traffic conditions into account considerably influences the trip configuration and route selection. Since changing the trip configuration and type of route have a direct effect on the value of social issues and on profits, the decision maker has to take traffic conditions into account to avoid the additional cost due to delays.

Table 4.4, addresses variations of transportation costs, delay penalty and social issues, related to situations under consideration. As we can see, applying updated traffic information causes more type-2 routes to be used, where the cost of using this type of route is lower than others. Moreover, selecting these rapid routes more frequently causes a reduction in delays and a 9.32% reduction in delay

costs. In contrast, rapid routes are correlated with increasing accident rates and vehicle noise emissions.

Table 4.4 Variation of transportation cost and delay cost in two scenarios

Scenario	Cost		
	Variable transportation cost	Delay cost	Social issues
Scenario (i)	2,107	161	0.06
Scenario (ii)	1,863	146	0.00

Indeed, Table 4.4, and Figure 4.3 show the effect of considering both variation of demand and traffic conditions in dynamic IRPs. In addition to uncertainty in traffic and demand, the decision makers must also take into account these points as two key parameters in dynamic IRPs.

As the proposed problem deals with distribution and inventory management of perishable products, we do a sensitivity analysis to show the effect of dynamic optimization on the quantity of expired products. Figure 4.4 shows variations in the quantity of expired products, against increasing re-optimization in each period. In this figure, when re-optimization is zero, the model is static. As we can see, in the static situation there are huge quantities of expired products, whereas when re-optimization is increased, the quantity of expired products declines. This happens because by taking updated information into account more and more, the model can predict the demand more accurately and thus reduce the quantity of expired products in the inventory.

This analysis shows that moving towards dynamic optimization causes a 39.63% improvement in the quantity of expired products. In fact, whenever a decision maker deals with perishable products it is vital to take into account dynamic optimization in IRPs.

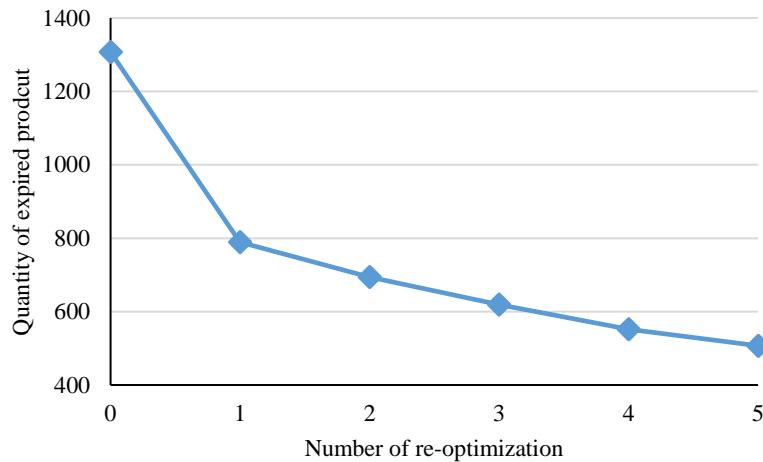


Figure 4.4 Quantity of expired products' variation against increasing number of re-optimization (Problem No.11)

As a final analysis, we show the impact of the number of re-optimization on delay costs and CPU time. Figure 4.5 demonstrates variation of delay costs and solving time against increasing number of re-optimization. As in the previous analysis, when re-optimization is zero, the model is in the static situation.

