Planification de la distribution en contextes de déploiement d'urgence et de logistique hospitalière

Thèse

Ana María Anaya-Arenas

Doctorat en sciences de l'administration – Opérations et systèmes de décision

Philosophiæ doctor (Ph.D.)

Québec, Canada

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Sous la direction de :

Jacques Renaud, directeur de recherche

Angel Ruiz, codirecteur de recherche

Résumé

L'optimisation de la distribution est une préoccupation centrale dans l'amélioration de la performance des systèmes industriels et des entreprises de services. Avec les avancées technologiques et l'évolution du monde des affaires, de nouveaux domaines d'application posent des défis aux gestionnaires. Évidemment, ces problèmes de distribution deviennent aussi des centres d'intérêt pour les chercheurs. Cette thèse étudie l'application des méthodes de recherche opérationnelle (R.O.) à l'optimisation des chaînes logistiques dans deux contextes précis : le déploiement logistique en situation d'urgence et la logistique hospitalière. Ces contextes particuliers constituent deux domaines en forte croissance présentant des d'impacts majeurs sur la population. Ils sont des contextes de distribution complexes et difficiles qui exigent une approche scientifique rigoureuse afin d'obtenir de bons résultats et, ultimement, garantir le bien-être de la communauté.

Les contributions de cette thèse se rapportent à ces deux domaines. D'abord, nous présentons une révision systématique de la littérature sur le déploiement logistique en situation d'urgence (Chapitre 2) qui nous permet de consolider et de classifier les travaux les plus importants du domaine ainsi que d'identifier les lacunes dans les propositions actuelles. Cette analyse supporte notre seconde contribution où nous proposons et évaluons trois modèles pour la conception d'un réseau logistique pour une distribution juste de l'aide (Chapitre 3). Les modèles cherchent à assurer une distribution équitable de l'aide entre les points de demande ainsi qu'une stabilité dans le temps. Ces modèles permettent les arrérages de la demande et adaptent l'offre aux besoins de façon plus flexible et réaliste.

Le deuxième axe de recherche découle d'un mandat de recherche avec le Ministère de la Santé et de Services sociaux du Québec (MSSS). En collaboration avec les gestionnaires du système de santé québécois, nous avons abordé la problématique du transport d'échantillons biomédicaux. Nous proposons deux modèles d'optimisation et une approche de résolution simple pour résoudre ce problème difficile de collecte d'échantillons (Chapitre 4). Cette contribution est par la suite généralisée avec la synchronisation des horaires d'ouverture de centres de prélèvement lors de la

planification des tournées. Une procédure itérative de recherche locale est proposée pour résoudre le problème (Chapitre 5). Il en découle un outil efficace pour la planification des tournées de véhicules dans le réseau des laboratoires québécois.

Abstract

Optimisation in distribution is a major concern towards the performance's improvement of manufacturing and service industries. Together with the evolution of the business' world and technology advancements, new practical challenges need to be faced by managers. These challenges are thus a point of interest to researchers. This thesis concentrates on the application of operational research (O.R.) techniques to optimise supply chains in two precise contexts: relief distribution and healthcare logistics. These two research domains have grown a lot recently and have major impacts on the population. These are two complex and difficult distribution settings that require a scientific approach to improve their performance and thus warrant the welfare among the population.

This thesis's contributions relate to those two axes. First, we present a systematic review of the available literature in relief distribution (Chapter 2) to consolidate and classify the most important works in the field, as well as to identify the research's gaps in the current propositions and approaches. This analysis inspires and supports our second contribution. In Chapter 3, we present and evaluate three models to optimise the design of relief distribution networks oriented to fairness in distribution. The models seek to ensure an equitable distribution between the points of demand and in a stable fashion in time. In addition, the models allow the backorder of demand to offer a more realistic and flexible distribution plan.

The second research context result from a request from Quebec's Ministry of Health and Social Services (*Ministère de la Santé et des Services sociaux* – MSSS). In partnership with the managers of Quebec's healthcare system, we propose an approach to tackle the biomedical sample transportation problem faced by the laboratories' network in Quebec's province. We propose two mathematical formulations and some fast heuristics to solve the problem (Chapter 4). This contribution is later extended to include the opening hours' synchronisation for the specimen collection centers and the number and frequency of pick-ups. We propose an iterated local search procedure (ILS) to find a routing plan minimising total

billable hours (Chapter 5). This leads to an efficient tool to routing planning in the medical laboratories' network in Quebec.

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Al autor de mis días

"[17] ¡Cuán preciosos, oh Dios, me son tus pensamientos!
¡Cuán inmensa es la suma de ellos!
[18] Si me propusiera contarlos,
sumarían más que los granos de arena.
Y si terminara de hacerlo, aún estaría a tu lado."
Salmos 139:17-18

À l'auteur de mes jours

« [17] Combien tes desseins, ô Dieu, sont, pour moi, impénétrables,
et comme ils sont innombrables!
[18] Si je les comptais, ils seraient bien plus nombreux
que les grains de sable sur les bords des mers.
Voici: je m'éveille, je suis encore avec toi. »
Psaumes 139 :17-18

Remerciements

D'après mon expérience, une thèse de doctorat est la combinaison de nombreux ingrédients. Évidemment, ce document contient le résultat de plusieurs années de recherche, de réflexions et d'analyses. C'est aussi l'aboutissement d'un travail acharné où j'ai dû faire preuve d'engagement, de ténacité, de persévérance et de patience. Je n'aurais pas pu achever ce projet si je n'avais été soutenue par de nombreuses personnes de mon entourage professionnel et personnel. Je suis ravie de pouvoir exprimer dans ces lignes mes plus sincères remerciements à tous ceux qui ont contribué d'une façon ou d'une autre à mon travail. Tout d'abord, j'aimerais remercier *el autor de mis días*, mon Dieu et mon Sauveur Jésus-Christ. Je suis le résultat de sa grâce et de son amour dans ma vie et je crois vivement que c'est sa bienveillance qui m'a guidée jusqu'à aujourd'hui.

Mes plus sincères remerciements vont à Jacques Renaud, mon directeur de thèse, qui a toujours était là pour moi et qui a su m'encadrer de façon attentive et respectueuse. Ses qualités humaines ainsi que ses fortes compétences en tant que chercheur et directeur m'ont soutenue aux moments nécessaires. Je tiens à reconnaître aussi l'encadrement et le soutien d'Angel Ruiz, mon codirecteur, qui grâce à sa créativité et à sa vision de nos problématiques de recherche, a souvent inspiré mon travail. Je le remercie surtout d'avoir su m'écouter et de m'apprendre à voler de mes propres ailes. Jacques, Angel, je vous remercie d'avoir embarqué avec moi dans cette aventure, d'avoir cru en moi et en mon potentiel. Dès le début et jusqu'à la fin, vous m'avez toujours amené à pousser mes limites. Cela a été un véritable plaisir de travailler avec vous pendant ces années et j'espère que l'on pourra réaliser beaucoup d'autres projets ensemble. J'aimerais aussi sincèrement remercier Fayez Boctor du département d'Opérations et Systèmes de Décision de l'Université Laval et Caroline Prodhon de l'Institut Charles Delaunay de l'Université de Technologie de Troyes, d'avoir accepté de faire partie de mon comité ainsi que pour nos moments d'échanges et de discussions qui ont enrichi mon travail. Je tiens également à remercier Marie-Ève Rancourt d'avoir accepté d'agir à titre d'examinatrice externe pour cette thèse.

Un profond et sincère remerciement à ma famille. Mes parents, mes sœurs, mes beaux-frères, et la joie de mon cœur : Pauli, Emi et AndrésDa (mes nièces et mon neveu). Merci de vos encouragements et votre appui à tout moment. Merci d'avoir rêvé avec moi et de m'avoir soutenue dans ma décision de partir et de rester si longtemps loin de vous. Mon cœur a été, il est et il sera toujours avec vous (*Gracias a mi familia bonita por todo su apoyo en este tiempo. Gracias por haber soñado conmigo cuando decidí continuar por este camino. Pero sobretodo, quiero darles las gracias por haber pagado conmigo el precio más alto que tiene este logro: alejarme de su cotidianidad. Así que gracias por perdonar mi ausencia para que pudiera vivir esta experiencia. Mi corazón simpre estuvo, está y estará con ustedes.)* Merci à ma famille ici à Québec : Guillaume, Nicole, Andrea, Nana, Natalia, Pablito, Gabie, Alain et Rachel, et toute la belle gang qui m'a accompagnée toutes ces années. Nos moments ensemble ont été décisifs pour la réalisation de ce projet. À plusieurs reprises, vous m'avez donné la force et le courage nécessaires de continuer sur ce chemin. Votre amitié est certainement l'un des plus beaux cadeaux que m'a offert ma vie québécoise.

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Avant-propos

Cette thèse de doctorat est la consolidation de mes travaux de recherche menés au sein du Centre interuniversitaire de recherche sur les réseaux d'entreprise, la logistique et le transport (CIRRELT) à la Faculté des sciences de l'administration de l'Université Laval. Les contributions de la thèse sont présentées sous la forme de quatre articles scientifiques. Chaque article a été écrit avec la collaboration d'autres chercheurs, principalement de mes directeurs de recherche : Jacques Renaud et Angel Ruiz. Pour chacun des quatre articles qui composent cette thèse, je me suis impliquée en tant que chercheuse principale et première auteure. Plus précisément, mon rôle fut de proposer les problématiques de recherche, les approches de modélisation et les méthodes de résolution, le tout en concertation avec les coauteurs. Je me suis également occupée du travail de programmation, de l'expérimentation, de l'analyse des résultats et de la rédaction de la première version des articles.

Le premier article intitulé « *Relief distribution networks : a systematic review* » a été coécrit avec Jacques Renaud et Angel Ruiz. Il a été accepté pour publication dans *Annals of Operations Research* le 19 mars 2014 et publié en décembre 2014 (Volume 223, Issue 1, pp 53-79). Ce projet a fait l'objet d'un tutoriel sur le déploiement logistique en situation d'urgence (*emergency logistics*) donné aux Journées de l'Optimisation 2012, du 7 au 9 mai 2012 à Montréal. J'ai aussi été invité à l'*Universidad Industrial de Santander* le 10 janvier 2013 en Colombie, et à l'Université de Technologie de Troyes le 28 mai 2015, afin de donner une séance d'introduction sur les réseaux logistiques en réponse aux sinistres.

Le deuxième article intitulé « *Models for a fair humanitarian relief distribution* » a été coécrit avec Jacques Renaud et Angel Ruiz et soumis pour publication dans *Production and Operations Management* le 24 août 2015. Une version préliminaire a été arbitrée par le comité d'évaluation et publiée dans les actes de la conférence internationale IESM 2013 (*International Conference of Industrial Engineering and Systems Management 2013*), qui a eu lieu à Rabat au Maroc du 28 au 30 octobre 2013. De plus, il a été présenté dans deux autres conférences internationales en 2013, soit aux Journées de l'Optimisation, du 6 au 8 mai 2013 à Montréal, et au *2013 INFORMS Annual Meeting* à Minneapolis du 6 au 9 octobre 2013.

Le troisième article intitulé « *Biomedical sample transportation in the province of Quebec: a case study* » a été rédigé en collaboration avec Thomas Chabot, Jacques Renaud et Angel Ruiz. L'article a été accepté dans un numéro spécial sur le transport dans la gestion de la chaîne d'approvisionnement du *International Journal of Production Research* le 29 janvier 2015 et publié en ligne le 9 mars 2015. Les résultats de cet article ont été présentés dans deux conférences internationales, soit le 56e congrès annuel de la SCRO à Ottawa du 26 au 28 mai 2014, et la conférence internationale *CORS/INFORMS* 2015 à Montréal, du 14 au 17 juin 2015.

Le quatrième article intitulé « *An ILS approach to solve the biomedical sample transportation problem in the province of Quebec* » a été coécrit avec Caroline Prodhon, Hasan Murat Asfar et Christian Prins, de l'Université de Technologie de Troyes. Cet article est le résultat du travail effectué lors d'un séjour de recherche réalisé entre mars et juin 2015 avec ces trois membres de l'équipe du laboratoire d'opérations et systèmes industriels (LOSI) à Troyes. La version incluse dans cette thèse a été acceptée le 15 juillet 2015 pour publication dans les actes de la Conférence internationale de génie industriel (CIGI) qui aura lieu à Québec du 26 au 28 octobre 2015.

Chapitre 1

Introduction générale

Dans le but d'améliorer la performance des entreprises et des organisations, la recherche opérationnelle (R.O.) se présente comme un outil clé pour la prise de décisions, particulièrement dans le domaine de la distribution. Les outils développés sont de plus en plus appliqués et utilisés par les gestionnaires qui, à leur tour, mettent à jour des nouvelles problématiques exigeant des solutions novatrices, rapides et efficientes. Dans ce chapitre introductif, nous allons présenter les grandes lignes de la thèse ainsi que les concepts de base sur lesquels elle se construit. D'abord, nous allons définir le contexte et les principales motivations de notre travail. Ensuite, nous allons présenter la problématique générale de la thèse et la méthodologie de recherche suivie. Finalement, les contributions de la thèse et la structure de l'ensemble du document seront décrites dans la dernière section de ce chapitre.

1.1. Mise en contexte et motivation de la thèse

Afin d'assurer une distribution efficace, le gestionnaire doit concevoir et piloter un réseau logistique flexible et adapté aux besoins précis du contexte traité. Cette thèse s'intéresse à la conception et au pilotage d'un réseau logistique en situation d'urgence, ainsi qu'à la planification du transport d'échantillons biomédicaux dans le réseau des laboratoires du Québec. Malgré la variété des études effectuées sur l'optimisation des réseaux logistiques, la distribution dans les contextes du déploiement d'urgence et de la logistique hospitalière demeurent des problématiques d'actualité pour les gestionnaires de ces systèmes. Plusieurs considérations réelles augmentent la difficulté du processus de distribution et requièrent des outils de planification qui intègrent les particularités de ces problématiques.

Dans le cas de déploiements d'urgence, par exemple, le nombre de personnes affectées et leurs besoins sont très difficiles à estimer. La demande peut évoluer très rapidement et de fortes variations peuvent aussi se présenter dans la capacité de réponse. La dynamique de la demande et de l'offre est essentielle dans la gestion de ce type de chaîne d'approvisionnement. D'ailleurs, la non-satisfaction de la demande peut mener à des pertes de vies humaines. Dans ce cas, les objectifs liés à la distribution, même s'ils ne sont pas toujours faciles à définir, dépassent généralement les intérêts économiques classiques. D'un autre côté, les activités de la logistique hospitalière comme le transport d'échantillons biomédicaux sont des opérations courantes qui se déroulent dans un contexte plutôt stable. Cependant, la courte durée de vie des échantillons biomédicaux impose de fortes contraintes sur l'organisation du réseau et la planification du transport. Dans ces deux situations, la distribution doit être très rapide pour garantir un niveau de service élevé aux demandes des usagers, ce qui requiert une chaîne de distribution agile et flexible. Toutes ces particularités constituent un défi important dans la gestion de la distribution.

1.2. Présentation de la problématique et de la méthodologie suivie

Outre l'intérêt scientifique des axes de recherche de cette thèse, la pertinence pratique de ces deux problématiques s'est confirmée par des appuis et des collaborations d'acteurs importants impliqués dans ces domaines. En ce qui concerne le déploiement d'urgence, nos travaux ont pour origine un important projet industriel appuyé et financé par la section Défense et Sécurité publique de Fujitsu Consulting (Canada) Inc. Cette collaboration nous a procuré une expertise pratique sur laquelle nous avons bâti nos recherches (contributions 1 et 2 de cette thèse). Pour la logistique hospitalière, un mandat du Ministère de la Santé et de Services sociaux du Québec (MSSS) nous a donné accès au contexte pratique et aux données réelles du réseau québécois, ce qui nous permet d'aborder de façon crédible le problème du transport d'échantillons biomédicaux au Québec (contributions 3 et 4). Ces opportunités de collaboration ont confirmé l'utilité des problèmes de recherche proposés.

Les quatre contributions de cette thèse sont appuyées sur une méthodologie systématique de recherche qui inclut l'analyse de la littérature et les besoins du contexte pour la définition de la problématique de recherche ciblée. Ensuite, la modélisation mathématique et un développement algorithmique sont proposés pour la résolution du problème. Finalement, une expérimentation numérique rigoureuse est faite pour mesurer la performance des propositions sur des instances réalistes. Afin d'avoir une meilleure compréhension des axes de recherche de cette thèse, une présentation générale des principales caractéristiques de chacun des domaines d'application sera effectuée dans les sous-sections suivantes.

1.2.1. Déploiement logistique en situation d'urgence

Le déploiement en situation d'urgence est un des nombreux thèmes couverts par une vaste littérature qui se regroupe sous l'appellation de « gestion de crises » (e*mergency management*). La gestion de crises est définie par Haddow et al. (2007) comme la discipline qui gère les risques reliés aux catastrophes. En considérant une vision purement temporelle, la gestion de crises peut être divisée en quatre grandes phases (Altay & Green III 2006; Galindo & Batta 2013; Haddow et al. 2007) : deux phases précédant l'évènement (atténuation et préparation) et deux phases post-crise (réponse et récupération). Le déploiement logistique est au cœur de la gestion de crises à plusieurs moments, mais il occupe plus particulièrement plus de 80 % des opérations nécessaires lors de la réponse à un sinistre (Van Wassenhove 2006). Dans cette thèse, nous nous intéressons plus précisément à la distribution de l'aide en réponse à un sinistre. Le déploiement logistique d'urgence a été défini par Sheu (2007) comme « *A process of planning, managing and controlling the efficient flows of relief, information, and services from the points of origin to the points of destination to meet the urgent needs of the affected people under emergency conditions.* » Bien que ce domaine de recherche soit assez nouveau, les contributions se multiplient rapidement dans plusieurs domaines de la gestion ainsi que dans l'optimisation du réseau logistique. Clairement, le déploiement logistique d'urgence se distingue des problèmes connus et habituellement traités dans le domaine industriel (Holguín-Veras et al. 2012; Kovács & Spens 2009; Van Wassenhove & Pedraza Martínez 2012). La dynamique de la demande, l'environnement d'opération instable et l'énorme coût lié à « l'insatisfaction de la demande » (c'est-à-dire ne pas répondre adéquatement aux besoins des sinistrés) sont quelques exemples des difficultés particulières reliées à la logistique d'urgence.

Dans le premier axe de recherche de cette thèse, nous proposons d'abord une synthèse de la littérature sur le déploiement d'urgence. Cette synthèse est motivée par la variété et la forte croissance du nombre d'articles publiés lors des dix dernières années. Cette révision systématique vient consolider et organiser les travaux disponibles pour les gestionnaires de crise et identifier des problématiques de recherche peu explorées et prometteuses. Par la suite, nous nous intéressons à la planification d'un réseau en situation d'urgence en considérant l'importance d'une distribution stable et équitable des produits. Ce travail nous permet de proposer des modèles détaillés pour la planification d'un réseau de distribution juste, rapide et efficace.

1.2.2. Logistique hospitalière

Le MSSS défini la logistique hospitalière comme « l'ensemble des activités permettant de synchroniser et de coordonner, voire de fluidifier les flux physiques, financiers, d'information afin que la prestation de soins de santé se réalise de manière sécuritaire, efficace et efficiente »[1]. Le deuxième axe de cette thèse se positionne dans le domaine de la logistique hospitalière, plus particulièrement sur la planification du transport des échantillons biomédicaux. Dans un réseau médical, plusieurs tests médicaux sont nécessaires afin d'assurer une bonne qualité des diagnostics et un traitement adéquat des patients. Cela se traduit par une grande variété de types d'échantillons biomédicaux à analyser qui sont prélevés dans des cliniques, des hôpitaux ou dans des centres de prélèvement (CP). Cependant, les CP ne sont pas outillés pour analyser les échantillons, et ce, dû aux coûts élevés des équipements d'analyse. Ces derniers sont répartis stratégiquement dans quelques laboratoires qui couvrent le territoire québécois. Les échantillons sont donc envoyés vers un laboratoire pour analyse, ce qui crée une importante demande de transport.

Notre problématique se concentre sur le transport des échantillons biomédicaux des CP vers les laboratoires. Ces opérations engendrent différents défis au niveau logistique. En premier lieu, le produit à transporter exige une gestion spéciale au niveau des temps de traitement, occasionnée par la durée de vie limitée de

[1] Guide en logistique hospitalière (http://www.msss.gouv.qc.ca/documentation/planification-immobiliere/app/DocRepository/1/Publications/Guide/110629_Guide_logistique_hospitaliere.pdf

l'échantillon une fois prélevé. Ceci conditionne l'exploitation du réseau logistique, en particulier la fréquence des ramassages aux CPs et la longueur des routes à construire. Dans ce contexte, il ne faut pas oublier que les véritables clients du réseau sont les patients. Ainsi, la perte d'un échantillon à cause d'une logistique inefficace implique non seulement des coûts réels non négligeables, mais surtout des coûts indirects encore plus importants (comme la prise d'un autre rendez-vous, le retard d'un diagnostic et d'un traitement, entre autres). Ceci implique que l'objectif principal du gestionnaire va au-delà de la minimisation des coûts pour garantir un niveau de service de qualité envers la communauté. Ce niveau de service doit être atteint tout en optimisant l'utilisation des ressources disponibles.

Dans le deuxième axe de recherche de la thèse, nous visons d'abord à faire une description détaillée du problème de transport d'échantillons dans la province de Québec. Nous proposons deux formulations alternatives pour le problème et nous avons développé une approche heuristique rapide et efficace afin de fournir au MSSS un plan de transport qui maximise l'efficience et respecte les contraintes sur la qualité du service. Dans un deuxième temps, nous proposons une extension de ce travail en incluant également la synchronisation des horaires d'ouverture des CPs. Pour ce cas, nous avons développé une méthode itérative de recherche locale.

1.3. Contributions et organisation de la thèse

Cette section présente les grandes lignes de chacune des contributions qui articulent les deux axes de recherche de la thèse. Chacune des contributions fait l'objet d'un chapitre (Chapitre 2 – Chapitre 5) ainsi que d'une publication scientifique (ou manuscrit soumis pour publication scientifique). Au total, tel qu'il a été précisé dans l'avant-propos, deux articles ont été publiés dans des revues scientifiques, un troisième a été soumis et un quatrième est publié comme acte de congrès. Une conclusion globale de la thèse, ainsi que des perspectives de recherche future sont présentées à la fin de ce document.

1.3.1. Contributions dans le domaine du déploiement d'urgence

Revue systématique de la littérature sur le déploiement d'urgence

Le Chapitre 2 présente la première publication de cette thèse. Cet article a trois apports fondamentaux. Tout d'abord, il vient consolider et centraliser de façon ordonnée les nombreuses études proposées dans la littérature sur le domaine. Plus de 170 articles ont été consultés sur cinq bases de données. Un total de 83 articles est finalement inclus et analysé dans notre revue. Deuxièmement, nous avons constaté que la littérature suit fidèlement la ligne décisionnelle des gestionnaires de crise. Quatre catégories de décisions sont identifiées (localisation, routage, localisation/routage, et autres) et pour chacune d'elle nous précisons clairement leurs principales caractéristiques, tant au niveau de la modélisation que de l'outil de résolution proposé. Troisièmement, avec cette revue de la littérature, nous avons pu identifier les problématiques abordées dans la littérature récente et faire ressortir des besoins et des opportunités de futures recherches dans le domaine.

Modèles pour une distribution juste de l'aide humanitaire

Dans le Chapitre 3, nous proposons divers modèles pour effectuer la configuration et l'exploitation d'un réseau de distribution en situation d'urgence. Les modèles sont conçus pour construire un réseau logistique maximisant la satisfaction de la demande tout en cherchant à effectuer une répartition juste des produits disponibles. Ce chapitre propose trois contributions principales : (1) donner aux gestionnaires de crise un outil précis pour la conception d'un réseau de distribution qui considère les défis propres au déploiement d'urgence; (2) considérer dans la décision de conception du réseau l'objectif d'équité pour assurer une répartition juste des ressources disponibles; et (3) évaluer différentes définitions possibles d'équité pour donner aux gestionnaires des critères de performance à examiner lors d'un déploiement d'urgence.

1.3.2. Contributions dans le domaine de logistique hospitalière

Transport d'échantillons biomédicaux dans la province de Québec : un cas d'étude

Dans cet article nous présentons en détail le cas du transport d'échantillons biomédicaux, tel qu'il est vécu dans la province de Québec. Cet article contient deux contributions précises : (1) dans un premier temps nous présentons deux formulations mathématiques alternatives pour résoudre cette problématique comme un problème de tournées de véhicules avec fenêtres de temps et plusieurs tournées par camion; (2) nous proposons une méthode de résolution simple et efficace pour la planification des tournées de transport d'échantillons biomédicaux sur le territoire québécois. Ces deux contributions ont été mises en commun dans le but de construire un outil d'aide à la planification pour les gestionnaires du réseau des laboratoires d'analyse au Québec. Plusieurs rapports de recherche déposés au MSSS sont basés sur ces développements.

Une méthode itérative de recherche locale pour résoudre le problème de transport d'échantillons biomédicaux au Québec

Le Chapitre 5 est une extension du travail présenté dans le Chapitre 4 et s'aligne avec les objectifs du Ministère afin de proposer des modifications structurelles au réseau, dont le nombre et les heures de passages dans les centres de prélèvement. Ce chapitre propose deux contributions précises. Tout d'abord, une extension de la problématique étudiée est formulée. Nous cherchons à synchroniser les heures d'ouverture des centres de prélèvement tout en effectuant le nombre optimal de collectes à chaque centre. L'objectif est de minimiser le temps facturable (durée totale des routes) en garantissant qu'aucun échantillon ne périsse. Deuxièmement, dû à la complexité du problème, une métaheuristique s'avère nécessaire pour une résolution efficace. Nous proposons une procédure itérative de recherche locale (ILS) et la qualité de la méthode est testée à l'aide d'instances réelles, tirées du réseau des laboratoires du Québec.

La *Figure 1.1* illustre le cadre général de cette thèse, ainsi que les deux axes de recherche principaux. Les contributions sont placées à l'intérieur des axes étudiés, encadrés par l'application de méthodes de recherche opérationnelle pour la planification de la distribution. Bien que ces deux axes de recherche soient liés à deux contextes logistiques différents, ils poursuivent un objectif commun : desservir les personnes concernées en visant leur bien-être et l'exploitation efficiente du système opérationnel.

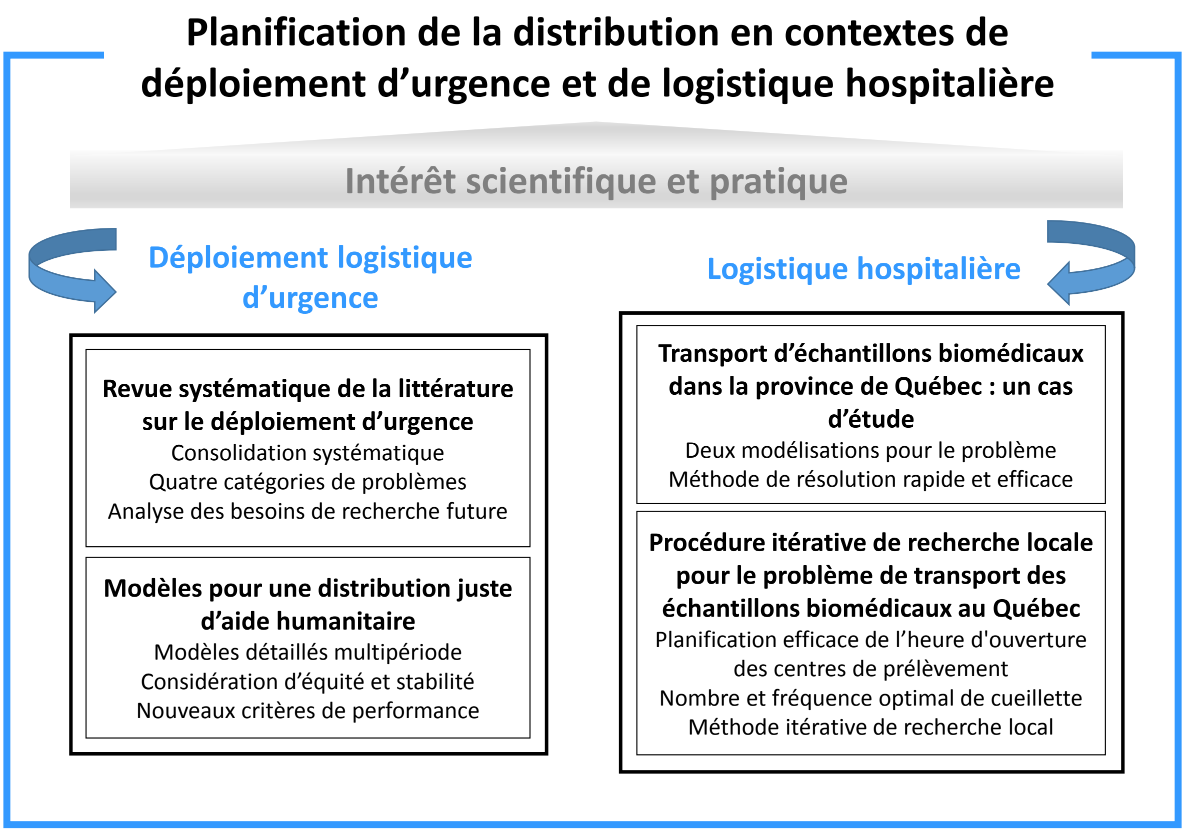

Figure 1.1 – Contributions de la thèse.

Chapitre 2

Revue systématique de la littérature sur le déploiement d'urgence

Depuis les vingt dernières années, la communauté scientifique s'est de plus en plus tournée vers le domaine de la gestion de crises, ou *emergency management*, et plus précisément vers le déploiement logistique lors de situations d'urgence. Le nombre et la variété des contributions dédiées au design ou à la gestion de la chaîne de distribution d'aide aux sinistrés ont explosés lors des dernières années. Ceci justifie le besoin d'une analyse systématique et structurée des travaux existants dans le domaine. Basé sur une méthodologie scientifique, cet article, qui consolide et classifie les travaux de recherche publiés, a trois objectifs. Premièrement, effectuer une mise à jour de la recherche disponible sur les réseaux de distribution d'aide en se concentrant sur le volet logistique du problème (volet qui a été négligé dans les études précédentes). En second lieu, souligner les aspects et les enjeux les plus importants dans les modèles et les stratégies de résolution existants. Finalement, identifier des perspectives de recherche future qui ont encore besoin d'être explorées.

Article 1: Relief distribution networks: a systematic review

Ce chapitre fait l'objet d'une publication sous la forme d'article de journal : Anaya-Arenas, A.M., Renaud, J. & Ruiz, A., 2014. Relief distribution networks: a systematic review. *Annals of Operations Research*, 223(1), pp.53–79.

Abstract In the last 20 years, Emergency Management has received increasing attention from the scientific community. Meanwhile, the study of relief distribution networks has become one of the most popular topics within the Emergency Management field. In fact, the number and variety of contributions devoted to the design or the management of relief distribution networks has exploded in the recent years, motivating the need for a structured and systematic analysis of the works on this specific topic. To this end, this paper presents a systematic review of contributions on relief distribution networks in response to disasters. Through a

systematic and scientific methodology, it gathers and consolidates the published research works in a transparent and objective way. It pursues three goals. First, to conduct an up-to-date survey of the research in relief distribution networks focusing on the logistics aspects of the problem, which despite the number of previous reviews has been overlooked in the past. Second, to highlight the trends and the most promising challenges in the modeling and resolution approaches and, finally, to identify future research perspectives that need to be explored.

2.1. Introduction

Natural disasters and catastrophes have always been part of the world's reality. Even with today's technology and advancements in disaster planning on our side, disasters' related casualties and financial losses can be very high. For example, March 2011 Japan's earthquake and tsunami resulted in more than 15 800 deaths and 3 600 missing persons[2] in the Tohoku district only, and over 210 billions of dollars in economic losses[3]. Due to the multiple natural and man-made catastrophes happening all over the world, the scientific community is increasingly interested in developing knowledge on Emergency Management (EM), an emergent multidisciplinary research field aimed at helping and enabling communities prepare for disasters and respond to extreme events.

In the last years, a large number of scientific contributions have been made to the EM field. Although classed under the EM umbrella, they differ greatly in regards to objective, scope, and motivation. For example, we noticed that terms like "emergency", "emergency logistics", "humanitarian logistics" and "response to crisis" are used in a wide range of contexts not related to relief distribution networks. When looking at the notion of emergency management, important distinctions must be made between daily emergencies, crisis situations and EM.

[2] Damage Situation and Police Countermeasures associated with 2011 Tohoku district - off the Pacific Ocean Earthquake - November 22, 2011 - http://www.npa.go.jp/archive/keibi/biki/higaijokyo_e.pdf

[3] EM-DAT data base, Disaster profile: Earthquake (seismic activity): http://www.emdat.be/result-disaster-profiles?disgroup=natural&period=1900%242011&dis_type=Earthquake+%28seismic+activity%29&Submit=Display+Disaster+Profile

EM, also known as disaster management, can be defined as a discipline dealing with disasters related risk (Haddow et al. 2007). According to the International Federation of Red Cross and Red Crescent Societies, a disaster is “a sudden, calamitous event that seriously disrupts the functioning of a community or society and causes human, material, and economic or environmental losses that exceed the community’s or society’s ability to cope using its own resources.”[4] Considering this, a distinction between emergency management and daily emergencies management must be made. Contrary to disasters, daily emergencies are usually well handled by the affected community‘s daily operations. Therefore, the context, challenges, urgency and impact of the operations in both cases are quite different. This was underlined by Simpson & Hancock (2009) who presented a review of 50 years in emergency response, covering the period between 1965 and 2007. The authors showed the literature’s shift in recent years, leaving the daily applications and turning more to disaster related emergencies.

Crisis management refers to different types of crisis and a large set of contributions may therefore be referenced under that term. Natarajarathinam et al. (2009) reviewed publications pertaining to supply chain management (SCM) in times of crisis. The literature selected by the athors’s focused on SCM disruptions i.e. business logistics reacting to unexpected crisis, either internal (company crisis) or external (sudden-onset and slow-onset disasters, financial crisis, market crises, etc.). A small part of the review related to catastrophes, defined as a part of external crisis.

EM is a discipline of continuous work on infrastructure and peoples’ awareness. Altay and Green (2006) were among the first to review the available scientific papers using Operations Research and Management Science (OR/MS) applied to EM. Their review of articles published between 1980 and 2004, provided statistics and classified contributions based on the approach, the phase of application, the review of publication and more. Galindo & Batta (2013) added to this work by reviewing papers from 2005 to 2010 and following up of the conclusions of Altay & Green (2006).

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[4] http://www.ifrc.org/en/what-we-do/disaster-management/about-disasters/what-is-a-disaster/

From a chronological standpoint, the literature often divides the EM's continuous process into four different phases (Altay & Green 2006; Haddow et al. 2007; McLoughlin 1985): mitigation, preparedness, response and recovery. The mitigation and preparedness phases take place before the disaster. These phases are aimed at lowering the probabilities of a disaster occurring or minimizing its possible effects. The response and recovery phases are post-disaster phases. The response phase seeks to minimize the disaster's effects by helping people as quickly as possible and preventing any more loss while the recovery phase supports the community in its effort to return to a normal state. The actual division of these phases will be discussed further on.

Many academic publications have contributed to the research done on one or more of these phases. According to Altay & Green (2006) and Galindo & Batta (2013) more than 264 papers have been published on EM and a special attention has been given to the response phase. More than 33% of the papers included in both reviews focused on the response phase, in which the major activities are logistic oriented (e.g. opening shelters, relief distribution centers, medical care and rescue teams dispatching, etc.). Indeed, we have come to conclude that 80% of EM concerns logistic activities (Van Wassenhove, 2006), reason why emergency logistics (EL) is a very popular research application nowadays.

2.1.1. Motivation for a relief distribution networks literature review

Many authors have acknowledged that the particularities of the emergency management context bring on some new challenges, especially in regards to logistics optimization (Holguín-Veras et al. 2012; Kovács & Spens 2007; Sheu 2007b; Van Wassenhove & Pedraza Martínez 2012). Very recently, Holguín-Veras et al. (2012) published a paper on the unique features of post-disaster humanitarian interventions. Their work elaborates on the differences between interventions made during the immediate response to disasters, and those made in the recovery phase. These efforts may also be divided into short-term and long-term recovery activities. The long-term recovery activities can be included in regular humanitarian actions carried out in the long term. Regular humanitarian actions also include the response to slow-onset disasters, like the delivery of food to regions afflicted with chronic crises or the delivery of medicines to people in developing countries, and have a more stable environment of operations. On the other side, the logistical efforts required by an immediate post-disaster's response distribution are made in extreme conditions and therefore demand new ways of organizations. The varying networks' goals, the associated organizations, the participants' interactions and the pressing nature of the distribution are all motivating factors in the elaboration of a new logistic structure's framework able to cope with these challenges. We recommend Lettieri et al. (2009) and Kovács & Spens (2007) for a review. Lettieri et al. (2009) also presented an analysis oriented on a disaster management theoretical framework, the phases in EM, the actors involved and the technology (DSS, GIS, etc). In order to define a general framework for the relief supply chain, Kovács & Spens (2007) included both academic and practitioner journals in their topical review. Without a doubt, an analysis of the distribution network's management challenges is vital to the development of DSS and tools for crisis managers. However, a large portion of the literature is devoted to the logistics aspects of the relief distribution. Holguín-Veras et al. (2012) highlighted the urgency in understanding the workings of the relief distribution network in specific logistics' aspects, like the knowledge of demand, the considered objectives, the periodicity and the decision-making structure. Until now, these major differences had been neglected, and our work comes to support the analysis that researchers need to do in order to approach this complex problem. *Figure 2.1* presents the specific interest of this review pertaining to relief distribution networks and its related fields.

Within the specific field of relief distribution networks, two recent literature reviews are relevant to our work. Caunhye et al. (2012) analyzed logistics optimization papers in a pre and post disaster context. Even if the motivations and global scopes are close to ours, our results showed that the authors' methodology (Content Analysis) left a good number of papers out their review. In addition, we can add to their work more than 40 papers published between 2010 and 2013.

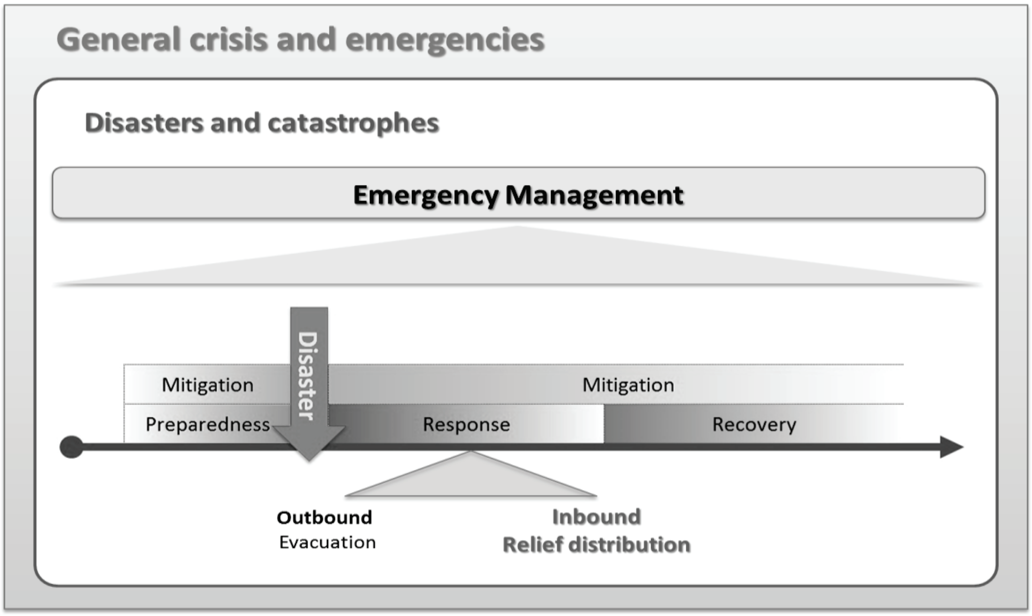

Figure 2.1 – Relief distribution networks domain.

Likewise, de la Torre et al. (2012) presented a review of academic and practitioner papers on the Vehicle Routing Problem (VRP). The main characteristics of the papers reviewed and their relationship with the academic/practitioner's point of view are presented. However, due to differences in motivation and scope, several academic contributions are not included in their review.

That being said, we believe that there is a need for a narrow literature review specifically focused on recent contributions in relief distributions networks because (1) the number of contributions to the field is larger each day, and it seems to keep on growing even faster; and (2) this crucial issue in EM requires that a specific analysis of the literature be devoted to it. In this context, our work pursues two main objectives. First, to provide a systematic review covering and classifying the numerous available studies in order to consolidate the body of knowledge. Our review process, which allows us to cover a large number of contributions, along with our classification framework, will provide a recent and organized overview of new optimization tools in the hands of emergency managers. In addition, this systematic review will become a powerful tool for introducing students and people interested in the discipline. Secondly, the evolution of this discipline needs to be studied, and especially the specific logistics features. This review will allow us to present the field's state of the art, highlight the literature's most significant contributions and, even more important, identify new research areas that need to be explored.

The rest of this article is organized as follows. Section 2 describes the process used to find and select the studies included in this review. Section 3 reports our research results, in which the research topics in relief distribution networks are summarized. The following four sections (4 to 7) present the papers' trends in each of the identified research topics. Section 8 provides a general discussion of our research results and future research recommendations, and section 9 draws our global conclusions.

2.2. Methodology: Systematic selection process

In order to cover as many pertinent documents as possible and given the variety of scientific papers in emergency logistics as well as the growing number of contributions, a systematic approach was required. This section presents the methodology used to guide the articles' selection process: the systematic review methodology (Kitchenham 2004; Staples & Niazi 2007; Tranfield et al. 2003). Although the systematic review methodology originated in the medical field, it has recently been applied to management topics. Tranfield et al. (2003) state that a systematic review is a key tool in developing the evidence base. The main objective of this methodology is to increase the quality of the review process by synthetizing research in a systematic, transparent and reproducible way. Indeed, every review process needs a framework definition subject to the scope of the problem and the research team's interests. Moreover, establishing a systematic procedure lends transparency to the review process and reduces the effects of the authors' bias. A clear and public definition of the review's objectives, the inclusion and exclusion criteria, as well as the process' results and the procedure itself, motivates the need for researchers to be explicit, consistent, and straightforward. Furthermore, the protocol's report maximizes the possibility of reduplication and even allows the continuity of the process. The methodology applied to this review can be summarized as follows:

1. The review's needs and general goals were established. Faced with the emergency logistics literature's state, with numerous and diverse contributions, our team felt the need for a detailed picture the research done on relief distribution networks. More precisely, this systematic review is about the relief supply chain deployed in immediate response to disasters. This meant that, the literature reviewed had to include an Operational Research (OR) component with the goal of optimizing the distribution center location, resource allocation, or humanitarian aid transportation after a disaster, as well as others logistics tasks, for relief distribution, as it was shown in *Figure 2.1.*

2. With this general thought, five relevant databases were selected as search engines for our process. Three of them were related to administration sciences: ABI/Inform Global, Academic Search Premier and Business Source Premier. The other two were OR oriented: Compendex for engineering and technology, and Inspec for calculations in physics, electronics, and information science. A multi-disciplinary database was included: ISI' Web of Science.

3. Based on our knowledge and expertise in the field, as well as the review of 20 well-recognized references in the literature, a set of key words was selected to define two search chains. These search chains were identified in the title, abstract, citation and/or subject of the articles. The words used our search chains were emergenc*; disaster*; catastroph*; "Extreme Events"; Humanitarian*; Aid; Assistanc*; Relief*; Logistic*; "Supply Chain"; Response; Distribution. The word "optimization" created an enormous restriction of the results and so, it was not considered in our search chains.

4. To help us to restrict our search results, a date range was defined. We only considered works published between 1990 and 2013. This decision was justified by the fact that the most significant advancements in the EM research field were done in the last decade. In addition, the previous studies focused on nuclear emergency response, a strong trend in the 1980s. At the time,

emergency management was not really structured or formalized (Altay & Green, 2006).

5. The great number of search results and the variety of contributions required that boundaries be established to limit the number of "hits". Different inclusion and exclusion criteria were defined and applied to our selection process. Before presenting these criteria, it is worth mentioning that this paper does not intend to be an exhaustive bibliographic study, but the result of a systematic scientific review method in the specific field of relief distribution networks.The review's inclusion and exclusion criteria used to narrow the search results are as follows:

2.2.1. Inclusion and exclusion criteria

We chose to limit our search to academic publications with a peer review process. We excluded all governmental and military reports from our selection as well as practitioner reviews research made by private organizations. Conference acts, congress papers and dissertations were also excluded. Other papers (e.g., case studies, response performance analysis or reports from EM organizations, such as the Federal Emergency Management Agency (FEMA), the United Nations (UN) or the International Federation of Red Cross and Red Crescent Societies (ICRC)) were excluded as well.