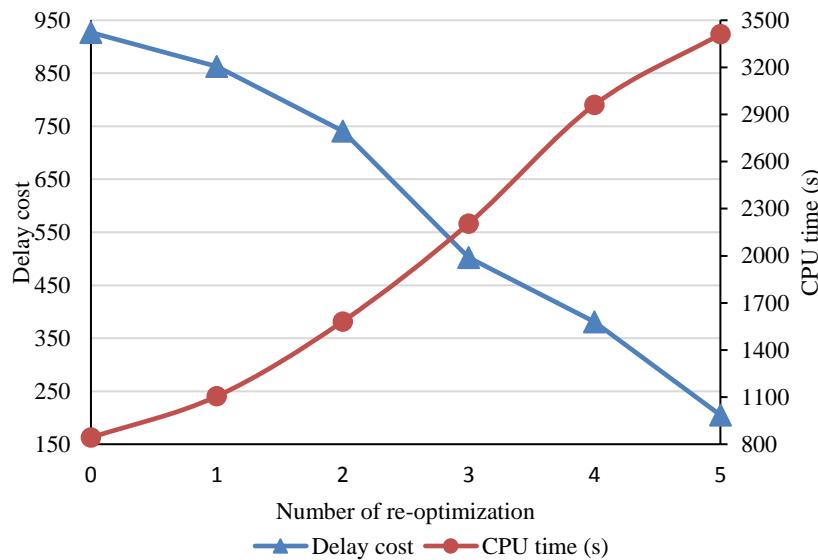


Figure 4.5 Variation of delay cost and solving time against number of re-optimization (Problem No.11)

As we can see, by applying the dynamic strategy, CPU time and delay costs increase and decrease respectively. This happens because by increasing re-optimization, the decision maker has more accurate information about traffic conditions. In this case, he or she is able to select the routes with better traffic conditions and thus ensure fewer delays. However, we should consider that there

is a solving time limitation when, by increasing the number of re-optimization, the CPU time increases.

As demonstrated in Figure 4.5, delay costs decrease with a high slope with respect to re-optimization times. However, after two times of re-optimization, CPU time exceeds a reasonable solving time. In other words, if the decision maker re-optimizes twice, he or she can reduce the delay cost by about 21% by reaching the solution in a reasonable time.

4.6 Conclusion

In this chapter, we presented an IRP where demand and traffic are considered as parameters which their values reveal over the time. In order to consider these two parameters, we defined a strategy and algorithm to apply the dynamic concept in the IRP. Moreover, in this research, the economic aspect of IRP is challenged by sustainable issues under uncertain parameters with regard to perishable products. We solved the problem in the static version, and then applied a dynamic strategy to investigate its impact on IRPs.

We then carried out analyses which we used to demonstrate the strength of the proposed algorithm, and described certain managerial insights. In particular:

- We showed that decision makers must consider the dynamic concept in both transportation and inventory management.
- We discovered that dynamic management is more efficient than static management as it enables decision makers to avoid 19.79% of backorders and improve profits by 12.26%.
- We showed that whenever decision makers deal with perishable products, it is vital to take into account dynamic optimization in IRPs. Moving toward dynamic optimization causes a 39.63% improvement in quantity of expired products.
- We proposed a framework which permits decision makers to numerically calculate the impact of x% profit variations on social issues. They are able to reach the best level of social issues by sacrificing at most 33% of the profits.

5

Conclusion and perspectives

5 Conclusion and perspectives

5.1 General conclusion

In this thesis, the impact of using real-time information in IRP is investigated; while economic aspect of IRP is challenged by sustainability and service level aspects.

Three mathematical models which are explained in sections two, three and four are developed. We tried to involve various variables and constraints according to the manager needs as well as the requirements of real world in each models.

In the two first proposed models, we did an attempt to integrate service level, environmental criteria and social issues in IRPs. In these two models, we presented multi-objective mathematical models by converting qualitative criteria into quantitative issues to measure green footprint, service level and social criteria. Moreover, we modeled perishability of products by two ways:

- Definition of expiration: The expired products should be recycled by an additional cost generating more GHG emission, which is added to other environmental criteria.
- Application of a discount mechanism in IRPs: the negative financial and ecological effect of dealing with perishable products motivates us to apply a nonlinear step function as a holding cost function in order to decrease the amount of expired products. We showed that this assumption is equivalent to the case where the holding unit cost is assumed to be fixed but where the retailers propose a discount price for non-fresh products that are transferred from one period to another.

Since the proposed models dealt with perishable products, the managers have to consider collecting and recycling these products after their expiration date. For this purpose, the concept of reverse logistics is applied.