On the other hand, to reflect our interest in the response phase, the contribution proposed by the articles selected had to be designed keeping in mind its application in the aftermath of an extreme event. This aspect was sometimes difficult to evaluate precisely because some papers can be applied in either the preparedness phase or the response phase, depending on whether or not the input data were predictions or real observations. In the latter case, they were included in this review.

Studies about preparedness activities, which are intended to be applied in advance of a disaster (e.g., evacuation planning, congestion analysis problems, provision sourcing selection and stock prepositioning for a long-term context) were also excluded from our review. Likewise, we excluded research on the recovery phase, in which the planning horizon defined for the problem is longer than the one for the response phase. Also, the research objective has a more strategically sustainable perspective. Although not considered in this review, we tend to point out the interest of these papers and the importance of their contributions.

Furthermore, given the large number of papers and the context particularities, we limited our search to papers considering sudden-onset disasters only (Van Wassenhove 2006), such as the 9/11 terrorists attacks in NYC or the earthquake in Haiti in January 2010. This means that the relief distribution in a slow-onset disaster context (e.g., famine or drought) is out of our scope.

6. After establishing the review's boundaries, the search process was executed in the different databases. The search was executed in two phases. A first databases search was conducted in June 2011, and 4169 papers were found. Then, as an update, we proceeded to a second in June 2013. We looked for papers published between June 2011 and June 2013, finding 368 new papers. A total of 4537 papers were found by the search engines. The title and abstract of the search results were considered and compared to our inclusion and exclusion criteria. This first filter left a total of 107 papers for further analysis. Additionally, the following additional sources were consulted to make the research as rich as possible: (1) a previous search in the references of the initial databases of the well-known articles led to the addition of 22 new references. (2) Furthermore, our search protocol led us to the discovery of seven previously published special issues in emergency management: Transportation Research, Part E, Vol. 43, No. 6, 2007; International Journal of Physical Distribution & Logistics Management, Vol. 39, No. 6, "SCM in time of crisis humanitarian," 2009; International Journal of Physical Distribution & Logistics Management, Vol. 40, No. 8-9, "Transforming humanitarian logistics," 2010; International Journal of Production Economics, Vol. 126, No.1, 2010; OR Spectrum, Vol. 33, No. 3, 2011; and Socio-Economic Planning Sciences Volume 46, Issue 1, "Special Issue: Disaster Planning and

Logistics: Part 1" and Volume 46, Issue 4, "Special Issue: Disaster Planning and Logistics: Part 2", 2012.

A total of 56 papers were found in these special issues. 23 of them were found in databases using our search system. The other 33 references that had not been found or selected were explored, and 13 of them were retained for a deeper analysis. (3) The references from the 16 articles of OR Spectrum, as well as the references from the six reviews papers, were explored to add 28 new references. We discovered that, in most cases, the mix of keywords defined by the authors was the reason behind the exclusion of those references from our original search results. A total of 170 papers were set apart for a more thorough reading. The 170 papers selected were read, analyzed and once again compared to our inclusion/exclusion criteria. This lead to the final set of 83 papers reviewed in this article.

2.3. Research topics in relief distribution networks literature

Generally speaking, the study of relief distribution networks includes the following sequence of decisions and tasks. Once the emergency alert is given, the authorities (who may be regional, national or even international, depending on the scale and gravity of the crisis) on the scene evaluate the situation. The affected zone, also called the hot zone, is delimited, and the logistics deployment starts. One of the first decisions to be made concerns the design of the distribution network and consists in electing the set of logistics centers, shelters and distribution centers that will be used to support the relief operations. Located in a safe area outside the hot zone, large distribution centers (DCs) receive and consolidate relief goods from external suppliers. DCs feed humanitarian aid distribution centers (HADCs) located inside the hot zone. HADCs distribute relief goods to the points of demands (PODs) which in fact represent a cluster of affected people. Usually, the site's selection for the DCs and HADCs is done from a set of pre-selected sites identified, and even prepositioned, during the preparedness phase. The second type of decisions in the logistic deployment concerns the allocation of available resources to HADCs taking into account the needs of the affected people they will be serving. The third type of decisions relates to the transport between HADCs and PODs. Emergency logistic networks imply an inbound flow of relief from the cold to the hot zone, but also an outbound flow aimed at moving people or materials towards safer areas located either inside or outside the hot zone. Despite of the importance of such outbound flows, this review focuses on the inbound part. *Figure 2.2* presents a diagram of the general emergency logistic network.

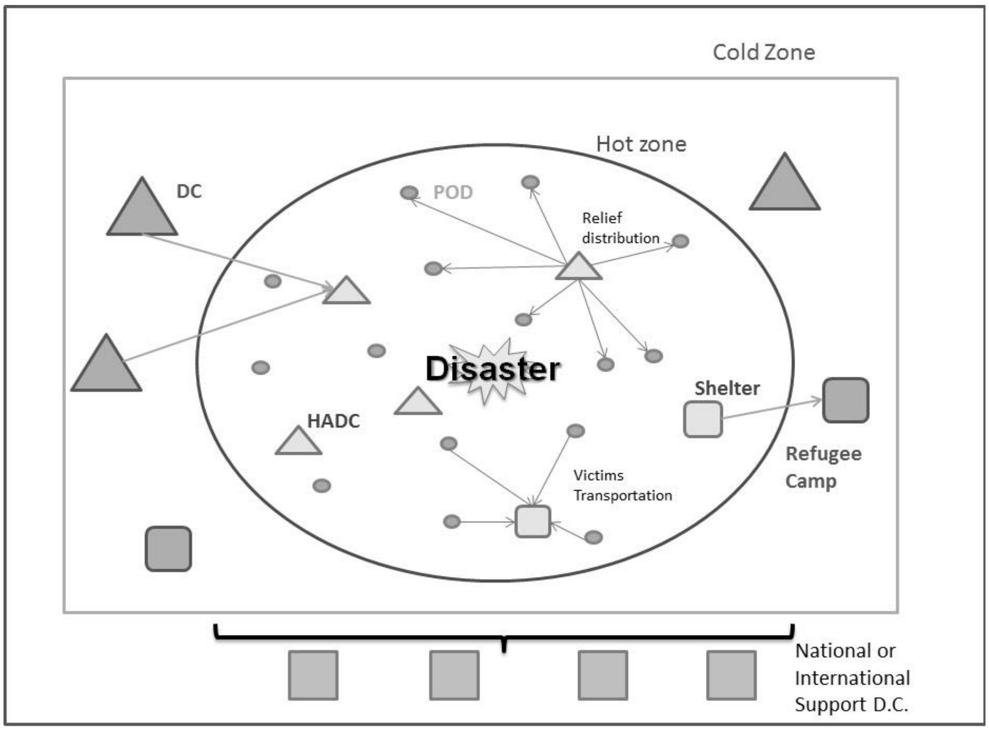

Figure 2.2 – Emergency response logistic network.

Our review process shows that the literature is well aligned with this decisional framework. Therefore, the papers reviewed were divided into the following categories: (1) location/allocation and network design problems, (2) transportation problems, (3) combined location and transportation problems, and (4) other less popular, but still important, topics in relief distribution. Note that, given that our interest is limited to relief distribution networks, the resource allocation problem is only defined for the commodities and capacity assignments in the HADCs. In most cases, this aspect is covered in the network design decisions.

Table 2.1 reports the articles found in each of these categories. 29 Articles out of the 83 selected papers are devoted to the location and network design problems and were published between 1991 and 2013.

Table 2.1 – Research topics in emergency logistics.

Research Problem	Total	Articles
Location and Network Design	29	Balcik & Beamon (2008); Bozorgi-Amiri et al. (2012); Campbell & Jones (2011); Chang et al. (2007); Davis et al. (2013); Drezner (2004); Drezner et al. (2005); Görmez et al. (2010); Hong et al. (2012); Horner & Downs (2010); Horner & Downs (2007); Iakovou et al. (1997); Jia, Ordóñez & Dessouky (2007); Jia, Ordóñez & Dessouky (2007); Kongsomsaksakul et al. (2005); Lee, et al. (2009a,b); Li et al. (2011); Lin et al. (2012); Murali et al. (2012); Nagurney et al. (2011); Rawls & Turnquist (2010, 2011, 2012); Sherali et al. (1991); Wilhelm & Srinivasa (1996); Yushimito et al. (2012) and Zhang et al. (2012, 2013a)
Transportation (relief distribution & casualty transportation)	30	Adivar & Mert (2010); Balcik et al. (2008); Barbarosoğlu & Arda (2004); Barbarosoğlu et al. (2002); Berkoune et al. (2012); Campbell et al. (2008); Chen et al. (2011); Chern et al. (2010); Gu (2011); Haghani & Oh (1996); Hu (2011); Huang et al. (2012); Jotshi et al. (2009); Lin et al. (2011); Najafi et al. (2013); Özdamar (2011); Özdamar et al. (2004); Özdamar & Demir (2012); Özdamar & Yi (2008); Shen et al. (2009); Sheu (2007a); Suzuki (2012); Tzeng et al. (2007); Vitoriano et al. (2009,2011); Wohlgemuthscha et al. (2012); Yi & Kumar (2007); Yi & Özdamar (2004); Yuan & Wang (2009) and Zhang et al. (2013b)
Location and Transportation	8	Afshar & Haghani (2012); Mete & Zabinsky (2010); Naji-Azimi et al. (2012); Nolz et al. (2010); Nolz et al. (2011); Ukkusuri & Yushimito (2008); Yi & Özdamar (2007) and Zografos & Androutsopoulos (2008).
Other important topics	16	Altay (2012); Duque & Sörensen (2011); Falasca & Zobel (2012); Feng & Wang (2003); Huang et al. (2013); Lodree Jr et al. (2012); Minciardi et al. (2007); Minciardi et al. (2009); Rottkemper et al. (2012); Rottkemper et al. (2011); Turner et al. (2012); Viswanath & Peeta (2003); Xu et al. (2010) and Yan & Shih (2007, 2009).

30 Articles focus on transportation problems; eight articles tackle both location and transportation problems either in an integrated or a sequential manner and, finally, 16 papers deal with other important topics, like dynamic demand management, prevision and road repairing, among other subjects.

2.3.1. Categories taxonomy

Before going into the details of each category, we propose a taxonomy used to classify and position the contributions of the reviewed articles according to general OR characteristics or criteria. This taxonomy will help identifying research trends in emergency logistics, classifying the different versions of problems, the considered attributes, and the modelling approaches proposed.

The first classification criterion refers to the type of data modelling approach used by the authors and, in particular, by the inputs' characteristics (i.e. demand, capacity, impacts or damages caused by the event…) considered by the models. In most cases, these aspects are generally modelled as either static or dynamic inputs. More precisely, some authors represent these inputs as a stochastic process with random variables, or even as fuzzy problems with fuzzy variables.

The second criterion concerns the scope or the decisional perimeter of the problem under consideration. It consists of classic OR elements like whether or not the research problem (i.e. location, transportation or other problem) is a single or a multi objective optimization problem, if the planning horizon encompasses one or more periods, if the network transports a single or several commodities, and the kind of main objective optimized by the model. This objective can be: (1) economic (i.e. cost minimization); (2) covering maximization objective (either demand or distance); (3) rapidity (minimization of the travelling time between network nodes); (4) social cost (fairness or similar); or (5) other.

The third criterion concerns the problem solving approach proposed by the authors (i.e. exact or heuristic methods). Finally, the column Tested over specifies if the proposition was applied over academic instances (Acad.) or real life inspired instances (CS). Clearly, many other classification taxonomies may be used, but we think that those used represent a good compromise and correspond to the most desired information. This general classification was applied to all the articles reviewed. Some other considerations or criteria will be presented later on when analyzing specific works.

2.4. Location and Network Design

In logistics deployment, the network's design is the first decision faced by the crisis manager. Among the network's design decisions, the selection of the HADC from a set of potential sites is the foundation to the location problem. *Table 2.2* presents the different contributions devoted to this question. In addition to the classification features defined in the previous section (i.e. Data Modeling, number of objectives – Objective, Periods, Commodity, and Resolution Method), we added three additional characteristics that are important to location and network design problems: capacity limits, sourcing considerations and the resource allocation approach.

The Cap. Limits column shows whether or not the model deals with a capacity limit in potential location sites. This consideration evidently adds constraints to the problem and makes it more difficult to solve. The Sourcing column indicates whether or not the authors restrict the supply sources. A single-sourcing restriction means that a client is forced to be supplied from only one depot; conversely, multiple-sourcing means that a client can be reached from various depots. Lastly, the resource allocation (RA) column lets us know whether or not the authors included resource allocation decisions (e.g., capacity allocation, stock prepositioning, or client's assignment) in their model.

The papers reviewed in this section are classified in two different categories, according to where the authors placed themselves on disaster response timeline (i.e. before or after disaster occurrence). The first type are the location decisions defined for a Post-event context, allowing authors to consider that, as we explained before, the evaluation of the affected zone is already done and the disaster effects and major needs are known to crisis managers.

Table 2.2 – Location and network design problems in relief distribution.

	Article	Data Modeling	Problem characteristics: Objective	Periods	Commodity	Cap. Limits	Sourcing	RA	Main Obj.	Resolution Method	Tested over
Post event context	Horner and Downs, 2010	Static	Single	Single	Single	Yes	Single	Yes	1	Exact	CS
	Horner and Downs, 2007	Static	Multi	Single	Single	No	Single	No	1	Exact	CS
	Iakovou et al., 1996	Static	Single	Single	Multi	Yes	Multi	Yes	1	Heuristic	CS
	Jia et al, 2007a	Static	Single	Single	Single	No	Multi	No	2	Exact	CS
	Jia et al., 2007b	Static	Single	Single	Single	No	Multi	No	2	Heuristic	CS
	Lee et al., 2009a	Static	Single	Single	Single	Yes	Single	Yes	2	Exact	CS
	Lee et al. , 2009b	Static	Single	Single	Single	Yes	Single	Yes	2	Exact	CS
	Lin et al., 2012	Static	Single	Multi	Multi	Yes	Single	Yes	2 3 4	Heuristic	CS
	Murali et al., 2012	Stochastic	Single	Single	Single	Yes	Multi	Yes	2	Heuristic	CS
	Zhang et al., 2012	Static	Single	Single	Multi	Yes	Multi	Yes	1	Heuristic	Acad.
Pre event context	Balcik and Beamon, 2008	Stochastic	Single	Single	Multi	Yes	Multi	Yes	2	Exact	Acad.
	Bozorgi-Amiri et al., 2012	Stochastic	Single	Single	Multi	Yes	Multi	Yes	1	Heuristic	Acad.
	Campbell and Jones, 2011	Stochastic	Single	Single	Single	No	Single	Yes	1	Exact	Acad.
	Chang et al., 2007	Stochastic	Single	Single	Multi	Yes	Multi	Yes	3	Heuristic	CS
	Davis et al., 2013	Stochastic	Single	Single	Single	Yes	Multi	Yes	1	Exact	CS
	Drezner T. 2004	Static	Multi	Single	Single	No	Multi	No	2	Exact	CS
	Drezner et al., 2005	Static	Multi	Single	Single	No	Multi	No	2	Heuristic	CS
	Görmez et al., 2011	Static	Multi	Single	Single	Yes	Multi	Yes	1 2	Exact	CS
	Hong et al., 2013	Static	Single	Single	Single	No	Single	Yes	1	Exact	CS
	Nagurney et al., 2011	Stochastic	Single	Single	Single	Yes	Multi	Yes	1	Exact	Acad.
	Rawls and Turnquist, 2010	Stochastic	Single	Single	Multi	Yes	Multi	Yes	1 2	Heuristic	Both
	Rawls and Turnquist, 2011	Stochastic	Single	Single	Multi	Yes	Multi	Yes	1 2	Exact	CS
	Rawls and Turnquist, 2012	Stochastic	Single	Multi	Multi	Yes	Multi	Yes	1 2	Exact	CS
	Wilhelm and Srinivasa, 1996	Stochastic	Single	Multi	Single	Yes	Single	Yes	1	Heuristic	CS
	Yushimito et al., 2012	Static	Single	Single	Single	No	Single	No	4	Heuristic	Acad.
	Zhang et al.,2013a	Static	Multi	Single	Single	No	Single	Yes	2	Heuristic	Acad.
	Kongsomsaksakul et al., 2005*	Static	Single	Single	Single	Yes	Multi	Yes	3	Heuristic	CS
	Li et al., 2010*	Stochastic	Single	Single	Multi	Yes	Multi	Yes	1	Exact	CS
	Sherali et al., 1991*	Static	Single	S&M	Single	Yes	Multi	Yes	3	Ex. / Heu.	CS

*Shelter location problems.

This hypothesis creates a “steady” environment that allows propositions in this category to define, as an input known a priori in the model, the demand and the location of clients, as well as the disaster impacts. Our review shows that the articles in this category present a more traditional facility location problem (FLP) structure, they are mainly static and seek to optimize a single objective (either cost minimization, covering maximization in distance or quantity or rapidity) and this, during a single period. In addition, most of the location and network design problems are directed to a single-commodity relief distribution, representing a global demand. Horner and Downs (2007; 2010), present a multi-echelon network designed for intermediate distribution facilities (Break of Bulk points). Iakovou et al. (1997) present the strategic and tactical decisions involved in locating the clean-up equipment for oil spill disaster. Other authors deal with the location-allocation of medical services in response to emergencies with a covering objective, forcing a minimum satisfaction of demand such as (Jia et al. 2007a; Jia et al. 2007b), and (Lee et al. 2009a; Lee et al. 2009b).

However, models able to accurately represent the disaster reality may be more desirable. Indeed, even after a disaster has hit the zone, information about demand is hard to obtain, and a stochastic modeling approach can be useful to represent the incertitude related to the process of the impact’s estimation. Recent contributions tackled this issue with stochastic models that maximized coverage (like Murali et al. 2012), models reflecting post-disaster challenges as disaster overlapping (Zhang et al. 2012), or fairness in distribution objectives (Lin et al. 2012). It is worth mentioning that, as we indicated before, the contributions in this section still present the classic structure of the FLP applied to emergency situations, without real insight into the context difficulties being reflected in their models. With the recent exception of the papers published in 2012, neither the objectives nor the constraints of the model present a particular feature in relief distribution. We firmly believe that these recent contributions come as an answer to the need for detailed models that supporting decision- making.

The second group contains the propositions with a Pre-event context. The strategic nature of the location problem has encouraged many authors to work on the right network design in order to prepare for disaster response. Even though our article selection process is limited to the relief distribution network in response to disasters, these models can also be applied as an immediate response to the disaster; therefore, these propositions are included in this review. Moreover, many contributions in this section actually consider both stages in their modeling approach, dealing with stock prepositioning decisions, and then reallocation after a disaster occurrence. For instance, some of the papers present stochastic models, in which the site location is chosen to satisfy demand under different possible disasters (Rawls & Turnquist 2010) or their impacts: Balcik & Beamon (2008) also includes pre and post disaster budget constraints; the service quality level (Rawls & Turnquist 2011); the possible locations of disaster related damages (Campbell & Jones 2011) or multilevel considerations for network design (Chang et al. 2007). Recently this has starting to shift towards a prepositioning problem that includes, beyond the risk of damages (demand), the demand location (Rawls & Turnquist 2012), available supplies (Davis et al. 2013), outsourcing needs (Nagurney et al. 2011) and even transportation and buying costs (Bozorgi-Amiri et al. 2012). Wilhelm & Srinivasa (1996) focus on the risks related to the reliability of the relief distribution network, which is still present in a post-disaster context. Other authors concentrate their efforts more towards a model definition with the main objective warranting relief distribution to its maximum capacity. In this case, a covering objective is used to minimize uncovered demand (Drezner 2004; Drezner et al. 2005; Görmez et al. 2010; Hong et al. 2012), including characteristics as social cost (Yushimito et al. 2012) or covering and rapidity objective (Zhang et al. 2013a).

Three papers considered the sheltering location (and allocation) problem in a pre-disaster context. Even though they are evacuation-oriented, these papers were retained, because the location decisions for the evacuation problem at this level are the same as for the distribution context. Kongsomsaksakul et al. (2005) and Sherali et al. (1991) defined an optimal sheltering network that minimizes transportation time, while Li et al. (2011) proposed a two-stage stochastic model to consider the shelter supply.

Aside from the points discussed before, our review shows that most of the authors, both in a pre and a post disaster context, kept the strategic aspect of the location problem in a single period planning horizon and a highly aggregated information level on demand having a single-commodity feature (i.e. only 10% of the papers include a multi-period feature and 30% a multi-commodity network). We see this as particularly odd, given the fact that the in the context of immediate response to disaster the planning horizon is more likely short, and networks need to be very flexible. In addition, over 50% of the papers have a cost minimization objective, which has been already accepted as a limited and inappropriate objective for the relief distribution networks.

Furthermore, almost 30% of the papers reviewed propose a maximum covering objective as main objective, *p*-media problem or *p*-center problem, which are common models in FLP. These models are focused on the covering of PODs in terms distance only (i.e. a POD is covered if an open HADC is inside a maximum distance). However, they usually ignore the resources' availability and total satisfaction is assumed. Another common hypothesis in the FLP is that the HADCs' supply is unlimited. Therefore, very few papers consider the upper level of supply (DCs) in their network design. A deeper analysis is needed in both of these areas in order to design a network that would include the demand satisfaction's real capacities.

Even if there is indeed a strong need for efficiency in the use of resources, other objectives like social cost or rapidity in distribution should be the main guideline for the network's design decisions. Lifting these hypotheses will result in contributions not only more realistic but also more likely to be useful in a complete DSS.

2.5. Transportation Problems

Once the logistic network has been established, the relief delivery plan has to be built, leading to transportation or distribution problems. Until very recently and because of the number as well as the variety of propositions, this topic was the most popular in emergency logistics research, In fact, we noticed that transportation contributions are closer to the specific challenges of relief distribution. Thanks to the operational basis of the transportation task, the problem definition of these contributions is more specific to the response to disaster context and allows for the definition of a more practical distribution problem. For instance, the objectives defined in the contributions' transportation problem are more varied than for location cases and focus more on the distribution's rapidity or the satisfaction of demand than on total operational costs.

Since the transportation problem's characteristics changed, the table structure proposed in the previous section was modified, leading to *Table 2.3*. The first four columns show the already defined general characteristics. The fifth is the Depots column, indicating if the problem is defined as a single depot or multiple depots. Then, some vehicle's characteristics of the model are observed. The Capacity Limits column summarizes whether or not the proposition limits the vehicle's capacity. This column shows the limitation considered: volume capacity, weight capacity, time of the driver's shift, cost, number of vehicles available, or the number of units to transport. The seventh column, Fleet Comp., shows whether the model uses a heterogeneous fleet of vehicles or homogeneous fleet to construct the route. This is an important feature in humanitarian logistics because several organizations are involved in emergency response activities and the need for numerous types of resources (i.e. vehicles) is very common. Finally, the column Tr. Mode shows whether the problem is stated as a multi-modal problem or the specific type of transportation mode (i.e. ground, air or water). The different papers concerned with relief transportation decisions are presented in *Table 2.3*.

It is well accepted that transportation and routing problems are very difficult to solve. Even in the industrial context, academics and practitioners have been working for decades on this optimization problem. The problem's difficulty increases as the model's level of detail increases.

Table 2.3 – Transportation problems in relief distribution.

	Authors	Data Modeling	Problem characteristics								Resolution Method	Tested over
			Obj.	Periods	Commodity	Depots	Capacity Limits	Fleet Comp.	Tr. Mode	Main Obj.		
Relief Distribution	Adivar and Mert, 2010	Fuzzy	Multi	Multi	Multi	Multi	Weight	Hetero.	Multi	1 5	Exact	CS
	Balcik et al., 2008	Dynamic	Single	Multi	Multi	Single	Vol./Time/Fleet	Hetero.	Ground	1 2	Exact	Acad.
	Barbarosoğlu et al., 2004	Stochastic	Single	Single	Multi	Multi	Units	Hetero.	Multi	1	Exact	CS
	Berkoune et al., 2012	Static	Single	Single	Multi	Multi	W./Vol./Time/Fleet	Hetero.	Ground	3	Heur.	Acad.
	Campbell et al., 2008	Static	Single	Single	Single	Single	No	Homo.	Ground	3	Heur.	Acad.
	Chen et al., 2011	Static	Single	Single	Single	Multi	Units	Homo.	Ground	3	Exact	CS
	Gu, 2011	Sta.-Fuz.	Single	Single	S&M	Multi	Units	Homo.	Ground	2	Exact	Acad.
	Haghani et al., 1996	Static	Single	Multi	Multi	Multi	Units/Fleet	Hetero.	Multi	1	Heur.	Acad.
	Hu, 2011	Static	Multi	Single	Multi	Single	No	Hetero.	Multi	1	Exact	Acad.
	Huang et al., 2012	Static	Single	Single	Single	Single	Units	Homo.	Ground	3 2 4	Heur.	Acad.
	Lin et al., 2011	Static	S&M	Multi	Multi	Single	W./Vol./Time/Fleet	Homo.	Ground	2 3 4	Heur.	Acad.
	Özdamar et al., 2004	Dynamic	Single	Multi	Multi	Multi	Weight/Fleet	Hetero.	Multi	2	Heur.	CS
	Shen et al., 2009	Stochastic	Single	Single	Single	Single	Units/Fleet	Hetero.	Ground	2 3	Heur.	Acad.
	Sheu, 2007a	Dynamic	Multi	Multi	Multi	Multi	Units/Fleet	Hetero.	Ground	2 1	Exact	CS
	Suzuki 2012	Static	Single	Single	Single	Single	Weight/Fuel/Time	Hetero.	Ground	2 4	Exact	Acad.
	Tzeng et al,2007	Dynamic	Multi	Multi	Multi	Multi	Volume	Homo.	Ground	1 3 4	Exact/Sim.	Acad.
	Vitoriano et al., 2011	Stochastic	Multi	Single	Single	Multi	Units/Fleet/Budget	Hetero.	Ground	1 3 4 5	Exact	CS
	Vitoriano et al., 2009	Stochastic	Multi	Single	Single	Multi	Units/Budget	Hetero.	Ground	1 3 4 5	Exact	CS
	Wohlgemuth et al., 2012	Dynamic	Single	Multi	Single	Single	Units	Homo.	Ground	3 1	Heuristic	Acad.
	Yuan and Wang, 2009	Static	S.&M.	Multi	Single	Single	No	Homo.	Ground	3 5	Heur./Sim.	Acad.
	Zhang et al. 2013b	Static	Single	Multi	Single	Single	No	Homo.	Ground	3	Heuristic	Acad.
	Jotshi et al., 2009[a]	Static	Multi	Single	Single	Multi	Units/Fleet	Homo.	Ground	2	Heur./Sim.	CS
Dist. and Evacuation	Barbarosoğlu et al., 2002	Static	Multi	Single	Multi	Multi	Weight/Fleet/Time	Hetero.	Air	1	Heur.	Acad.
	Chern et al., 2010	Dynamic	Multi	Multi	Multi	Multi	Units/Fleet/Fuel	Hetero.	Multi	2 3 1	Heur.	Acad.
	Najafi et al., 2013	Stochastic	Multi	Multi	Multi	Multi	W./Vol./Units/Fleet	Hetero.	Multi	2 1	Exact	CS
	Özdamar and Demir, 2012	Static	Single	Single	Multi	Multi	Fleet/Units	Hetero.	Ground	3	Heur.	Acad.
	Özdamar and Yi., 2008	Static	Single	Multi	Multi	Multi	Units/Fleet	Hetero.	Ground	3	Heur.	Acad.
	Özdamar, 2011	Static	Single	Single	Multi	Multi	Weight/Time/Units	Homo.	Air	3	Heur.	Acad.
	Yi and Kumar, 2007	Static	Single	Multi	Multi	Multi	Weight/Fleet	Hetero.	Ground	2	Heur.	Acad.
	Yi and Özdamar, 2004	Fuzzy	Single	Multi	Multi	Multi	Weight/Fleet	Hetero.	Multi	2	Exact	CS

[a] Causality transportation problem

If we deal, all at the same time, with stochastic data, heterogeneous vehicle fleet, in a multi-period and multi-commodity network context (which is probably the closest to reality), the resulting model will be extremely hard to solve; which is not at all wanted when looking for fast and efficient solutions. Therefore, authors will usually choose the factors that best adapt to their study context and will establish hypotheses on the other features to simplify the model. For instance, some authors have a traditional approach to the data type (e.g., a deterministic static or dynamic data model) in order to consider a multi-period planning horizon (Wohlgemuthscha et al. 2012; Yuan & Wang 2009; Zhang et al. 2013b) or a multi-commodity network (Berkoune et al. 2012; Gu 2011; Hu 2011), or even both (Balcik et al. 2008; Haghani & Oh 1996; Lin et al. 2011; Özdamar et al. 2004; Sheu 2007a; Tzeng et al. 2007). Even though their data setting is deterministic, these papers define a complex distribution network close to the relief distribution's reality, with a proper level of detail to reflect the crisis manager's challenges. We believe this to be a very important point to establish models for decision making for the daily operations of relief distribution.

On the other side, some authors have a "traditional" approach to their problem's characteristics (i.e. static data, single-commodity and single period considerations) but with the objective of exploring new approaches to the relief distribution problem. For example, the transportation contributions have varied objectives beyond cost minimization. The most popular objective regarding these problems is the rapidity objective, usually defined through a minimum travel time objective or a minimum latest arrival time. Campbell et al. (2008) were among of the first to explore the major difference between relief and commercial distribution by proposing three different objectives for a fast delivery. Chen et al. (2011) defined a distribution problem integrated in a DSS with the support of a Geographic Information System (GIS). Suzuki (2012) had a static consideration but studied a coverage and equity objective that also included fuel limitation. On the other hand, Huang et al. (2012) defined three main objectives for the relief distribution challenge: rapidity, demand satisfaction and equity (i.e. equity, efficacy and efficiency). Theirs was one of the first propositions to approach the equity objective in an explicit way.

Through random or fuzzy variables, many authors also considered the uncertainty related to the relief distribution context that are reflected in demand, arc capacity, travel time or network reliability (Adivar & Mert 2010; Barbarosoğlu & Arda 2004; Shen et al. 2009; Vitoriano et al. 2009; Vitoriano et al. 2011). These papers' main contribution acknowledges the different sources of uncertainty in a post-disaster context, thus providing crisis managers with a more robust distribution plan. However, these contributions left aside the dynamic aspect of the problem and focused on a single period planning horizon. We believe this to be a useful twist that should soon be included in the emergency logistics planning. As we stated before, the changing environment is an important challenge in this context and a flexible network is still a major need.

When working on transportation problems, one should also consider the problems related to the transportation of casualties. During our review process, we noticed how the evacuation's planning decisions demand another type of analysis on an operational level (i.e. traffic assignment problems and congestion analysis, among others), which are out of the scope of our review. Contrariwise, the casualty transportation problem is sort of a "victims' transportation problem" and is part of the tasks needed to bring relief to affected people, which allowed us to review casualty transportation problems in this paper. In fact, some authors tackled both relief distribution and casualty transportation problems in their optimization model. In general, the model finds the optimal route to distribute relief products and transport victims from the danger zone to health centers. This results in a much more complex network problem, becoming a multi-commodity problem often presented with a multi-period planning horizon. Some of them have a static data setting, planning helicopter scheduling (Barbarosoğlu et al. 2002; Özdamar 2011) or a heterogeneous vehicle problem (Özdamar & Demir 2012; Özdamar & Yi 2008; Yi & Kumar 2007). Others present a dynamic problem (Chern et al., 2010) or a fuzzy stochastic problem (Najafi et al. 2013; W. Yi & L. Özdamar 2004). Finally, in their paper, Jotshi et al. (2009) dealt exclusively with the casualty transportation problem.

In general, one of the features common to most of the contributions' modeling approach is the use of a heterogeneous vehicle fleet that even considers a multi-modal problem. We believe this to be an interesting feature to include in the modeling process of relief distribution optimization for two main reasons. On one hand, it is one of the classically features studied in transportation optimization. The number of models and resolution methods that consider the variety of the fleet (in capacity, cost, use and/or purpose) is quite large nowadays, and this give even more tools to academics and practitioners to define applied problems. On the other hand, considering a heterogeneous fleet and, even more, a multi-modal context in their problem definition opens the door to include the variety of actors involved in relief distribution tasks. Indeed, different government, international agencies, NGOs, and even private sector participants put their resources together to overcome a crisis. Therefore, even if the advancements on this area are significant, and over 50% or the papers reviewed include a heterogeneous fleet, there is still a good opportunity to further explore this area and make the relief distribution process even more efficient.

Finally, another common feature in the transportation contributions is the consideration of a multi-depot network in order to elaborate the distribution plan (almost 60% of the reviewed papers acknowledge this reality). We encourage this practice because, as with the fleet composition feature, a multi-depot consideration will enable the crisis managers to plan not only a more complex and realistic network, but will also promote a better distribution of resources available, helping them to cope better with products' shortages.

2.6. Combined Location - Transportation Problems

As we stated before and as proven by the various contributions reviewed in the previous two sections, the location and transportation problems are the two main stages in relief distribution management. The OR literature has already established that the location problem's decisions have a direct influence on the efficiency of the distribution tasks. The choice of depots, as well as the center's required capacity, directly affects the distribution decisions. Therefore, the natural evolution for the decision optimization process is to approach these two problems from an integrated perspective that includes the analysis of the interrelation between these two decisional levels.

Many contributions have been made on one stage or the other, but the integrated-approaches are still rare. Only 8 of our 87 reviewed articles have tackled the location and transportation problems together. These articles and their characteristics are presented in *Table 2.4*. Some of them addressed the problem in an independent sequential manner (Mete & Zabinsky, 2010; Zografos & Androutsopoulos, 2008), with a stochastic or static data setting. Nolz et al. (2010, 2011) and Naji-Azimi et al. (2012) presented a tour-covering problem in which the routes are constructed, integrating the site selection decisions inside the covering zone. Ukkusuri & Yushimito (2008) and Yi & Özdamar (2007) presented an integrated Location-Routing Problem (LRP). Ukkusuri & Yushimito (2008) used this modeling approach for the stock prepositioning and distribution problem, considering the path's reliability. Yi & Özdamar (2007) solved a complex distribution problem, including casualty transportation. Based on dynamic demand's updates, the model will decide to open new care centres. An interesting contribution has recently been made by Afshar & Haghani (2012) who proposed a detailed complex network design and transportation problem to develop an integrated decision problem.

2.7. Other contributions

Some articles highlight a research problem that is less popular than the location or routing problems, but still represent an important advancement in relief distribution networks. For example, many authors chose to approach resource allocation independently of the location or the transportation problems.

These contributions are specifically oriented to inventory location or relocation before and/or after a disaster occurrence (Lodree Jr et al. 2012; Rottkemper et al. 2012; Rottkemper et al. 2011), and others treated the equipment allocation (Altay 2012; Minciardi et al. 2007; Minciardi et al. 2009), dealing strictly with the resource allocation problem where the real-time dynamic aspects of problems are approached.

Table 2.4 – Combined Location-Transportation problems in relief distribution.

Authors	**Data Modeling**	**Problem characteristics**										**Resolution Method**	**Tested over**
		Objective	**Periods**	**Commodity**	**Site capacity**	**R.A**	**Depots and Sourcing**	**Tr. Capacity Limits**	**Fleet Comp.**	**Tr. Mode**	**Main Obj.**		
Afshar and Hagani, 2012	Dynamic	Single	Multi	Multi	Yes	Yes	Multi	Units/Fleet/Weight	Hetero.	Multi	2	Exact	Acad
Mete and Zabinsky, 2010	Stochastic	Single	Single	Multi	Yes	Yes	Multi	Units/Fleet	Hetero.	Ground	1 3	Exact	CS
Naji-Azimi et al., 2012	Static	Single	Single	Multi	No	No	Single	Weight/Fleet	Hetero.	Ground	3	Heuristic	Acad
Nolz et al.,2010	Static	Multi	Single	Single	Yes	No	Single	Units/Fleet	Hetero.	Multi	2 3	Heuristic	CS
Nolz et al., 2011	Static	Multi	Single	Single	Yes	No	Single	Units/Fleet	Homo.	Ground	5 3	Heuristic	CS
Ukkusuri and Yushimito, 2008	Static-Stoch.	Single	Single	Single	No	No	Single	Budget/Fleet	Homo.	Ground	1	Exact	Acad
Yi, W. and Özdamar, L., 2007	Dynamic	Single	Multi	Multi	Yes	Yes	Multi	Weight	Hetero.	Ground	2	Heurisitic	CS
Zografos and Androutsopoulos, 2008	Static	Multi	Single	Single	Yes	Yes	Single	Units/Fleet	Homo.	Ground	3 5	Heuristic	CS

On the other hand, (Duque & Sörensen 2011; Feng & Wang 2003; Viswanath & Peeta 2003; Yan & Shih 2009; Yan & Shih 2007) proposed the problem of planning the urgent repairs in the response network.

Recent contributions described other specific challenges in response to disaster and relief distribution, like Huang et al. (2013) who suggested a routing problem for the assessment of the affected zone, which is probably one of the first steps in response to disaster. Usually, most of the studies use the hypothesis that this assessment work has been done before the location and transportation decisions.

Falasca & Zobel (2012) approached the specific problem of volunteer assignment which, until now, has been equally neglected. In their paper, Turner et al. (2012) proposed a water distribution using pressurized zones to satisfy the demand in uncovered areas.

Sheu (2010) and Xu et al. (2010) presented a very interesting and useful proposition to manage and forecast demand. Clearly, this is one of the major challenges in emergency logistics response and it is often ignored in the literature propositions. Sheu (2010), with the help of a multicriteria analysis, proposed a complete system that forecasts, groups and ranks the demand after a disaster. By using a hybrid method to forecast demand instead of traditional statistics, Xu et al. (2010) produced better results.

2.8. Literature analysis and future research perspectives

This section first presents our analysis of the reviewed papers, depicting the most recent advancements made in the field. It then identifies some research trends that are, in our opinion, the most challenging directions in emergency logistics.

2.8.1. Analysis of the reviewed literature

Our first observation concerns the lack of uniformity and accuracy in the definition of Emergency Management, the multidisciplinary research discipline pertaining to the particular field of relief distribution. In fact, EM is so vast and has grown so fast in the recent years that the need for scientific works devoted to the formalization of the discipline and its boundaries has become a matter of urgency. As shown in the Introduction, the terms “emergency”, “emergency logistics”, “humanitarian logistics” and “response to crisis”, among others, are applied in a wide range of contexts and from diverse standpoints, making it difficult to consolidate the knowledge and the scientific contributions.

Furthermore, and despite its theoretical value, the relevance of some structuring works to the relief distribution’s practice, like the 4-phases definition commonly accepted in the literature, is debatable. In fact, we have shown that many of the proposed location models for a pre-disaster phase can also easily be applied during the response phase. A response model, embedded in a Decision Support System, can be used in the training and preparedness process. Similarly, once the data has become available, a preparedness model can lead to an optimal response plan. We can conclude that, unlike the traditional approach in EM literature, the location and network design problem are not exclusive to the pre-disaster phase. Moreover, we think that the disaster timeline and the related operations need to be refined to harmoniously encompass the response as well as the short and long-term recovery activities.

Our second observation concerns the well-established differences between business and humanitarian logistics. Pioneer contributions in the field defined general response models, mostly within a multi-commodity network (Barbarosoğlu & Arda 2004; Barbarosoğlu et al. 2002; Drezner 2004; Drezner et al. 2005; Haghani & Oh 1996; Özdamar et al. 2004; Viswanath & Peeta 2003; Yi & Özdamar 2004). Despite their efforts, it seems that most of these contributions did not focus adequately in the specific characteristics of humanitarian logistics like the knowledge of demand, the considered objectives, the periodicity and the decision-making structure (Holguín-Veras et al., 2012). Hopefully, our knowledge and comprehension level of humanitarian challenges increases and recent articles present more sophisticated models, which better suit the specific context and needs, especially in the case of transportation problems (Berkoune et al. 2012; Gu 2011; Huang et al. 2012; Lee et al. 2009a; Lin et al. 2012; Lin et al. 2011; Murali et al. 2012; Özdamar 2011; Yan &

Shih 2009). Nonetheless, we think that the sudden and dramatic nature of humanitarian problems should be emphasized in future research works.

Our third observation concerns the difficult tradeoff between modeling the desired level of detail and the model's solvability. As more and more sophisticated, yet realistic models appear, it becomes increasingly difficult to solve them efficiently, particularly in a response context where decisions need to be made quickly. Thereby, papers proposing approximated methods (e.g. Nolz et al. 2010; Yi & Özdamar 2007; Berkoune et al. 2012; Lin et al. 2012; Murali et al. 2012; Wohlgemuthscha et al. 2012) are becoming more and more popular than the ones, focusing in modeling aspects, where commercial software is used to solve the proposed mathematical formulation (Horner & Downs 2010; Jia, Ordóñez & Dessouky 2007; Lin et al. 2011; Rawls & Turnquist 2011).

The stochastic and dynamic propositions are still rare. Even during the response phase, the level of uncertainty and, more so, the variability level are quite high, and a deterministic static modeling approach can easily lead to a low performance of the distribution tasks. However, stochastic and dynamic models being much harder to solve, significant effort is needed to efficiently solve the propositions.

Our fourth observation, which is in fact a set of observations, pertains specifically to the works on network design. First, we think that the nature of the different nodes or sites in the network needs to be revised and refined. Although the use of distribution centers and distribution points similar to those in the business SC seems to be widely accepted, we should not forget that, in the business case, those facilities are designed and built to perform logistic activities, which is not the case in a post-disaster context. Indeed, most humanitarian sites rely on the transformation of facilities like arenas or schools making it difficult to anticipate their flows and capacity to handle humanitarian activities. In general, the literature has neglected the aspect related to the "ability" of a facility to perform a given humanitarian and it would be interesting to see it included in future works. Even more important, we found that a very few of papers tackled multi-period cases in network design, neglecting the fact that the deployed network is usually temporary and needs to be flexible to accommodate the demand's variation. Moreover, in a multi-period planning horizon, facilities can be opened, closed and reopened during the planning horizon; therefore sites costs and capacities strongly impact the decisions. However, including this analysis and defining opening and closing costs in a manner relevant in a practical context still presents a challenge. For instance, one can account for the time and efforts required to open and prepare a given site by reducing its capacity during the period in which the site is open, while others may limit the number of sites to be open by constraining the number of available human resources to operate them.

Finally, we have already discussed the type of objectives that should direct the design decisions, and the small variety of modeling objectives (most articles present a cost minimization objective). However, while limited discussion have been devoted to justify whether or not single objective models are more suitable than multi-objective ones (Lin et al., 2012; Drezner et al., 2005), neither were about the choice of measures encompassed by the objective function.

Our fifth observation is related to works on transportation problems. It includes two comments and conclusions. Our first remark concerns once again the goal of the proposed models. The most popular objective in these problems is "rapidity", usually achieved by minimizing the total travel time or the latest arrival time. However, recent works have identified new and appealing objectives like minimization of the risk associated to the loss of a truck and its load, or the fair relief distribution (e.g. Vitoriano et al. 2009; Vitoriano et al. 2011). More specifically, Huang et al. (2012) is the only paper to highlight the paramount importance of a fair sharing of the available relief among the people in need. For their part, Lin et al. (2011); Tzeng et al.(2007); Vitoriano et al. (2009) and Vitoriano et al. (2011) considered it more as a secondary objective. The notion of "equity", overlooked in the literature, becomes even more important when multi-period contexts are considered. Since available relief and demand may vary from one period to another, it seems reasonable to expect some flexibility in the way that demand is satisfied. This offers the possibility of delivering lower quantities to some people, provided that they receive higher quantities in the subsequent periods. Nonetheless, our review did not report any paper dealing explicitly with the possibility of relief backordering. We believe that this should be presented in order to offer a better support to the distribution decisions.

Our second comment on the reviewed papers relates to whether relief is distributed by truck routes or by dedicated trips. In fact, an analysis of this aspect has been disregarded in the literature, and both options are valid approaches on relief distribution. de la Torre et al., (2012) presented a review of papers on relief distribution where trucks performed delivery routes. On the other hand, other authors (see for example Berkoune et al., 2012) proposed a multi-trips approach to satisfy the PODs' demand.

Our sixth observation concerns the works that we have classified as "Combined location-transportation problems". The number of papers dealing with location-allocation problems have, without a doubt, increased very quickly in the last two years, with a total of nine papers published between 2011 and 2013 (31% of the location papers). We believe that the increasing attention devoted these types of problems indicates that there is a new research stream seeking to adopt a more integrated approach in order to cope with the diverse decisional levels related to relief network problems. As in the business SC case, where combined location and transportation problems have now been studied for several years, (Nagy & Salhi 2007; Salhi & Rand 1989) models addressing the links and dependencies of these two problems in a relief distribution context are required. Even more so, distributed modeling approaches are promising research areas and their application goes beyond the integrated location-routing problem to suit the global framework of response to disasters.