Moreover, some parameters such as demand, transportation cost and vehicle speed are considered as uncertain. To handle uncertainty in these problems, fuzzy probabilistic and scenario-based stochastic approaches are adapted and applied. Finally, NSGA-II and MOSA algorithms are tuned and adopted to obtain optimal Pareto frontier. Based on the obtained results, some managerial insights are provided to help managers producing more accurate and robust decisions.

In chapter 4, an attempt has been made to investigate the impact of dynamic optimization in IRPs. For this purpose, we simplified the proposed mathematical model and applied a multi-optimization mechanism function of real time data collected about the IRP demand and traffic status.

From applicability point of view, dynamic optimization and resolution approaches in this thesis can be investigated not only for the products with different perishability levels but also are appropriate to nonperishable ones as

well. Moreover, the presented models could be used by companies in different industries like as the distribution of industrial gas, food and vegetables, pharmaceutical and *etc.*

In companies, target service levels are generally a corporate strategy or marketing matter. Inventory holding and distribution costs are logistics matters. These two matters are, in some firms, decided separately. The social and green footprint are an ethical/legislation (in some countries) matter. The presented models allow and help the managers to check the impact of x% increase of the service level/ social criteria on the logistics costs as well as the green footprint. In addition, these models enable managers to make robust decisions with regards the variation of the different parameters such as demand, traffic speed and transportation costs. The obtained results increase the capability of managers to provide a compromise decision according to the managerial preferences. We list in the following some of the managerial insights deduced from our study:

- We presented the connection between the profit, social issue, environmental criteria and service level measurement under an IRP framework. The obtained results could be interpreted differently, based on the judgmental weight that the decision maker could assign to each objective.
- We analyzed and classified the results to find the set of solutions where a small variation of the profit has a significant impact on the social, environmental or service level criteria. This set of solutions is valuable solutions for companies that are faced with pressure in a competitive marketplace or from governmental and non-governmental agencies to consider social issues, and that want to postpone their corrective actions in order to improve mentioned concerns.
- We explored the cost of product non-freshness and its impact on the performance of IRPs. Moreover, results show that whenever managers deal with perishable products, it is vital to taking into account dynamic optimization in IRPs.
- We proved the efficiency of proposed stochastic approach against variation of parameters. For example, we showed, if managers ignore 13% of best profits and 11% of social issues in a deterministic situation, they could obtain a robust solution that is feasible in different scenarios.
- We explored that a dynamic management is more efficient than the static one while decision maker is able to avoid 19.79% backorder's quantity and improves profit by 12.26%.

5.2 General perspectives

We propose in this section, some limitations of our results and propose directions for future research in this field. We particularly propose four main future research directions: (i) improving the quality of the results, (ii) using new methods to decrease the resolution computational time, (iii) integrating new measures in modeling sustainable and service level issues and (iv) going further in analysing the obtained results to propose more efficient managerial insights.

As previously mentioned, in this thesis we focused on modelling issues that have not been considered by previous research investigations. For this reason, we used the resolution approaches (NSGA-II and MOSA) whose efficiency are already proven. In order to have more accurate results, new approaches such as exact, heuristic, Meta heuristic and hybridized of the existing methods can be applied as future research.

As mentioned in Chapter 4, we propose a re-optimization mechanism to deal with the dynamic IRP. In this case, for large size of problem instances, the CPU time was about 30 minutes. Obviously, vehicle driver should have the decision-making tools to dynamically optimize the IRP by taking into account real time information. It means we need to re-optimize the problem in a very short time. It is needed to develop more efficient and faster resolution approach. Since in this situation, it is necessary to analyze a huge amount of information, applying new methods such as neural networks techniques, simulation and data mining may help to decrease computational time.

In addition, according to the decentralized nature of supply chains, taking into account the production stage in the proposed models can improve their applicability.

We also do think that other social, ergonomic, environmental and service level measures, such as job severity of drivers, their working time charegload, gaz emissions due to inventory activities, *etc.* can be taken into account. Furthermore, proposing the transshipment option in the dynamic optimization can improve the efficiency of the IRP.