As a whole, it appears to us that research on relief distribution is now entering a consolidation phase, where academics have cumulated a good knowledge of disaster relief operations. The research approaches, originally very inspired from the business SC ones, have become more specialized and closer to the specific relief distribution context. Hence, the number of real-life inspired instances tackled in the literature is rather high, ranging from 33% in the case of transportation problems to up to 72% in the case of location and network design problems.

2.8.2. Trends and challenges

Nowadays, there is an increasing interest in tackling new subjects, such as the international scheme in response effort, service quality, equity and social objectives, or the integration of technological advances. See, for instance, Adivar & Mert 2010; Chen et al. 2011; Huang et al. 2012; Mete & Zabinsky 2010; Rawls & Turnquist 2011; Turner et al. 2012. Also, we are beginning to see the application of other classic OR/MS problems to the humanitarian logistics field. For example, contributions aimed at improving the organization or the management of other support activities can still be explored, especially in a dynamic real-time context (e.g., demand estimation, inventory management and personal management). Research on stock relocation and stock management (e.g., Rottkemper et al., 2011) would help supporting the response phase's daily operations better. Furthermore, the research done on casualty transportation is still very limited. To the best of our knowledge, this important topic has only been addressed by Jotshi et al. (2009), and the few combined flow contributions (like Özdamar 2011).

In addition, coordination is a challenging subject that still may be improved upon. However enough has been said on the importance and critical stage of coordination in humanitarian logistics and we now need to find a way to merge with the logistics optimization problems (e.g. coordination level indicators, collaboration planning models, etc.).We firmly believe that a deeper analysis of this area by way of a wider, probably hybrid, modeling approach could achieve the integration of these relationships.

Meanwhile, additional efforts need to put forth to increase the coherence between the hypothesis and considerations used to design the relief distribution networks and the decisions actually made in those networks. We still find discrepancy and separation in, among others, the objectives sought by the optimization and the manager's problems, the hypothesis, the planning horizons and the limitation of resources. In this sense, the alignment of objectives must not only be achieved through the logistic network stages (the different problems) but also through the different levels of the distribution chain (external supply sources, supply, temporal distribution facilities, final distribution). Our research shows that this aspect of relief distributions optimization network can be explored further (e.g. recent contributions like Adivar & Mert 2010; Afshar & Haghani 2012).

Finally, we believe that the next step in the optimization of relief distribution networks path is start bringing research and practice together, especially since the final goal of this research field is to improve the crisis managers response's capacity by supporting the decision-making process. In this sense, researchers are more and more concerned about defining practical and measurable objective functions. Also, increasing attention is being given to the development of integrated decision support systems (DSS), allowing crisis managers to interact, in real-time or pseudo real-time, with models and algorithms. In order to support these integrated models, we need newer solving tools able to optimize large instances in a very short time.

2.9. Conclusion

This article presents a systematic review of the literature on relief distribution networks. Our review focus in one of the most popular and fast-growing field of the last 5 years. A scientific research process was designed and executed to explore more than 5000 references. A transparent, systematic selection process was then applied to highlight 83 relevant articles for review. By doing so, we were able to efficiently gather and present a detailed portrait of relief distribution networks' situation. Our research shows that the scientific community has developed a growing interest in EM and many the contributions were done on the optimization of relief distribution systems in response to disasters, focusing on two major areas: (1) location and network design problems and (2) transportation and routing problems. The first problem usually dealt with during the disaster preparedness phase, but it can, and should, be extended to response phase. The second problem develops vehicle management and routing problems in a relief distribution context.

The challenge for the academic community is now to focus on designing more complex but realistic models that actually reflect the difference with the classical SCM approach. The new objectives, hypothesis, capacity limits, and planning horizon, among others, are trends in this field. In addition, we recognize the need for integrated and harmonized models, which better support the crisis managers' decisions, considering other logistic activities, such as demand management, resource allocation or inventory management. Furthermore, we acknowledge that this level of detail demands efficient resolution approaches. A strong challenge lies in the development of resolution methods, in which advanced heuristic proposals can enhance the complex modeling process to support decision-makers in the race for an efficient relief distribution. We hope that this paper provides a good guideline to academics interested in the field so it can continue to grow; but also to practitioners, so it can be complemented and translated into a truly effective relief distribution network.

Finally, we can conclude that, both from a theoretical and a practical point of view, this research field is not only interesting, but crucial. On the theoretical side, the advancements in this research field complement the general logistics research. In fact, many things have been said about the possibility of cross learning between emergency and business logistics (Van Wassenhove, 2006; Kovács & Spens, 2007). From the practical point of view, advancements in location and distribution problems in emergency logistics, are important tools in improving the quality of response to disaster, which is the key to saving more lives.

2.10. References

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Chapitre 3

Modèles pour une distribution juste de l'aide humanitaire

La « justice » au moment de la distribution de l'aide humanitaire est devenue un concept clef pour les gestionnaires dans le déploiement logistique d'urgence. Après un désastre, au moment où les besoins surpassent la capacité de réponse, une distribution efficiente et juste de l'aide disponible est attendue de la part des décideurs. Cette prémisse est supportée par l'analyse de la littérature effectuée au Chapitre 2 ainsi que par nos travaux précédents en partenariat avec l'équipe de la section Défense et Sécurité publique de Fujitsu Consulting (Canada) Inc. Lors de cette collaboration, nous avons développé un système de d'aide à la décision (DSS) pour la distribution d'aide suite à un désastre (Rekik et al. 2013). Le système inclut deux modules, un premier pour la localisation et l'approvisionnement des différents centres de distribution d'aide humanitaire (CDAH), et un second dédié à la planification du transport à partir des CDAH afin de satisfaire les besoins des points de demande. Finalement, un outil d'analyse multicritère permet de supporter la prise de décision des gestionnaires. En analysant les solutions proposées par le DSS, nous avons constaté que lorsque la capacité totale est inférieure aux besoins, plusieurs points de demande peuvent être complètement ignorés alors que d'autres sont pleinement satisfaits. Ceci est le résultat d'un système de planification guidé exclusivement par des critères d'efficacité et d'efficience. Un tel comportement n'était pas acceptable par nos partenaires. En effet, l'une des préoccupations majeures des gestionnaires de crise est de s'assurer que les besoins de la population touchée soient satisfaits avec justice et équité.

Cet article présente trois modèles multipériodes pour supporter la prise de décisions lors de la distribution de l'aide suite à une catastrophe. Les modèles prennent en considération l'objectif de justice et tiennent compte des variations de l'offre et de la demande qui peuvent émerger dans ce contexte. Les modèles gèrent également les arrérages avec équité afin de compenser les besoins de la population dès que possible.

Cet article étudie aussi la notion de « justice » dans la distribution et développe les concepts de stabilité et d'équité ainsi que plusieurs mesures de performance. Des instances académiques sont utilisées pour tester et analyser le comportement des modèles proposés.

Article 2: Models for a fair humanitarian relief distribution

Ce chapitre a été soumis pour publication au journal *Production and Operations Management* : Anaya-Arenas, A.M., Renaud, J. & Ruiz, A., 2015. Models for a fair humanitarian relief distribution. *Production and Operations Management*, submitted for publication.

Abstract Fairness has recently become a key concern for crisis managers. In the aftermath of a disaster, when needs overcome response's capacity, decision makers are expected to distribute the available relief efficiently, but also in such a way that nobody might perceive any injustice in the access to relief. This paper presents three multi-period models to support relief distribution decisions. The models consider fairness but also tackle the demand's and offer's changes over time. In addition, demand can be backordered as it is the case in realistic situations. The paper discusses the notion of fairness and proposes several proxies to measure it. Numerical tests are run on a set of academic instances to analyze the behaviour of the considered models and assess their performance.

3.1. Introduction

In the past decade, the number of scientific contributions on relief distribution has grown significantly and nowadays *humanitarian logistics* has become an independent and important body of research. In particular, *relief distribution logistic*s, have many characteristics that differentiates them from business logistics (Holguín-Veras et al. 2012; Kovács & Spens 2007). Among them, three major features inspire and motivate this work. Firstly, demand is uncertain and it may evolve very quickly as the population might tend to mobilize after a disaster. Thus multi-period models are needed to tackle the demand's dynamics. Secondly, relief distribution logistics focuses on demand satisfaction rather than profit maximization or costs minimization, because if the relief demand is not satisfied in terms of both quantities and time, the safety and well-being of the affected people are jeopardized. Thirdly, relief must be distributed in a "fair" manner among the people in need (Anaya-Arenas et al. 2014; Holguín-Veras et al. 2012; Holguín-Veras et al. 2013). Our concern on justice in distribution was also promoted by Fujitsu Consulting (Canada) Inc., one of our previous partners in emergency logistics developments. Past results on design and planning of relief distribution (Rekik et al. 2013) showed that when the response's capacity is smaller than demand, and if fairness is not seek explicitly in the optimization models, some PoDs can be completely neglected while others are fully covered. This behavior was rejected by our partner, understanding then the importance of the principals of justice and impartiality for humanitarian decision makers.

This paper proposes two main contributions. Firstly, we propose a multi-period formulation for the design of a relief distribution network where the opening decisions of humanitarian aid distribution centers (HADC), and the allocation of demand to the HACDs, are reconsidered at every period. In addition, because of the limited amounts of relief available, we allow the demand to be backordered, although only for a limited time or number of periods. A limited backorder of demand allows us to provide a more flexible and realistic logistic plan. Secondly, since this network must be planned in such a way that it maximizes fairness in the distribution, three different objective functions will be proposed and their performance assessed using a set of metrics.

The rest of this article is organized as follows. Section 2 reports the most relevant works in the literature. Section 3 presents a discussion on the notion of fairness, and what we expect from a fair relief distribution plan. Section 4 states the addressed problem. Section 5 presents three different mathematical formulations for fair distribution network design and operations. Section 6 presents numerical experiments, while Section 7 concludes this work and suggests research perspectives.

3.2. Fair relief distribution in humanitarian logistics

Relief distribution logistics (also called post disaster humanitarian logistics) have received increasing attention in recent years. For instance, in their review, Anaya-Arenas et al. (2014) reported 83 articles, from which 76 were published after 2004. However, the most recent works claim that despite of the important contributions made up to date, additional efforts must be made in order to truly understand the complexity of relief distribution and capturing the challenges of disaster response in optimization models.

One of these challenges is to capture the variety of managers' objectives. According to Anaya-Arenas et al. (2014)'s review of the existing literature, 50% of the relief distribution literature focuses on cost minimization. However, the acknowledgment of saving lives as the ultimate purpose of relief distribution motivates the proposition of different objectives as satisfaction of demand (20% of the literature) or rapidity of the response (20%). To the best of our knowledge, only 10% of the literature on relief distribution networks has considered the fairness concept, and it is almost exclusively done from a routing problems' perspective. For instance, Tzeng et al. (2007) proposed a multi-objective optimization problem for a transportation problem. Fairness of distribution is the third objective, after cost and rapidity, and it is sought by maximizing the minimum satisfaction level among clients. Suzuki (2012) used a similar approach. Lin et al. (2011) also proposed a transportation problem for relief distribution with three different objectives, and it is pursued by the minimization of the maximum gap of the unsatisfied demand. Vitoriano et al. (2010; 2009) proposed a multi-criteria optimization model as well, where fairness is sought by minimizing the deviation of normalized unsatisfied demands. The model considered both costs and routes' reliability. Finally, Huang et al. (2012) presented three different ways to measure what they call equity. The first approach computed a deviation measure like the one used in Lin et al. (2011) and Tzeng et al. (2007). The second one measured the standard deviation of the demand satisfaction using a non-linear formulation. The third approach used a piecewise-linear function to penalize inequity. They tested the three approaches on a set of routing instances and compared their efficiency. Only two contributions on the relief distribution network design literature included the fairness objective. Lin et al. (2012) included a penalty cost for unfairness in service in its cost minimization objective function to design temporal depots in the affected-area, and Yushimito et al. (2012) used an economic function including social cost. As we can see, the use of fairness objectives is still spare, and the most common approach for it is a deviation minimization. However, we will show how other cost functions can indeed be more efficient, as it was presented by Huang et al. (2012) and Holguín-Veras et al. (2013).

Holguín-Veras et al. (2013) is one of the few works to underline the need for objective functions to represent the real challenge of post-disaster humanitarian logistic models. They discussed how social costs must be included in the objective function, in addition to the logistics cost. To do it, a monotonic, non-linear and convex cost function, in respect to the deprivation time, is proposed to estimate the human suffering caused by the supplies' deficit of goods or services to a community in the aftermath of a disaster. Their contribution was later extended in Pérez-Rodríguez and Holguín-Veras (2015) were this proposition was applied for a routing and inventory allocation problem. Through their analysis, they underlined the opportunity cost linked to the satisfaction of clients' demand and the need for multi-period models that account for the temporal effect of demand's dissatisfaction. These two aspects are highly important for the development of a fair distribution chain and are therefore captured in our proposition.

Although several objectives are pursued when designing and operating a relief distribution network, the fairness objective is the major focus of our work. This is due to its significance and rareness, which also makes this principle the hardest one to define and measure. The next section discusses fairness and how to apply and measure it in a relief distribution network design.

3.3. What should be expected and how to measure fairness in relief distribution?

Relief distribution decisions need to be anchored in the principle of fairness and justice. The principle of justice is based on how *each person has an inviolability founded on justice that even the welfare of society as a whole cannot override* (Rawls 2009). In the context of goods or relief distribution, several aspects need to be observed. First, in terms of demand satisfaction, equity should be pursued. The term equity implies that everyone's demand will be satisfied to the same proportion, according to their needs. Since each point of demand (PoD) may require a different amount of help, equity should be measured as a percentage of satisfied demand or, alternatively, as a percentage of the demand's shortage. Furthermore, this idea of equity in demand satisfaction (or dissatisfaction) needs to be refined in a dynamic, multiperiod context. What we mean by this is that, even if all the PoDs have the same percentage of demand satisfaction at the end of the planning horizon, the way in which they receive relief during the planning horizon is of paramount importance. Clearly, a fair relief distribution should ensure that every PoD maintains a supply level as close as possible, not only to its total needs, but to its needs at each period. It follows that eventual shortages should be "distributed" in a fair manner among the PoD and, whenever there is a shortage at a given PoD, it should be "compensated" as soon as possible. Finally, response time should be, in the best possible way, the same for every PoD, and this interest is beyond a distance minimization objective. Of course, geography and population distribution make this goal very difficult to attain, but a fairness's perception can be reinforced by ensuring that every PoD can be supplied in less than a given time by at least one open HADC. The next subsection discusses how to assess the fairness of a given distribution plan.

3.3.1. Fairness metrics

Beamon and Balcik (2008) developed a complete framework for performance measurement inspired by commercial supply chains. They suggested that a good relief distribution network needs to achieve a high performance in efficiency, effectiveness and flexibility. They recognised the need of fairness, but they did not specify any indicator or proxy related to it.

We believe that in a multiperiod context, fairness needs to be achieved within the same period, and across periods. With *fairness within periods* we aim at minimizing the differences on the percentage of demand satisfaction between PoDs in a given period. Consequently, if there is a shortness at a given period t, it is preferred to deliver to each customer an equal fraction of their demand rather than fully satisfy some PoDs while leaving others suffering important shortages. On the other hand, *fairness across periods* refers to how the distribution plan balances eventual shortages by "rationing" the available supplies among the PoDs during the planning horizon. In other words, it might be preferable to deliver PoDs with a portion of their demand, rather than to fully satisfy demand in a period and fully unsatisfying it in another. In the following, we name the fairness within periods as "equity" and fairness across periods as "stability". Aiming at quantifying the fairness of a given distribution plan, we define four measures on the differences in shortage among the deserved PoDs. These measures are based on the range and the dispersion and specifically concern equity and stability.

Equity and stability as ranges in proportion of demand shortage

Let u_{zt} be the shortage (in percentage) of PoD z at period t. We define the two following range-based measures:

$$\overline{R_1} = \frac{\sum_{t \in T}(\max_z\{u_{zt}\} - \min_z\{u_{zt}\})}{|T|} \quad \text{and} \quad \overline{R_2} = \frac{\sum_{z \in Z}(\max_t\{u_{zt}\} - \min_t\{u_{zt}\})}{|Z|}$$

where T refers to the set of periods in the planning horizon and Z to the set of PoDs. Range $\overline{R_1}$ computes the average, over all periods, of the demand shortage ranges of PoDs for each period. Alternatively, range $\overline{R_2}$ computes the average, over all PoDs, of the range of each PoD shortage over all periods. Therefore, whereas a small value in $\overline{R_1}$ shows that all the PoDs are similarly satisfied at each period, a small value of $\overline{R_2}$ testifies that, on average, PoDs have received a relatively stable satisfaction of demand.

Equity and stability in terms of global dispersion

Variance and standard deviation are measures used to quantify the dispersion of a set of data around its average value. Let us define $u_{..}$ as the global average of the demand shortage over all PoDs and all periods (in percentage), and ${\sigma^2}_{global}$ be the shortage's global variance over all PoDs and periods computed as:

$$ {\sigma^2}_{global} = \frac{\sum_{t \in T} \sum_{z \in Z} (u_{zt} - u_{..})^2}{|T| \times |Z| - 1} $$

The following paragraphs show how a classic analysis of variance allows us to identify the components of equity (within a period) and stability (across periods) in the relief distribution decisions. The numerator of ${\sigma^2}_{global}$ is a Total Sum of Squares (TSS) of the deviations of the shortages' values from their average value. Taking periods as a main factor, TSS can be decomposed in two independent terms: Sum of Squares Within periods ($SSWT$) and Between periods ($SSBT$). This decomposition let us quantify how much of the global dispersion is due to the variability inside (within) the periods and how much is due to the variability of distribution decisions between the periods. More precisely,

$$ \sum_{t \in T} \sum_{z \in Z} (u_{zt} - u_{..})^2 = TSS = SSWT + SSBT $$

with:

$$ SSWT = \sum_{t \in T} \sum_{z \in Z} (u_{zt} - u_{.t})^2 \qquad \text{and} \qquad SSBT = |Z| \sum_{t \in T} (u_{.t} - u_{..})^2 , $$

where $u_{.t}$ is the average over all PoD's of the shortage percentage for period *t* (i.e. $u_{.t} = \sum_{z \in Z} u_{zt} \, / \, |Z|$). $SSWT$ measures in the planning horizon if, period by period, the PoDs are all similarly satisfied; therefore, it is the basic component of *equity* among PoDs. On his side, $SSBT$ shows the dispersion of the average demand shortage per period around the global mean value ($u_{..}$). Therefore, $SSBT$ is related to the *stability* of the distribution decisions in time (all PoDs combined). We believe that $SSBT$ is a good measurement of how the distribution decisions are able to "smooth" the supply variations in the planning horizon.

Since global variance ($\sigma^2{}_{global}$) is computed by dividing TSS by its degrees of freedom ($|T| \times |Z| - 1$), one can find the mean value of each component by dividing it by its respective degree of freedom. Therefore, and based in the previous decomposition analysis, it is possible to define two dispersion measures, named $\overline{WT}$, $\overline{BT}$, as follows:

$$\overline{WT} = \frac{SSWT}{|T| \times (|Z| - 1)} \quad \text{and} \quad \overline{BT} = \frac{SSBT}{|T| - 1}$$

It is worth mentioning that, although the variance decomposition presented in the previous paragraphs uses periods as main factor, a similar decomposition could have been done using the PoDs as the main factor. Indeed, doing so, the decomposition exercise would have led to two alternative dispersion measures on stability ($\overline{WZ}$) and equity ($\overline{BZ}$) :

$$\overline{WZ} = \frac{\sum_{t\in T}\sum_{z\in Z}(u_{zt} - u_{z\cdot})^2}{|Z| \times (|T| - 1)} \quad \text{and} \quad \overline{BZ} = \frac{|T|\sum_{t\in T}(u_{z\cdot} - u_{\cdot\cdot})^2}{|Z| - 1}$$

3.4. Problem definition and formulations

This section defines the considered distribution context and proposes three different mathematical formulations that aimed tackling explicitly the notion of fairness in the satisfaction of the PoDs' demand. We consider a multi period planning horizon composed of $t \in T$ periods. The network includes three types of nodes: the outside suppliers $s \in S$, the potential HADCs $l \in L$, and the PoDs $z \in Z$. The exact location of all the nodes is known, and the transportation time between each two nodes i and j is denoted c_{ij}. We consider a set of different products' families or relief's kits, named in the following humanitarian functions $f \in F$ such as *survival* (e.g., meals, water), *safety*, *medical*, *technical*, etc. (Rekik et al, 2013). We assume that each PoD z has a given demand d_{zft} for each particular function f and period t, expressed in number of pallets or any other standard measure.

If a PoD does not receive its complete demand for a given period, we assume that it can be backordered and fulfilled within the next period. If the backordered demand is not delivered during the next period, this demand is considered lost. We have fixed the limit of backordered demand to one period, considering that compensating demand after more than one period can be too late and cause as much damage as if demand is never delivered. Evidently, this can be adjusted accordingly to the time's discretization used and the needs of the crisis managers. Please notice that the formulation can be easily extended to consider two periods of backorder or more. On the other side, allowing backorders gives flexibility to managers, but it must be avoided whenever possible. To reflect this, we establish a penalty cost β_{1f} if the demand for a function f is delayed by one period, and β_{2f} if demand is lost, with $\beta_{2f} \gg \beta_{1f}$.

Each HADC l has a specific global capacity limit by period ($Glob_{lt}$) and a capacity limit by function ($CapD_{lft}$), also by period. This capacity is expressed in number of pallets. On the other hand, suppliers' capacity is also limited to a number of pallets for each function at each period ($CapS_{sft}$). Finally, each HADC needs a specific number of professionals (n_l) to operate at its full capacity. However, there is a restriction on the total number of personnel N_t available at each period t, which in fact limits the total number of HADC to open. Also, the opening of an HADC requires some setting-up activities, decreasing in practice the center's available operation time for the period. We therefore assume that, during the period when a center is open, its capacity of incoming and outgoing flow is reduced by a factor $\alpha < 1$. Contrariwise, a center can be closed at any period without any additional cost.

The transportation of relief (from suppliers to HADCs and finally from HADCs to PoDs) is assumed to be done by truckloads of capacity P (same vehicle type). A transportation capacity limit is established for both the number of trips between a supplier s and a center l (Vs_{sl}), as well as the number of trips between a pair of HADC l and PoD z (Vd_{lz}) at any period.

The proposed optimization models seek to define a relief distribution network focusing in three primary aspects. First, we seek to minimize the demand shortage while maximizing fairness. The secondary objective (efficiency) is achieved by minimizing the total travel time, affecting directly the allocation decisions. Lastly, rapidity in distribution is not included in the objective function, but assured using maximum access time constraints for the supply (τ_1) and the distribution (τ_2). In the following, we introduce additional notation and then we present common constraints for the three models. Finally, each of the alternative objective functions are proposed. Notice that all the quantities as well as capacities are expressed in pallets, but they can be expressed using any other standard measure.

Sets

S_l Set of suppliers within the maximum distance of HADC l ($s \in S_l : c_{sl} \leq \tau_1$);

L_s Set of HADCs that are within the maximum distance of supplier s ($l \in L_s : c_{sl} \leq \tau_1$);

L_z Set of HADCs that are within the maximum distance of PoD z ($l \in L_z : c_{lz} \leq \tau_2$);

Z_l Set of PoDs that are within the maximum distance of HADC l ($z \in Z_l : c_{lz} \leq \tau_2$);

Decisions variables

x_{tl} binary variable equal to 1 if the HADC l is open at period t, zero otherwise;

y_{tl} binary variable equal to 1 if the HADC l is operating at period t, zero otherwise;

Qs_{slft} quantity of function f sent from supplier s to HADC l at the beginning of period t;

Qd_{lzft} quantity of function f sent from HADC $l \in L_z$ to PoD $z \in Z$ during period t;

$S^-_{zft,t+1}$ quantity of function f not delivered at PoD z during period t, scheduled to be delivered at period $t + 1$;

$S^-_{zft,t+2}$ quantity of function f not delivered at PoD z during period t, and that will not be delivered at the end of period $t + 1$, so it is counted as lost demand;

I_{lft} inventory at HADC l of function f at the end of period t;

3.4.1. Common constraints

The following set of constraints defines the general framework of the described system (as the distribution and flow dynamics) and the basic restrictions of the resources (capacity limits). These constraints are common to the three proposed models.

$$S^{-}_{zf1,2} + S^{-}_{zf1,3} + \sum_{l\in L_z} Qd_{lzf1} = d_{zf1} \qquad \forall\, z \in Z, f \in F \qquad (1)$$

$$S^{-}_{zft,t+1} + S^{-}_{zft,t+2} + \sum_{l\in L_z} Qd_{lzft} = d_{zft} + S^{-}_{zft-1,t} \qquad \forall\, z \in Z, f \in F, t = 2, \dots T \qquad (2)$$

$$S^{-}_{zft,t+1} + S^{-}_{zft,t+2} \leq d_{zft} \qquad \forall\, z \in Z, f \in F, t \in T \qquad (3)$$

$$\sum_{l\in L_z} (x_{lt} + y_{lt}) \geq 1 \qquad \forall\, z \in Z, t \in T \qquad (4)$$

$$\sum_{l\in L_s} Qs_{slft} \leq CapS_{sft} \qquad \forall\, s \in S, f \in F, t \in T \qquad (5)$$

$$I_{lf0} = 0 \qquad \forall\, l \in L, f \in F \qquad (6)$$

$$I_{lft} = I_{lft-1} + \sum_{s\in S_l} Qs_{slft} - \sum_{z\in Z_l} Qd_{lzft} \qquad \forall\, l \in L, f \in F, t \in T \qquad (7)$$

$$\sum_{f}^{F} I_{lft} \leq Glob_{lt}(x_{lt} + y_{lt}) \qquad \forall\, l \in L, t \in T \qquad (8)$$

$$I_{lft} \leq CapD_{lft} \qquad \forall\, l \in L, f \in F, t \in T \qquad (9)$$

$$\frac{\sum_{f}^{F} Qs_{slft}}{P} \leq Vs_{slt}(\alpha x_{lt} + y_{lt}) \qquad \forall\, s \in S_l, l \in L, t \in T \qquad (10)$$

$$\frac{\sum_{f}^{F} Qd_{lzft}}{P} \leq Vd_{lzt}(\alpha x_{lt} + y_{lt}) \qquad \forall\, z \in Z_l, l \in L, t \in T \qquad (11)$$

$$\sum_{l}^{L} n_l(x_{lt} + y_{lt}) \leq N_t \qquad \forall\, t \in T \qquad (12)$$

$$x_{lt} + y_{lt} \leq 1 \qquad \forall\, l \in L, t \in T \qquad (13)$$

$$y_{lt} \leq x_{lt-1} + y_{lt-1} \qquad \forall\, l \in L, t = 2 \dots T \qquad (14)$$

$$y_{lt-1} + x_{lt} \leq 1 \qquad \forall\, l \in L, t = 2 \dots T \qquad (15)$$

$$x_{lt-1} + x_{lt} \leq 1 \qquad \forall\, l \in L, t = 2 \dots T \qquad (16)$$

$x_{lt}, y_{lt} = \{0,1\}$ $\forall\, l \in L, t \in T$ (17)

$S^{-}_{zft,t+1}, S^{-}_{zft,t+2}, Q_{slft}, Q_{lzft}, I_{lft}, \geq 0$ $\forall\, s \in S_l\, z \in Z_l, l \in L, f \in F,$ $t \in T$ (18)

Constraints set (1) defines the quantity of the humanitarian function f not delivered to PoD z at period 1, which are scheduled to be delivered at period 2 or will be considered as lost. This equation is generalized in constraints (2) for the other periods. Constraints (3) limit the quantity that can be backordered (or lost) for a given period to the demand of the period. These constraints also assure that backordered demand is delivered during the period where it is expected. Constraints (4) require that an active HADC (opened or already in operation) within the covering distance of each PoD must be open at every period. Constraints (5) state that the total flow of a given function sent to the HADCs from a given supplier s at period t must respect the supplier's capacity. Constraints (6) and (7) stablish the balance of flow to define the inventory levels at each center l, at each period t and for each function f. This inventory level has to respect the total capacity limit of every HADC (8), as well as the capacity limit by function (9), at every period. Constraints (10) and (11) define the number of loads that will traverse an arc (s, l) and (l, z), respectively, at period t considering that each trip can carry P pallets, and state that the total number of trips, from suppliers to HADCs and from HADCs to PoDs, needs to respect the imposed limits. They also consider that the capacity of a center l is reduced by α at its opening period. Finally, constraints (12) establish the available staff's limit at every period. Constraints (13) to (16) link the opening and the operation variables for every HADC at every period. They ensure that a HADC cannot be operating and opened at the same period (constraint 13) and if it is operating a certain period t, it is because it was already opened or operating (constraint 14). Constraints 15 states that in order to open a HADC in a period t, it has to be closed (not operating) in the previous period. Finally, constraints (16) state that a HADC cannot be opened for two periods in a row. These last two constraints are only useful in the specific case where the global capacity is greater than the demand; otherwise they are redundant with constraints (10) and (11).

3.4.2. Fair distribution modeling approaches

As mentioned before, among the variety of objectives that can be pursued in the design of relief distribution networks, this paper seeks to minimize the percentage of unsatisfied demand with a major focus on fairness. We therefore present three objective functions to seek a fair relief distribution. In addition we include an efficiency objective by minimizing the total travel time seeking to guide the model to make smart decisions in the use of resources. Thus, we propose three different multi-criteria objective functions to be minimized using *weighted-sum* optimization method. The details of each objective function and the additional constraints required for each model are presented in the following.

M1: Minimization of the penalty associated to the total unsatisfied demand

The first model is one of the most popular in relief distribution. It concentrates in minimizing the penalty due to the unsatisfied demand. However, this approach has been adapted to account for backordered and lost demand. Finally, it includes the efficiency objective of minimizing total travel time. To present this three objectives in a single objective function, each term i is affected by a penalty factor δ_i. Let u_{zft} be the percentage of unsatisfied demand of humanitarian function f at PoD z in period t, if any. We define *Obj*1 (19) as the penalty cost for the percentage of unsatisfied demand penalized by factor δ_1; *Obj*2 (20) is the penalty cost of backordered and lost demand penalized by factor δ_2; and *Obj*3 (21) is the cost associated with the number of trips multiplied by their distance and penalized by factor δ_3. Each objective is formulated as follows:

$$Obj_1 = \delta_1\left(\sum_{t\in T}\sum_{z\in Z}\sum_{f\in F} u_{zft}\right) \tag{19}$$

$$Obj_2 = \delta_2\left(\sum_{t\in T}\sum_{z\in Z}\sum_{f\in F}\beta_{1f}\frac{S^{-}_{zft,t+1}}{d_{zft}} + \sum_{t\in T}\sum_{z\in Z}\sum_{f\in F}\beta_{2f}\frac{S^{-}_{zft,t+2}}{d_{zft}}\right) \tag{20}$$

$$Obj_3 = \delta_3\left(\sum_{t\in T}\sum_{s\in S}\sum_{l\in L} c_{sl}\frac{\sum_f^F Qs_{slft}}{P} + \sum_{t\in T}\sum_{l\in L}\sum_{z\in Z} c_{lz}\frac{\sum_f^F Qd_{lzft}}{P}\right) \tag{21}$$

Model 1 (M1) is then formulated as:

$$\text{Min } Obj_1 + Obj_2 + Obj_3 \tag{22}$$

subject to:

$u_{zft} \geq 1 - \frac{\sum_{l \in L_z} Qd_{lzft}}{d_{zft}}$ $\forall\, z \in Z, f \in F, t = 1, \dots T$ (23)

$u_{zft} \in [0,1]$ $\forall\, z \in Z, f \in F, t \in T$ (24)

in addition to constraints (1) to (18) .

M2: Minimization of the maximum gap

The second approach to maximize distribution fairness is similar to the one in Tzeng (2007) and Lin et al. (2011). It consists in minimizing the largest gap among the unsatisfied demand (in percentage) for all pairs of zones. We have adapted and extended this approach to take backorders into account. Let $\gamma_{ft,t+1}$ be the maximum gap between PoDs of the percentage of demand of humanitarian function f that is backordered at period t to be payed at period $t+1$. Likewise, we define $\gamma_{ft,t+2}$ as the maximum gap among the PoDs of the percentage of demand of humanitarian function f that is lost at period t. We thus define Obj_4 (25) as the penalty cost for unsatisfied demand's range, penalized by factor δ_4 and we add constraints (27) and (28) to the model.

$$Obj_4 = \delta_4\left(\sum_{t \in T} \sum_{f \in F} \beta_{1f}\gamma_{ft,t+1} + \beta_{2f}\gamma_{ft,t+2}\right) \tag{25}$$

In this model we include also the minimization of backorders and lost demands and total travel time as presented in M1 (Obj_2 and Obj_3)

The second model (M2) can be stated as follows:

$$\text{Min } Obj_4 + Obj_2 + Obj_3 \tag{26}$$

Subject to:

$\frac{S^-_{ift,t+1}}{d_{ift}} - \frac{S^-_{jft,t+1}}{d_{jft}} \leq \gamma_{ft,t+1}$ $\forall\, i,j \in Z\ (i \neq j), f \in F, t \in T$ (27)

$\frac{S^-_{ift,t+2}}{d_{ift}} - \frac{S^-_{jft,t+2}}{d_{jft}} \leq \gamma_{ft,t+2}$ $\forall\, i,j \in Z\ (i \neq j), f \in F, t \in T$ (28)

in addition to constraints (1) to (18).

M3: Minimum dissatisfaction cost with a piecewise penalty function

We were inspired by Holguín-Veras et al. (2013) and Huang et al. (2012), which suggested the use of a monotonic, non-linear and convex function to express the cost associated to human suffering caused by the deficit of supplies or services in the aftermath of a disaster. Indeed, the perception of the people in need is clearly not linear, and higher values of dissatisfaction of demand must be penalized more strongly than lower values. In a similar manner, delays of two periods in demand's satisfaction has a larger cost (penalty) than twice the penalty for one period delay. We propose to model penalties related to the percentage of unsatisfied demand as an exponential function. Using non-linear penalties in the objective function is a way to seek fairness. In order to introduce such effect in our model while keeping its linearity, we approximated the penalty curve for a given unsatisfied demand percentage of PoD z, humanitarian function f at period t (i.e. u_{zft}) by a piecewise linear function as depicted in *Figure 3.1,* where it can be observed that the penalty increases significantly from one piece k to the next one. We refer the reader interested in the mathematical aspects of this linearization to Padberg (2000).

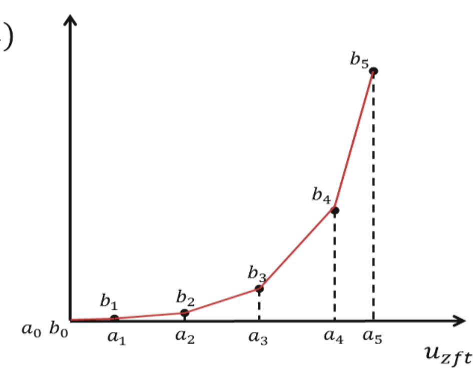

Figure 3.1 – Example of a piecewise cost function for u_{zft}.

In addition, we need to adapt this approach to take backorders and lost demands into account. We thus define *Obj*$_5$ (29) as the piecewise penalty cost for the percentage of total dissatisfaction percentage with a penalty weight of δ_5 and *Obj*$_6$ (30) as the piecewise penalty cost for backordered and lost demand percentage with a penalty weight of δ_6:

$$Obj_5 = \delta_5 \sum_{t \in T} \sum_{z \in Z} \sum_{f \in F} \left[\hat{f}\left(u_{zftk}\right)\right] \tag{29}$$

$$Obj_6 = \delta_6\left[\beta_{1f}\hat{f}\left(u_{zft,t+1,k}\right) + \beta_{2f}\hat{f}\left(u_{zft,t+2,k}\right)\right] \tag{30}$$

Then, we include the efficiency objective (Obj_3) as is done in M1 and M2. M3 can be stated as follows:

$$Min\ Obj_5 + Obj_6 + Obj_3 \tag{31}$$

The first two terms of (31) accounts for the penalty associated to unsatisfied demand (as well as the backorder and lost demand) for each product, each PoD and each period. This is given by the piecewise linear function defined by the following functions:

$$\hat{f}\left(u_{zftk}\right) = \sum_{k=1}^{K} c_k\ u_{zftk} \tag{32}$$

$$\hat{f}\left(u_{zft,t+1,k}\right) = \sum_{k=1}^{K} c_k\ u_{z,f,t,t+1,k} \tag{33}$$

$$\hat{f}\left(u_{zft,t+2,k}\right) = \sum_{k=1}^{K} c_k\ u_{z,f,t,t+2,k} \tag{34}$$

where $u_{zftk} \in [0, a_k - a_{k-1}]$ is the percentage, of the demand of function f not delivered to PoD z at period t, that is inside the piece k, c_k is the slope of piece k ($c_k = \frac{b_k - b_{k-1}}{a_k - a_{k-1}}$) and (a_k, b_k) is the breaking point of the piecewise function related to piece k (same for backorder and lost demand). The last term computes the penalty associated to distribution time as in the previous models. Model M3 requires the following constraints (in addition to constraints (1) to (18)):

$$\sum_{k=1}^{K} u_{zftk} \geq 1 - \frac{\sum_{l \in L_z} Qd_{lzft}}{d_{zft}} \qquad \forall\ z \in Z, f \in F, t = 1, \dots T \tag{35}$$

$$\sum_{k=1}^{K} u_{z,f,t,t+1,k} = \frac{S^{-}_{zft,t+1}}{d_{zft}} \qquad \forall\ z \in Z, f \in F, t = 1, \dots T \tag{36}$$

$$\sum_{k=1}^{K} u_{z,f,t,t+2,k} = \frac{S^{-}_{zft,t+2}}{d_{zft}} \qquad \forall\ z \in Z, f \in F, t = 1, \dots T \tag{37}$$

$$u_{zftk} \leq (a_k - a_{k-1}) \qquad \forall\ z \in Z, f \in F, t = 1, \dots T, k \in K \tag{38}$$

$$u_{zft,t+1,k} \leq (a_k - a_{k-1}) \qquad \forall\, z \in Z, f \in F, t = 1, \dots T, k \in K \qquad (39)$$

$$u_{zft,t+2,k} \leq (a_k - a_{k-1}) \qquad \forall\, z \in Z, f \in F, t = 1, \dots T, k \in K \qquad (40)$$

$$u_{zftk}, u_{zft,t+1,k}, u_{zft,t+2,k} \in [0,1] \qquad \forall\, z \in Z, f \in F, t \in T \qquad (41)$$

Constraints (35) to (37) link the piecewise variables and the demand shortage quantities, computing the total percentage of unsatisfied demand, the demand backorder at periods $t + 1$ and $t + 2$ (lost demand) respectively, divided by demand of period t. Notice that in the case of a compensation (i.e. if backordered demand is paid in a given period t), the total delivery might be higher than the demand of t. In this case, the dissatisfaction percentage is computed as null. Constraints (38) to (40) ensure that variables $u_{ztf,t+1,k}$ and $u_{ztf,t+2,k}$ cannot be greater that the length of interval k. These constraints, together with the objective function, force the sequential use of each piece of the piecewise function for variables $u_{zftk}, u_{zft,t+1,k}, u_{zft,t+2,k}$ respectively. Constraint set (41) define the domain for the piecewise variables. Needless to say, the quality of the solutions produced by model M3 depends on the number and the bounds of the pieces used in the piecewise function. Therefore, a heuristic procedure is proposed to find a good compromise in this matter. This method is presented in the next paragraphs.

3.4.3. Iterative approach to construct the piecewise linear function

The number of pieces in the piecewise linear function and their breakpoints have a strong influence on the quality of the solution as well as on its solvability. Three considerations must be kept in mind when designing the piecewise function. First, a better approximation of the exponential function may be obtained by using more pieces, but by doing so the model becomes more difficult to solve. Second, since the piecewise cost function is intended to enforce equity by trying to group all PoDs in the same dissatisfaction level (the same piece) pieces should be small enough. Third, the fairest value of unsatisfied demand depends on the offer/demand ratio of a period and its evolution in time. In other words, the proper number and value of each piece can differ according to the specific instance. We therefore propose a heuristic procedure to fix the number of pieces, the bounds of each one as well as the slope of each piece by an iterative approach.

In the following, we illustrate the algorithm used to set the piecewise function of a particular humanitarian function f (i.e. considering u_{zft} as u_{zt}). The heuristic is initialized with only two pieces per variable ($|K| = 2$). We define A as the set of breakpoints a_k. A is initialized with the minimum value of the ratio offer/demand in the horizon (named $min_t\, \rho_t$), seeking to fix an upper bound of dissatisfaction i.e. $A = \{0; \min_t \rho_t\, ;\ 1\}$. Then, M3 is solved to optimality and the solution produced is analyzed in order to decide if new pieces should be added to the piecewise function and the model solved again (next iteration).

At a given iteration i, the average unsatisfied demand's percentage ($u_{..}^{i}$) and the global standard deviation (σ_{global}^{i} as defined in Section 3.1) of the present solution are computed. If σ_{global}^{i} is greater than the standard deviation goal (σ_{wanted} set arbitrary to zero), three new pieces are added around $u_{..}^{i}$, with three new breakpoints added to set A as $\left\{u_{..}^{i} - \frac{\sigma_{global}^{i}}{2};\ u_{..}^{i}\ ;\ u_{..}^{i} + \frac{\sigma_{global}^{i}}{2}\right\}$. Slopes for all the pieces are recalculated. To this end, we set a base penalty value for the first piece in the function, and then the slope for each piece is increased by 1.1 times the rate between the highest and the lowest demand (i.e. $c_k = c_{k-1} \times 1.1\ \frac{D_{max}}{D_{min}}$). After the recalculating the cost piecewise function, the model is redefined and solved again. If the new solution results in a reduction in σ_{global}^{i} a new iteration $i + 1$ begins. If no improvement is achieved, the same procedure is applied over the backorder and lost demand variables. The procedure is repeated until a given stop criterion is met (e.g. maximal number of iterations, or until the improvement obtained with current iteration is not significant or null). At the end, the last solution is retained and reported as the solution of M3. The *Algorithm 3.1* allows us to adapt the shape of the piecewise function dynamically.

Algorithm 3.1 – Procedure to construct our piecewise function.

1. Initialize: **Set** $|\mathrm{K}| = 2$ with $A = \{0; \min_t \rho_t\ ;\ 1\}$, $\sigma^0_{global} = \infty$; $i = 0$ and maxIter = 5.
2. **Set** $i = i + 1$, $s \leftarrow$ MIP Solution to optimality using A as bounds, estimate σ^i_{global} and $u_{..i}$
3. **If** $\sigma^i_{global} > \sigma_{wanted}$ and $\sigma^i_{global} < \sigma^{i-1}_{global}$ **then**

   Go to step 4

   else

   Go to step 6.
4. Estimate breakpoints of three new pieces:

   4.1. **Fix** breakpoint = $u_{..i} - \sigma^i_{global}/2$

   4.2. **Fix** breakpoint = $u_{..i}$

   4.3. **Fix** breakpoint = $u_{..i} + \sigma^i_{global}/2$
5. **If** the new bounds defined do not exist in A and $i \leq maxIter$, **then**

   5.1 add the bounds to A

   5.2 go to step 2;

   else

   Go to step 6.
6. **Return** s

3.5. Numerical experiments

This section seeks to examine and to analyse, through numerical experiments, the behaviour of the three different modeling approaches for a fair relief distribution over different scenarios.

3.5.1. Problem generation and demand scenarios

In order to test the models, a flexible instance generator was designed to define and create a large variety of test scenarios. All the parameters specified in the following paragraphs can be adapted to the needs of a particular problem. The size of an instance is defined by the cardinality of the following sets: PoDs (|Z|), HADCs (|L|), suppliers (|S|), humanitarian functions (|F|), and the number of periods in the planning horizon (|T|). A problem is defined over a total area (TA) of $[1000 \times 900]$, inside of which we define an affected area (AA) of $[600 \times 500]$. The PoDs' and HADCs' location is randomly generated inside the AA, and the set of suppliers inside the TA, but outside the AA. The demand for each PoD at the first period is randomly generated in the range of [20;70] for every humanitarian function. The capacity of any HADC l is set at 60% of the total demand ($CapD_{lft} = 0.6 \sum_{z \in Z} d_{zft}$). In all our numerical experiments we seek to represent our main interest in minimizing the unsatisfied demand percentage and the fairness objective, which has been overlooked in the past. Therefore, in M1 we applied $\delta_1 \gg \delta_2 \gg \delta_3$, with $\delta_1 \cong 100\delta_2 \cong 1000\delta_3$; for M2 we applied $\delta_4 \gg \delta_2 \gg \delta_3$, with $\delta_4 \cong 100\delta_2 \cong 1000\delta_3$ and for M3 we applied $\delta_5 \gg \delta_6 \gg \delta_3$, with $\delta_5 \cong 100\delta_6 \cong 1000\delta_3$.