As final perspective, it is necessary to analyze the obtained results and propose managerial insights to decision makers. But converting the information to knowledge yet needs more analysis than what presented in this thesis. In this way we can trasnform results from the mathematical model to some operational instructions which are more useful and understandable by managers. For this purpose, applying and using neural networks techniques and data mining approaches for analyzing the results can be as a new perspective in IRPs.

5.3 Related publication

The results of this thesis is published / submitted in different international journals and conferences.

- M. Rahimi, A. Baboli, Y.Rekik, “Multi-objective inventory routing problem: A stochastic model to consider profit, service level and green criteria” International Journal of Transportation Research Part E, Volume 101, May 2017, Pages59-83
- M. Rahimi, A. Baboli, Y.Rekik, “A bi-objective model for the sustainable inventory routing problem: products perishability and reverse logistics considerations” International Journal of Production Economics (submitted)
- M. Rahimi, A. Baboli, Y.Rekik, “Dynamic stochastic inventory routing problem for perishable products considering sustainable issue” International Journal of Production Research (submitted)
- M. Rahimi, A. Baboli, Y.Rekik, (2016) “Sustainable inventory routing problem for perishable products by considering reverse logistic” 8th IFAC conference on Manufacturing modeling, management & control (MIM), Jun. 28-30, Troyes, France, 6 pages.
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Appendix A: Abbreviations

ACO	Ant Colony Optimization
ALNS	Adaptive Large Neighborhood Search
ATS	Average Traffic Speed
AVS	Average Vehicle Speed
CG	Column Generation
CPU	Central Processing Unit
CrR	Crossover Rate
DIRP	Dynamic Inventory Routing Problem
ED	Euclidean Distance
GA	Genetic Algorithm
GHG	Greenhouse Gas
GPS	Global Positioning System
GRI	Global Reporting Initiative
IC	Imperialist Competitive
IRP	Inventory Routing Problem
JIT	Just In Time
MaxIt	Maximum Iteration
MOSA	Multi-Objective Simulated Annealing
MuR	Mutation Rate
NIOSH	National Institute for Occupational Safety and Health
Npop	Number of population
NS	Neighborhood Search
NSGA-II	Non-dominated Sorting Genetic Algorithm II
OFV	Objective Function Value
PSO	Particle Swarm Optimization
SA	Simulated Annealing
SAGA	Self-Adaptive Genetic Algorithm
SKU	Stock Keeping Unit
SM	Spacing Metric
TS	Tabu Search
UT	Updating Time
VMI	Vendor Managed Inventory
VNS	Variable Neighborhood Search
VRP	Vehicle Routine Problem
WBCSD	World Business Council on Sustainable Development

Appendix B: Notations

Sets	
d	index for loading equipment type ($1, 2, \dots, D$)
d'	index for unloading equipment type ($1, 2, \dots, D'$)
f	index for product ($1, 2, \dots, F$)
k	index for vehicle type ($1, 2, \dots, K$)
M	set of retailers, index for retailer ($1, 2, \dots, M$)
M'	set of retailer and supplier, $M \cup \{0\}$
r	index for route type ($1, 2, \dots, R$)
t, t'	index for period ($1, 2, \dots, T$)
u	index for vehicle technology ($1, 2, \dots, U$)