Depending on the nature and the gravity of the event (demand) and the availability of resources (number and capacity of responders), different supply scenarios can be considered. Following that, we defined two basic theoretical scenarios.

Scenario 1 - Temporary shortness of resources

In the first periods in the aftermath of a disaster, the available resources are limited and vary from one period to another on the planning horizon. In other words, periods of shortness alternate with others showing reasonable offer levels corresponding to the arrival of help from national and international organizations. In this case, the backordering of the unsatisfied demand becomes an interesting solution available to crisis managers.

Scenario 2: Extreme shortness of resources

In this scenario, the available supplies, in addition to the foreseen arrivals of relief, will be systematically under the requirements. Crisis managers cannot make a commitment towards future deliveries to compensate for the shortness. In this case, crisis managers would try to distribute the available relief in the most fair manner.

We model both of our instances' scenarios for a particular humanitarian function on an offer/demand ratio ρ_t for each time periods. In temporary shortness, suppliers have the capacity to respond to the demand during the first periods. Then, ρ_t drops under one when local supplies are finished, and finally external supplies start to arrive ($\rho_t >$ 1). In extreme shortness, we consider that, during the first periods, local capacity is limited ($\rho_t \approx 0.8$), and then it decreases until a deep strong ($\rho_t \approx 0.2$). In the following, numerical results produced for temporary shortness are presented, followed by those produced for extreme shortness.

3.5.2. Models' performance in a temporary shortness scenario

In order to characterize the behavior of the solutions produced by the three models with respect to fairness, we will use in this section a set of 10 small instances (two suppliers, three HADCs, six PoDs, one humanitarian function, and eight periods). Instances were solved to optimality with Gurobi v.6.0 for M1, M2, and M3. This later is solved several times according to the iterative heuristic described in section 4.3.

We have thoroughly analyzed the solutions produced to the first instance I1 where ρ_t, the offer/demand ratio at each period, is set to {1.0; 1.0; 0.7; 0.5; 0.9; 1.2; 1.2; 1.2}. In other words, after two periods in which the demand can be satisfied, there is three periods of shortness where the offer falls to only 70% and then to 50% of the demand. From period five, offer rises to 90% of the demand and, during the last three periods, it exceeds the requirements. *Figure 3.2* shows the dissatisfaction percentage at each PoD and period in the solutions produced by M1 (leftmost chart), M2 (central chart) and M3 (rightmost chart) and how they behave in very different manners.

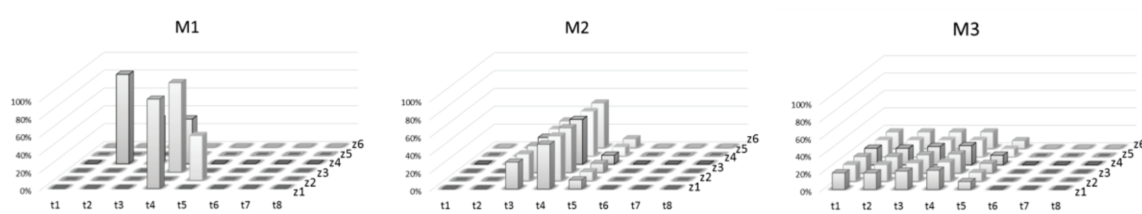

Figure 3.2 – Dissatisfaction percentage for instance I1.

If we look at how shortage is shared between the PoDs for a given period, M2 and M3 split the shortness in a rather homogeneous manner: all the PoDs suffer similar shortages. However, M1 concentrates shortages only on a few PoDs, and those will experience very high values of dissatisfaction. For instance, PoD four's demand is 100%, 50% and 50% unsatisfied in periods two to four. If we now look at how the global shortage is handled in time, we observe that M1 and M2 simply distribute the available quantities at each period. However, M3 shows a more elaborated behavior, which translates in a smoother distribution. In fact, M3 reserves some quantities during periods one and two in order to minimize the impact of the shortage in periods three to five. Doing so, the maximum dissatisfaction percentage suffered by any PoD and at any period is under 20%, while in M1's solution some PoDs experience up to 100% of unsatisfied demand and in M2's solution PoDs suffer up to 60%. The piecewise approximation achieves a rationalization of resources, resulting in an equitable distribution among PoDs (the same or almost the same dissatisfaction level) in a period, and this in a stable matter across time in the shortness periods. To sum up, both M2 and M3's solutions achieve a good "equity" between the PoDs, but M3 is also able to achieve an excellent "stability".

Let us now see how these behaviors are captured by the proposed numerical indicators. *Table 3.1* reports the numerical results produced by models M1, M2 and M3. To measure the quality of the distribution plan obtained by each model, we report two global measures: the global average dissatisfaction percentage ($u_{..}$), and the global standard deviation (σ_{global}), which concerns to the dispersion in distribution. Then, we also compute mean sum of squares within time ($\overline{WT}$) and between time ($\overline{BT}$) and the two range indicators ($\overline{R_1}$ and $\overline{R_2}$). Finally, we calculate the total traveled distance (D) and record the total computation time to solve each model in seconds.

Let us consider first the results produced for I1. We observe that M1 achieves a lower value for $u_{..}$ (i.e. a better global satisfaction). The reason is that, although all the three models distribute the same quantity of help, M1 prefers to give slightly higher quantities to PoDs 5 and 6 because the marginal impact of a single additional help unit is higher for PoDs with small demand. On the other hand, doing so deteriorates the equity and stability objectives. In fact, M1 is clearly outperformed by both M2 and M3 for almost all the others indicators (excluding $\overline{BT}$ in which M2 shows the poorest performance). As expected, concerning σ_{global} (global dispersion over all PoDs and periods), M2 achieves 18% and is clearly dominated by M3, which produces only 9%. As per range indicators, $\overline{R_1}$ and $\overline{R_2}$ show the poor performance of M1. M2 has a perfect score in terms of equity ($\overline{R_1}$) and M3 shows an almost equal performance, but M3 offers a better performance with respect to stability ($\overline{R_2}$). This particular behaviour is confirmed by the dispersion indicators. Indeed, M2 and M3 achieve equal "perfect" scores for equity ($\overline{WT}$), but M3 offers better results for stability ($\overline{BT}$). This result is easily explained by the cost function structure of M3. The fact that the domain of u_{zft} is discretized in different pieces, with a higher cost function (slope) for each successive piece, makes it possible to seek the same (or almost the same) dissatisfaction percentage for each period, PoD and humanitarian function.

We now analyze the rest of the results in *Table 3.1*. Lines *Avg.* show the average values for each column over the 10 instances and lines # *best* counts the number of instances in which the model achieved the best value of the indicator.

Table 3.1 – Results produced for 10 small instances (temporary shortness).

		$u_{..}$	σ_{global}	$\overline{WT}$	$\overline{BT}$	$\overline{R_1}$	$\overline{R_2}$	**D**	**Sec.**
I1	M1	9%	26%	6%	12%	37%	50%	364	0.2
	M2	11%	18%	0%	21%	0%	50%	367	0.2
	M3	11%	9%	0%	6%	1%	21%	371	0.6
Avg.	M1	9%	24%	5%	11%	35%	45%	1338	0.2
	M2	11%	17%	0%	19%	0%	50%	1329	0.1
	M3	11%	9%	0%	6%	3%	20%	1380	0.6
# best	M1	10	0	0	0	0	0	3	4
	M2	0	0	10	0	10	0	7	7
	M3	0	10	10	10	0	10	0	0

Globally speaking, results are quite similar to the ones produced for instance I1. M1 systematically achieves the best average percentage of unsatisfied demand but at the cost of a very poor equity and stability performances. M2 offers the best performance with regards to $\overline{R_1}$, but M3's performance is always very close to M2's. As expected, M3's stability performance is the best over the three models. To sum up, M2 and M3 achieve equal (perfect) scores for $\overline{WT}$ (equity indicator), but M3 offers better results when measuring stability ($\overline{BT}$).

Before moving on to the experiments on extreme shortness scenario, let us say few words about the efficiency of the produced solutions. Both M1 and M2 produce the shortest total distance for three and seven instances. However, M3's average total distance is only 3.9% higher than M2. We can therefore conclude that an equitable and smooth distribution does not cost much in terms of transportation efficiency.

3.5.3. Models' performance in an extreme shortness scenario

In an extreme shortness scenario, when resources are really scarce, assuring equity in a period and across the horizon is of the highest importance, because rationalization is the only way to minimize suffering and reduce disparity in the relief given to affected people.

To validate the behavior of the solutions produced by the three proposed models, we use the same set of instances of section 5.2., but this time the offer/demand ratio ρ_t per period was set to $\{0.8, 0.8, 0.8, 0.6, 0.6, 0.2, 0.2, 0.6\}$. In the same way as it was done in previous section, we'll use a single instance (I11) as an illustrative example to carefully explain each model's behavior. *Figure 3.3* the dissatisfaction percentage at each PoD and period.

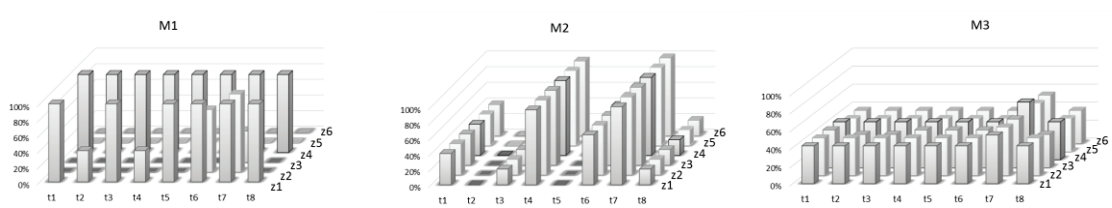

Figure 3.3 – Dissatisfaction percentage for instance I11.

First, it can be observed that M1 never visits PoD4, which is the POD with the highest demand. On the other hand, PoDs 5 and 6, the ones having the lowest demand, are always visited. PoD1 is also strongly penalized and is not visited in six out of eight periods. We believe that this behaviour should not be tolerated in practice. On its side, M2 shares the amount of relief available, assuring equity at every period, but again, it is not able to balance deliveries between periods. Hence, all PoDs suffer equivalent penuries, but theirs demand is fully met in some periods and totally unsatisfied in others (periods 4 and 7). We consider this as a questionable decision because the lowest offer/demand ratio on the horizon is 20%. Indeed, M3 is the only formulation that allows for equity among PoDs and stability throughout time, thus reducing the maximum non-satisfaction level from 80% to 54% (in period seven) and 42% in the other periods. *Table 3.2* reports the performance values achieved by the solutions produced by models M1 to M3.

As expected, M1 achieves again the lowest total dissatisfaction value. M3 shows a total deviation of only 5% while M1 and M2 produce values of up to 46% and 35%, respectively. Again, M2 shows a perfect balance for all the PoDs within the same period, and M3's results are not far. Indeed, M3 also achieves a perfect score of 0% for $\overline{WT}$ and only 4% for $\overline{R_1}$. On the other hand, M3 clearly outperforms both M1 and M2 in terms of distribution stability. We extend our analysis to nine more random generated instances. The numerical results are reported in *Table 3.2.*

Table 3.2 – Results produced for 10 small instances (extreme shortness).

		$u_{..}$	σ_{global}	$\overline{WT}$	$\overline{BT}$	$\overline{R_1}$	$\overline{R_2}$	**D**	**Sec.**
I11	M1	35%	46%	24%	8%	100%	33%	204	0.1
	M2	42%	35%	0%	86%	0%	97%	219	0.0
	M3	42%	5%	0%	2%	4%	16%	219	0.4
Avg.	M1	33%	46%	24%	4%	100%	22%	824	0.1
	M2	42%	31%	0%	68%	0%	89%	813	0.1
	M3	42%	5%	0%	2%	4%	14%	819	0.6
# best	M1	10	0	0	7	0	2	3	4
	M2	0	0	10	0	10	0	6	6
	M3	0	10	10	8	0	8	1	0

As in the temporary shortness case, M3 minimizes global deviation and offers the best possible equity and stability performances at a negligible increase in the distribution distance.

3.5.4. Models' performance in larger-sized instances

We will dedicate the last part of this section to show the models' performance over a set of 20 instances with a more realistic size. The objective is to test the models' capacity to ensure a fair distribution over a much larger set of PoDs, and to test, at the same time, the computational effort of each model. Following the pattern described in section 5.2 and 5.3, we solve 10 instances for temporary shortness and 10 instances for extreme shortness cases. For each scenario we test five medium-size instances and five large-size instances. We define as "medium-size" instances with a total of 20 PoDs, 10 potential HADCs, six suppliers, one humanitarian function and eight periods. Large-size instances have 50 PoDs, 20 HADCs, six suppliers, one function and eight periods. *Table 3.3* and *Table 3.4* summarize the results for the temporary and extreme shortness scenarios respectively.

Table 3.3 – Results produced for larger-sized instances in temporary shortness.

		$u_{..}$	σ_{global}	$\overline{WT}$	$\overline{BT}$	$\overline{R_1}$	$\overline{R_2}$	D	Sec.
Avg. over 5 medium instances	M1	9%	26%	6%	35%	62%	45%	3590	0.1
	M2	11%	17%	0%	63%	0%	49%	3475	2.3
	M3	11%	9%	0%	18%	3%	19%	4005	1.6
Avg. over 5 large instances	M1	9%	27%	6%	89%	62%	49%	8003	0.3
	M2	11%	16%	0%	143%	0%	49%	7782	35.3
	M3	10%	9%	0%	45%	4%	19%	8840	3.4

Table 3.4 – Results produced for larger-sized instances in extreme shortness.

		$u_{..}$	σ_{global}	$\overline{WT}$	$\overline{BT}$	$\overline{R_1}$	$\overline{R_2}$	D	Sec.
Avg. over 5 medium instances	M1	33%	47%	23%	6%	100%	12%	2110	0.1
	M2	43%	30%	0%	205%	0%	93%	2062	2.9
	M3	42%	2%	0%	0%	4%	4%	2069	1.4
Avg. over 5 large instances	M1	33%	47%	22%	1%	100%	4%	4751	0.2
	M2	42%	26%	0%	413%	0%	76%	4657	10.2
	M3	42%	3%	0%	1%	5%	4%	4723	0.9

In the following, we will concentrate our analysis to models M2 and M3, because M1 shows still the poorest performance in most of the indicators. *Table 3.3* and *Table 3.4* confirm that the models' behaviors follow the same line observed in the smaller instances. M2 and M3 achieved almost the same dissatisfaction percentage, but distributed the limited resources in a very different way. M3 achieves the best score in average global dispersion of only 9% and around 3% for the temporary and extreme shortness cases respectively. Therefore, we can observe that increasing the number of PoDs did not have an impact in the quality of the solution. M3 can still ensure an equitable distribution among PoDs as M2 does and a much stronger stability in time. For the temporary shortness case, M3 has an $\overline{R_2}$ of only 19% vs. 49% for M2, while for the extreme shortness case M3 has an $\overline{R_2}$ of only 4% vs. 93% and 76% for M2.

The numerical values previously reported show their sensibility with respect to the specific type of the scenario considered. In the extreme shortness scenario the obtained values tend to be higher than in the temporary shortness one. This is related to the variability of the offer/demand ratio defining each type of scenario. Finally, let us take a second to analyze the computational effort needed to solve larger instances. All the models can be solved to optimality in short time (less than a minute in average), even for large instances. However, M2 shows a high variability in CPU time, having a lot of trouble to close the optimality gap. For instance, in the temporary shortness case (for large instances) M2 takes 35 seconds on average with a standard deviation of 27 seconds due to extremes values in three out of five instances, while M3 takes 3,4 seconds on average with a standard deviation of only 0,4 seconds. We can conclude that M3 is the modeling approach that best suits the different objectives set for the complex problem of relief distribution.

3.6. Conclusions and future research

In this paper we proposed and discussed three different approaches for the design and the operation of a relief distribution network. This work is mainly centered in two important components that had been overlooked in the past: the fairness principle and the multi-period nature of relief distribution. We strongly believe that these major aspects need to be covered in response logistics, and they need to be addressed from the beginning of the response plan (the network design phase) in order to improve the other logistic tasks (procurement, delivery plans and transportation problems). Three important contributions were made in the fair relief distribution problem. First of all, a discussion on what can be defined as a fair distribution was presented, concluding that in order to obtain fairness, crisis managers should warrant equity in distribution within periods, but also, stability in delivery in the best possible way. In addition, we considered and modeled shortness by including the possibility of backordered demand. This allows crisis managers to gain flexibility in the distribution and seek compensation of unsatisfied PoDs on the planning horizon. Secondly, we proposed and adapted five performance indicators to measure the two components of fairness. Finally, we proposed and tested three different formulations to handle the complex context of relief distribution. These formulations seek mainly minimization of unsatisfied demand and effectiveness in distribution, but also two of them explicitly include the fairness objective. We compared them in some numerical examples and concluded that, M2 achieves a perfect score in equity in distribution in a single period, but is unable to maintain a stable distribution on the planning horizon. We proved, on its side, that M3 accounts for both equity and stability.

Several promising research paths are currently being considered. For instance, the extension of our proposition to include routing planning, supplying an integral planning tool to CMs in response and preparedness of relief distribution.

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Chapitre 4

Transport des échantillons biomédicaux dans la province de Québec : un cas d'étude

Le transport d'échantillons biomédicaux joue un rôle central dans un système de santé efficace. Développé dans le cadre d'une collaboration avec le Ministère de la Santé et des Services sociaux du Québec (MSSS), cet article décrit les défis du transport d'échantillons biomédicaux pour la province du Québec. Ce problème est modélisé comme une variante du problème de tournées de véhicules avec fenêtres de temps et plusieurs voyages. Les routes sont planifiées à partir d'un laboratoire pour satisfaire les requêtes de transport d'échantillons qui proviennent des centres de prélèvement du réseau, tout en considérant plusieurs contraintes pratiques. On considère que ces routes sont effectuées par un transporteur externe et facturées en termes de distance (nombre total de kilomètres à parcourir). Autrement dit, il n'y a pas un coût fixe à payer pour l'utilisation d'un véhicule. Cependant, le gestionnaire du réseau a toujours intérêt à avoir une estimation du nombre total de véhicules qui sont demandés dans le plan de transport. Nous proposons deux formulations mathématiques alternatives ainsi que quelques heuristiques rapides pour minimiser la distance totale parcourue dans le processus de transport. La performance de la méthode proposée est testée sur un cas d'étude réel de la province de Québec.

Article 3: Biomedical sample transportation in the province of Quebec: a case study

Ce chapitre fait l'objet d'une publication sous la forme d'article de journal : Anaya-Arenas, A.M., Chabot, T., Renaud, J. & Ruiz, A., 2015. Biomedical sample transportation in the province of Quebec: a case study. *International Journal of Production Research*, (ahead-of-print), pp.1–14.

Abstract: Biomedical sample management plays a central role in an efficient healthcare system and requires important resources. Based on our collaboration with the Quebec's *Ministère de la Santé et des Services sociaux* (Ministry of Health and

Social Services), this article describes the challenging context of biomedical sample transportation in the Canadian province of Quebec. It is modeled on a variant of the multi-trip vehicle routing problem with time windows where routes need to be planned from a *laboratory* to satisfy the multiple pick-up requests of each *sample collection center* (SCC) under some practical constraints. We propose and evaluate two alternative mathematical formulations, as well as fast heuristics, to minimize total transportation distances. The performance of the proposed methods is assessed over a large case study based on the network of laboratories in the province of Quebec.

4.1. Introduction

Biomedical tests play an important role in helping physicians make accurate diagnoses. To perform such tests, thousands of biomedical samples or "specimens", need to be transported daily from the different healthcare network's facilities where they are collected (hospitals, private clinics or other *samples collection centers* - SCCs) to *laboratories* where they will be analyzed. Although large hospitals often own on-site laboratories where collected specimens can be analyzed, most of the SCCs are not equipped to analyze the samples they collect, so they must ensure that the samples are adequately transported to the laboratories.

This research seeks to formalize and to improve the biomedical sample transportation practices used in the province of Quebec, Canada, where the *Ministère de la Santé et des Services sociaux* (Ministry of Health and Social Services – MSSS) is in charge of supporting and overseeing the province's health network to ensure the well-being of Quebecers. At the present, there is neither formal structure in charge of the specimens' transportation, nor are there directives ruling such activities. Thus, each laboratory and SCC is responsible for selecting the transportation services they use and how they use them. In most cases (around 70%), SCCs have signed blanked transportation contracts with local carriers, so SCC employees order a transportation service whenever they feel it is necessary. In the rest of the cases, SCCs simply calls a taxi service. These multiple and uncontrolled transportation modes result in two negative consequences related to the tracking and control of (1) the costs of specimen transportation and (2) the quality of the transportation done by the transportation providers.

Aiming at improving the services offered to the population and controlling the associated costs, the MSSS engaged in a supply chain optimisation project named *Optilab*. Optilab seeks to enhance the quality of the services provided by the network of laboratories in terms of security, accessibility, efficiency and efficacy (MSSS, 2012). To this end, Optilab intends to formalize and consolidate the transportation of biomedical specimens in Quebec. In fact, the MSSS plans to contract samples' transportation services to private carriers selected through a public tender process specifying the technical requirements and physical conditions ruling the samples' transportation. However, in order to receive realistic bids, the MSSS cannot only provide the total number of samples to transport and the list of origins and destinations. Instead, the MSSS must provide a statement of works (SOW) translating their requirements into "transportation efforts" expressed in terms of approximated number of pickups and deliveries to perform, realistic number of vehicles needed, the shape and distance of the routes, and other logistic information. This is precisely the goal of the present research aimed at organizing and establishing daily transportation operations for biomedical samples. The results of this research will help the MSSS to estimate their transportation needs rather than biomedical ones, in order to compose their future SOW, allowing the private providers to determine their best bids.

This paper presents two major contributions. Firstly, it describes the Quebec's biomedical sample transportation context and proposes two alternative formulations for solving it. Secondly, it proposes a solving approach able to produce transportation plans to deal efficiently with the daily sample transportation needs of the Quebec's healthcare network. These plans will provide good estimations of the logistic work to be performed by external contractors and will assist the MSSS in refining their future SOW.