Parameters	
$[a_i, b_i]$	earliest and latest authorized arrival time at retailer i
ATS_{ijrt}	average traffic speed in the route r between retailer/supplier i and j at period t
AVS_{ijkrt}	average speed of vehicle type k in route r between retailer/supplier i and j at period t
c_{ij}	distance between retailer i and j
c_{ijr}	distance between retailer/supplier i, j by route r
cap_k	capacity of vehicle type k
cap_{ku}	capacity of vehicle type k with technology u
\tilde{d}_{ift}	quantity of product f send from retailer i at period t
DP_i	penalty cost per unit of time due to visiting the retailer i after latest possible arriving time
fc_k	fixed transportation cost for vehicle type k
fc_{ku}	fixed transportation cost for vehicle type k with technology u per trip
fcr_k	fixed reverse transportation cost for vehicle type k
G	a large value number
GE	average of produced emission by recycling one unit of expired product
GL_d	GHG emission produced through equipment type d for loading 1kg of product
GT_{ku}	GHG emission produced by vehicle type k with technology u in one unit of distance
$GU_{d'}$	GHG emission produced through equipment type d' for unloading 1kg of product
GHG_k	produced GHG emission by vehicle type k in one unit distance
$GHG_{t, total}$	maximum allowed produced GHG emission at period t
h_{if}	inventory holding cost at retailer i per unit of product f per period
I_{if0}	initial inventory level of product f at retailer i
IC_{if}	maximum inventory capacity of retailer i for product f
L_f	shelf life of product f , which is a specific percentage of time horizon
LC_d	loading cost of one unit product through equipment type d
MA_f	mass of one unit product f
O_{if}	ordering cost of product f for retailer i
R_{ft}	revenue of whole system for one unit product f at period t
s_{ijk}	speed of vehicle type k with technology u in the route between i and j
sp_k	required time to unload one unit product from vehicle k
sp_{ku}	required time to unload one unit product from vehicle k & technology u
$UC_{d'}$	unloading cost of one unit product through equipment type d'
v_{kr}	variable transportation cost per unit and distance for vehicle type k in

\tilde{v}_{ku}	route r variable transportation cost per unit and per distance for vehicle type k with technology u
vr_{kr}	variable reverse transportation cost per unit and per distance for vehicle type k in route r
wt	maximum working time of tours
Y_{if}	backordering cost of one unit of product f at retailer i
a_k	constant parameter related to vehicle type k
θ_f	recycling cost of one unit of expired product f
$\lambda_{(difi)}$	discount factor based on quantity of demand
ϑ_f	rate of minimum demand should be satisfied at each period for retailer i and product f
Variables	
B_{ift}	quantity of backordered product f of retailer i at the end of period t
C_{ift}	1 if product f is delivered to retailer i at period t , otherwise 0
DT_{irt}	delay in visiting retailer i due to using route r at period t
EX_{ift}	quantity of expired products f in inventory of retailer I at the end of period t
I_{ift}	inventory level of product f at retailer i at the end of period t
n_{it}	1 if delay occurred in visiting retailer i at period t , otherwise 0
$q_{iktt'; t < t'}$	quantity of received product by retailer i through vehicle k at period t for being used at period t'
$q_{iktt'; t > t'}$	quantity of received product by retailer i through vehicle k at period t to satisfy the backordering quantity
$q_{ijkut'; (t < t')}$	quantity of product f received by retailer i through vehicle k with technology u at period t for being used at period t' , and which is loaded by equipment d and unloaded by equipment d'
$q_{ijkut'; (t > t')}$	quantity of product f received by retailer i through vehicle k with technology u at period t to satisfy the backordering quantity, and is loaded by equipment d and unloaded by equipment d'
r_{it}	1 if backorder occurred in visiting retailer i at period t , otherwise 0
T_{ikrt}	arriving time to retailer i by vehicle k and rout r at period t
T_{ikut}	arrival time at retailer i by vehicle k with technology u at period t
x_{ijkrt}	1 if retailer j is visited exactly after retailer i by vehicle type k using route r at period t , otherwise 0
x'_{ijkrt}	1 if retailer j is visited exactly after retailer i by vehicle type k using route r at period t for revers logistics of expired products, otherwise 0
x_{ijkut}	1 if retailer j is visited exactly after retailer i by vehicle type k and technology u at period t , otherwise 0
y_{kt}	number of vehicle type k at period t
y'_{ki}	number of vehicle type k at period t for revers logistics
y_{kut}	number of vehicle type k with technology u at period t
z_{ikrt}	1 if retailer i is served at period t by vehicle k and route r , otherwise 0
z'_{ikrt}	1 if retailer i is visited at period t by vehicle k , route r for revers logistics of expired products, otherwise 0
z_{ikut}	1 if retailer i is served at period t by vehicle k , technology u , otherwise 0
φ_{it}	1 if there is expired product in inventory of retailer i at period t , otherwise 0