This article is structured as follows. Section 2 describes the biomedical sample transportation context. Section 3 reviews the related literature. Section 4 presents two mathematical formulations, and Section 5 introduces heuristic approaches to solve it.

Real data and computational results are presented in Section 6. Section 7 concludes this article and offers some research perspectives.

4.2. Problem statement

The network considered is composed of *sample collection centers* (SCCs) and *laboratories* (Labs). SCCs are health facilities that patients visit in order for the requested biomedical samples to be collected. Then, the specimens are pretreated and prepared to be sent to a lab for analysis. Following the structure imposed by the MSSS, the Quebec province is divided into territories, and each SCC in a territory is assigned *a priori* to a given lab. Hence, each transportation network is composed of a set of SCCs (clients) assigned to a lab (that we consider as a *depot*). Finally, even if hundreds of different specimens are collected, they are all grouped and transported in standard refrigerated sample boxes. As a box may contain up to 80 samples, an SCC rarely requests transportation for more than one or two boxes at a time. Sample boxes are rather small, so a single vehicle can transport several of them. This is why vehicles capacity, as well as the precise number of boxes at each SCC, is irrelevant, and thus we will only consider *transportation requests* of each SCC. We assume that, according to the MSSS objective, these transportation requests will be satisfied by external carriers under contract with the SCCs, and these external carriers will be paid on the basis of the traveled distance. We also assume that each driver may perform multiple routes during the working day. More precisely, drivers must begin routes at the lab, where they get empty sample boxes to exchange with full boxes at every visited SCC. Drivers return to the lab to deliver the collected samples before starting any other route. Finally, the drivers' schedule must respect the maximum number of driving hours per day set by the Quebec province regulation. Since the MSSS intends to count on external carriers, we assume that there is not any a priori limitation on the number of available vehicles. Finally, emergency requests may probably occur. If it is the case, they will be handled by on-call taxis, or as exceptions by the transportation supplier who will plan them outside the regular routes.

The biomedical samples' collection from SCCs to the lab has some characteristics that make it a challenging optimisation problem. The hardest constraints are the samples' maximum transportation time and the multiple transportation requests at each SCC. Unlike other related contexts, such as blood collecting (Doerner et al., 2008 and Doerner and Hartl, 2008) which considers that the product starts deteriorating right after the donation, we assume that as long as samples are kept at SCCs, their deterioration is slowed down due to the controlled temperature and optimal storage conditions. However, as soon as samples are out of the SCC facilities, the samples integrity cannot be guaranteed, even if they are transported in cooler boxes. Therefore, we modeled this limitation on a *maximal transportation time*, which depends on the type of the particular samples collected, to preserve the samples' lifespan. Thus, after collection, each sample box must arrive at the lab within a given time frame. Otherwise, samples deteriorate and may become unusable, increasing tremendously both the lab's costs and affecting the quality of the service. In fact, an unusable sample forces the patient to make a second collection, which delays the analysis and doubles the operations costs of the entire process (collecting, transporting and analyzing).

On the other hand, and despite the ideal environmental conditions at SCCs, the samples maximum lifespan is limited, so SCCs does not want to keep the collected specimens for too long a time. This is why each SCC may make a different number of samples transportation requests, depending on its daily opening hours. For example, if an SCC is open from 9am to 1pm, it is not desirable to keep the samples during the entire morning, and then make a single transportation request at the end of the day. Instead, it is preferable to make at least two different pick-up appointments. Moreover, these two appointments should not be too close (e.g., it would not be useful to make a visit at noon and another one at 1pm) because this can prove as inefficient as just making one pick-up. Hence, we allowed SCCs to propose time windows for theirs transportation requests according to the particularities of their own clients and practices; for example, a very active SCC open between 9am to 1pm could require a first pick-up between 10:30 and 11, and a second one between 13 and 13:30. These multiple pick-ups are also desirable because they contribute to ensure a smoother supply of sample boxes to labs and thus help balancing their workload.

Given the particular underlying context of the biomedical sample transportation described, the aim of this research was to find the minimum distance set of routes in order to satisfy all the transportation requests of each SCC, while respecting the imposed time windows, the maximum transportation times of all the collected samples and the drivers' maximum working time.

4.3. Related literature

The biomedical sample transportation problem (BSTP) is characterized by multiple visits to each customer, a time window for each visit time, multiple routes (trips) for each vehicle and other practical constraints that will be explained later on. Therefore, it is clearly grounded in the vehicle routing literature and relates specifically to the vehicle routing problem with time windows (VRPTW) and the multi-trip vehicle routing problem (MTVRP). Since there is ample literature on these subjects, the next paragraphs aim solely at outlining some key reviews or the most recent works on these topics. Then, a more detailed outlook is devoted to some works pertaining to BSTP's specific transportation time constraints, such as the blood collecting problems.

The literature on VRPTW is very rich. The wide review of Cordeau et al. (2002), and those by Bräysy and Gendreau focused on local search algorithms (2005a) and metaheuristics (2005b) are key contributions to the field. We refer the interested reader to Kallehauge (2008) and Baldacci et al. (2011; 2012) for up-to-date information on the most recent and most efficient exact algorithms for solving the classical capacitated VRPTW. As per the multi-trip vehicle routing problem (MTVRP), Fleischmann (1990), Taillard et al. (1996) and Brandão and Mercer (1997; 1998) were among the first to propose to deal with such class of problems. Brandão and Mercer (1997; 1998) proposed several tabu search algorithms for solving an MTVRP with different constraint types, including time windows. Olivera and Viera (2007) used an adaptive memory programming algorithm to solve the classical MTVRP, leading to better results than those produced by both Brandão and Mercer (1998) and Taillard et al. (1996). Prins (2002) considers a MTVRP with two objectives (the total distance and the number of required vehicles) and reported results to a problem inspired from the case of a French furniture manufacturer. Recently, Mingozzi et al. (2013) proposed an exact algorithm and solved benchmark instances with up to 120 customers.

As one could expect, recent research has addressed situations merging time windows with multi-trip vehicle routing problems (MTVRP-TW). Battarra et al. (2009) solved a MTVRP-TW with multiple incompatible commodities, with the objective of minimizing the number of vehicles. Cattaruzza et al. (2014) proposed an iterated local search algorithm for the MTVRP-TW. Martínez and Amaya (2013) used a tabu search algorithm for solving an MTVRP-TW with loading constraints. Azi et al. (2014) developed an adaptive large neighborhood search algorithm for the MTVRP where the objective is first to maximize the number of served customers, and then to minimize the total distance traveled by the vehicles. Wang et al. (2014) proposed a metaheuristic based on a pool of routes to solve the MTVRP-TW. We can conclude that MTVRP-TW is a rather new, yet challenging, problem reflecting the aim of researchers to incorporate real life features or attributes into their routing models. Vidal et al. (2013) presents a very detailed survey compiling most of the constraints and attributes proposed in the literature for routing problems, as well as the heuristic approaches developed to deal with them. Later, they developed a unified and generic solution framework for multi-attribute routing problems (Vidal et al. 2014).

Our review of the related literature allowed us to identify five specific works which deals with the collection or transportation of biomedical products or presents characteristics making them appear to be very close to the BSTP. Therefore, it is worth positioning the BSTP with respect to them. First, Liu et al. (2013) studied a routing problem where biomedical samples needed to be collected and delivered to laboratories. In their case, four types of deliveries and pick-up requirements were considered. As in the BSTP, visits had to respect time windows, but in their case each node required only one visit and each vehicle performed a single route.

The two following papers, Doerner et al. (2008) and Doerner and Hartl (2008), dealt with a blood collection problem. As in our context, they assumed a limit on the transportation time to preserve the blood's quality, and allowed the planning of multiple pick-ups at each customer location. However, as mentioned previously, they considered that the product's deterioration process began right after the donation so, assuming that a donation is performed just after a pick-up is done, a limit on the next pick-up time is automatically imposed. Thus, as emphasized by the authors, time windows are interdependent and therefore the number of pickups and their time windows are decision variables to be set by the model, while in our case they are fixed by the SCCs.

Finally, both Azi et al. (2010) and Hernández et al. (2014) addressed variants of the MTVRP-TW where the total duration of each route was limited. In these works, the length of each route, in time, is limited by forcing the last customer to be served no later than a maximum time set after the route departs. However, our maximum transportation time constraint is quite different from the one used in Azi et al. (2010) and Hernández et al. (2014). In order to illustrate this point, we refer to *Figure 4.1*, where trips durations are given on the arcs. On each node are shown the vehicle's arrival time (*Arrival*) and STT_i the time that the sample i, the first sample collected in the route, has spent up to now in the vehicle. In this example, we assume that the maximum transportation time and maximum route duration are set to three time units.

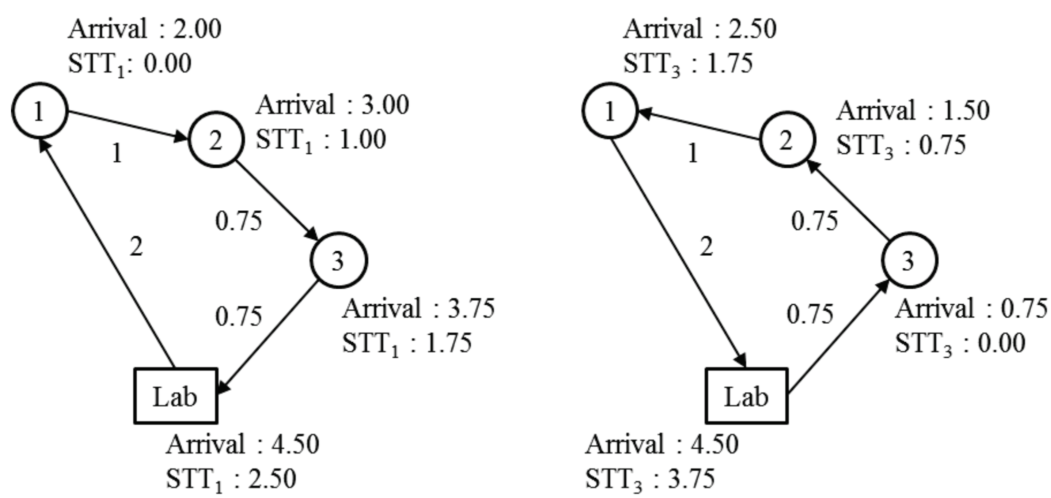

Figure 4.1 – Feasible or unfeasible routes with respect to the sample transportation time.

The route outlined in the left part in
Figure 4.1 is not feasible for Azi et al. (2010) and Hernández et al. (2014), because the vehicle leaves the last node (node 3) later than three time units after the route's start. However, the route is feasible with respect to our maximum transportation time constraint as samples collected at node 1 only travel 2.50 units before arriving at the lab. The route depicted on the right part visits the same nodes but in a reverse order. In this case, Azi et al. and Hernández et al. constraint is respected (vehicle arrives at the last node on the route within three time units) but it is unfeasible with respect to our constraint because the sample collected at node 3 travels 3.75 time units before arriving at the lab.

We conclude that, despite the similarities to other previous works, the practical particularities of BSTP make it a new and challenging problem. The next section presents two different formulations for the BSTP.

4.4. Mathematical formulations

This section proposes two formulations for the BSTP. The first one deals explicitly with the multiple transportation requests at each SCC, while the second one duplicates the SCC, such as each node only has one transportation request.

4.4.1. Model 1: Multiple transportation requests per SCC (BSTP-MR)

The BSTP is modeled over a complete graph $G = \{V, A\}$, where $V = \{v_0, v_1, \dots, v_n, v_{n+1}\}$ is the set of nodes in the network, composed by the n SCCs (set $N = \{v_1, v_2, \dots, v_n\}$) that generate transportation requests and the lab $\{v_0, v_{n+1}\}$ where every route must start and end. We define the arc set $A = \{(v_i, v_j): v_i, v_j \in V, i \neq j, i = 0, \dots, n, j = 1, \dots n+1\}$, and a travel time ($t_{ij}$) and a travel distance (d_{ij}) is assigned to each arc (v_i, v_j). K uncapacited vehicles are available for satisfying SCCs transportation requests. Each vehicle can perform multiple routes ($r = 1, \dots R$) within a work shift, but it must respect a limit on the length of its working day (T_k).

Each SCC i requires a specific number of transportation requests ($q = 1, \dots, Q_i$). For SCC i, its q^{th} pick-up has to be done inside a time window $[a_{iq}, b_{iq}]$, where a_{iq} is the earliest time the transport may arrive (otherwise, it has to wait) to perform the pick-up q of SCC i, and b_{iq} is the latest accepted arrival time. Time windows are considered to be hard constraints. In addition, we need to consider the loading time (τ_i) at each SCC and the unloading time (τ_0) of the vehicle at the Lab before a new route can be started. Furthermore, let T_{max}^{i} be the maximal transportation time for the types of samples collected at SCC i.

In order to define a transportation plan that respects the practical constraints of our problem and minimize transportation costs, we define the following decision variables.

x_{ijkr} Binary variable equal to 1 if the arc (i,j) is used by vehicle k in its route r; 0 otherwise.

y_{jqkr} Binary variable equal to 1 if the q^{th} request of SCC j is done by vehicle k in its route r; 0 otherwise.

u_{ikr} Continuous variable that indicates the visit time of SCC i by vehicle k in route r.

Model BSTP-MR is stated as follows:

$$Min \sum_{i=0}^{n} \sum_{j=1}^{n+1} \sum_{k=1}^{K} \sum_{r=1}^{R} d_{ij} x_{ijkr} \tag{1.1}$$

Subject to:

$\sum_{i=0}^{n} x_{ijkr} \leq 1$ $\quad j = 1, \dots, n; k = 1, \dots, K;\ r = 1, \dots, R$ (1.2)

$\sum_{i=0}^{n} x_{ijkr} - \sum_{l=1}^{n+1} x_{jlkr} = 0$ $\quad j = 1, \dots, n; k = 1, \dots, K;\ r = 1, \dots, R$ (1.3)

$\sum_{j=1}^{n} x_{0jkr} \leq 1$ $\quad k = 1, \dots, K; r = 1, \dots, R$ (1.4)

$\sum_{j=1}^{n} x_{0jkr} - \sum_{j=1}^{n} x_{j,n+1kr} = 0$ $\quad k = 1, \dots, K; r = 1, \dots, R$ (1.5)

$\sum_{j=1}^{n} x_{0jkr} - \sum_{j=1}^{n} x_{0jkr-1} \leq 0$ $\quad k = 1, \dots, K; r = 2, \dots, R$ (1.6)

$$\sum_{k=1}^{K}\sum_{r=1}^{R} y_{jqkr} = 1 \qquad j = 1, \dots, n;\ q = 1, \dots Q_j \qquad (1.7)$$

$$\sum_{q=1}^{Q_j} y_{jqkr} - \sum_{i=0}^{n} x_{ijkr} = 0 \qquad j = 1, \dots, n; k = 1, \dots, K;\ r = 1, \dots, R \qquad (1.8)$$

$$u_{ikr} + \tau_i + t_{ij} - u_{jkr} \leq T_k(1 - x_{ijkr}) \qquad i = 0, \dots, n; j = 1, \dots n+1;\ k = 1, \dots, K; r = 1, \dots, R \qquad (1.9)$$

$$a_{jq} - T_k(1 - y_{jpkr}) \leq u_{jkr} \leq b_{jq} + T_k(1 - y_{jpkr}) \qquad j = 1, \dots, n; k = 1, \dots, K\ r = 1, \dots, R; q = 1, \dots, Q_j \qquad (1.10)$$

$$u_{0kr} \geq u_{n+1,k,r-1} \qquad k = 1, \dots, K; r = 2, \dots, R \qquad (1.11)$$

$$u_{n+1kr} - u_{jkr} \leq T_{max}^{j} + T_k\left(1 - \sum_{i=0}^{n} x_{ijkr}\right) \qquad j = 1, \dots, n; k = 1, \dots, K;\ r = 1, \dots, R \qquad (1.12)$$

$$u_{n+1,kr} - u_{0,k1} \leq T_k \qquad k = 1, \dots, K; r = 1, \dots, R \qquad (1.13)$$

Objective (1.1) is to find a transportation plan that minimizes the total traveled distance. Constraints (1.2) ensure that an SCC j is visited at most once per route r of vehicle *k*. Constraints (1.3) force the flow of each vehicle k for each of its routes r to be balanced at each SCC of the network. This means that if an arc enters node j on a route r of vehicle k, there must be an arc that leaves the same node for the same (k, r) combination. Constraints (1.4) state that a truck k can start a route r or not, but (1.5) if the vehicle starts a route, it must come back to depot (node $n + 1$). Constraints (1.6) order the routes; thus, route r is started if and only if route $r - 1$ has already been created. Constraints (1.7) and (1.8) verify the pick-up request satisfaction. Constraints (1.7) state that each pick-up q for each SCC j is done by one, and only one, vehicle route (k, r) combination; constraints (1.8) link the arc to the pick-up variables, which means that if a pick-up is done by route r of truck k it is because an arc of this combination entered to the node j. Constraints (1.9) to (1.13) handle the time constraints. Constraints (1.9) have two main purposes: first, it estimates the arrival time at every node (clients or dummy depot), and second, it forces the sub-tours' elimination. Then, constraints (1.10) set the upper and lower bound of the time windows, forcing a pick-up q from client j and done with vehicle k on its route r ($y_{jqkr} = 1$), to fall within the time window of the pick-up request;

otherwise, the constraints are irrelevant (when $y_{jqkr} = 0$). Here T_k is used as a big M value. Constraints (1.11) ensure that the starting time of route r is later than the arriving time of route $r-1$ at node (n+1). Constraints (1.12) impose the maximum transportation time length limit (returning time to the lab minus the pick-up time at any j is less than the limit T^j_{max} if j is visited by vehicle k on its route r). Constraints (1.13) force vehicle k to comply with the total length of its work shift.

Formulation BSTP-MR is difficult to solve due, in part, by the homogeneity of the considered fleet because there are numerous possible equivalent solutions. Therefore, and in order to strengthen the formulation, we adapted the two symmetry breaking constraints proposed by Coelho and Laporte (2014) to our context.

$$\sum_{j=1}^{n} x_{0jk1} - \sum_{j=1}^{n} x_{0jk-1,1} \leq 0 \qquad k = 2, \dots, K \qquad (1.14)$$

$$\sum_{r=1}^{R} y_{jqkr} - \sum_{i=1}^{j-1} \sum_{l=1}^{Q_j} \sum_{r=1}^{R} y_{ilk-1,r} - \sum_{l=1}^{q-1} \sum_{r=1}^{R} y_{jlk-1,r} \leq 0 \qquad j = 1, \dots, n; q = 1, \dots Q_j, \; k = 2, \dots, K \qquad (1.15)$$

Constraints (1.14) state that a vehicle k can be used (leave the depot for the first time) if, and only if, a vehicle $k-1$ has already been used in a tour. This restriction is extended to the clients' nodes with constraints (1.15). These constraints state that if a request q of a SCC j is performed by any route of vehicle k, then a vehicle $k-1$ is used and performs the request of at least one client with a smaller index ($i < j$), or a request of SCC j with smaller index than q ($l < q$).

4.4.2. Model 2: Extended graph (BSTP-EG)

In the BSTP-EG, each transportation request is represented by a specific node, so if SCC i requires Q_i pick-ups, i is represented by Q_i nodes located at the same place, each needing one request. Therefore, the original set N is extended into a set P of p nodes ($p = \sum_{i=1}^{n} Q_i$).

We define a complete graph $G_2 = \{V_2, A\}$, where $V_2 = \{v_0, v_1, \dots, v_p, v_{p+1}\}$ is the set of nodes in the network, which includes the laboratory as nodes $\{v_0, v_{p+1}\}$ and the set

$P = \{v_1, v_2, \ldots, v_p\}$, with the p transportation requests of the SCCs. We also define P_n as the set of nodes representing the pick-ups requested by the original SCC n. Therefore, node set P is composed of a set of pick-ups originating from different SCCs (i.e. $P = \bigcup_n P_n$). Finally, we consider the arc set $A = \{(v_i, v_j): v_i, v_j \in V_2, i \neq j, i = 0, \ldots, p, j = 1, \ldots p+1\}$. Clearly, t_{ij} and d_{ij} are equal to zero for every (v_i, v_j) if i and $j \in P_n$ (i.e. nodes i and j correspond to two requests from the same SCC). In addition, each request needs to be performed within its original time window $[a_j, b_j]$. Finally, no more than one node from each P_n can be visited on any route. The rest of the notation of model BSTP-MR is also valid for model BSTP-EG. The following decisions variables are used:

x_{ijkr} Binary variable equal to 1 if the arc (i, j) is used by vehicle k on its route r; 0 otherwise.

u_{ikr} Continuous variable that indicates the visit time of pick-up i by vehicle k on route r.

$$Min \sum_{i=0}^{p} \sum_{j=1}^{p+1} \sum_{k=1}^{K} \sum_{r=1}^{R} d_{ij} x_{ijkr} \tag{2.1}$$

Subject to:

$$\sum_{k=1}^{K} \sum_{r=1}^{R} \sum_{i=0}^{p} x_{ijkr} = 1 \qquad j = 1, \ldots, p \tag{2.2}$$

$$\sum_{j \in P_n} \sum_{i=0}^{p} x_{ijkr} \leq 1 \qquad n = 1, \ldots, N; k = 1, \ldots, K; r = 1, \ldots, R \tag{2.3}$$

$$\sum_{i=0}^{p} x_{ijkr} - \sum_{l=1}^{p+1} x_{jlkr} = 0 \qquad j = 1, \ldots, p; k = 1, \ldots, K;\ r = 1, \ldots, R \tag{2.4}$$

$$\sum_{j=1}^{p} x_{0jkr} \leq 1 \qquad k = 1, \ldots, K; r = 1, \ldots, R \tag{2.5}$$

$$\sum_{j=1}^{p} x_{0jkr} - \sum_{j=1}^{p} x_{j,p+1kr} = 0 \qquad k = 1, \ldots, K; r = 1, \ldots, R \tag{2.6}$$

$$\sum_{j=1}^{p} x_{0jkr} - \sum_{j=1}^{p} x_{0jkr-1} \leq 0 \qquad k = 1, \dots, K; r = 2, \dots, R \qquad (2.7)$$

$$u_{ikr} + \tau_i + t_{ij} - u_{jkr} \leq T_k(1 - x_{ijkr}) \qquad i = 0, \dots, p; j = 1, \dots p + 1; \; k = 1, \dots, K; r = 1, \dots, R \qquad (2.8)$$

$$a_j - T_k\left(1 - \sum_{i=0}^{p} x_{ijkr}\right) \leq u_{jkr} \leq b_j + T_k\left(1 - \sum_{i=0}^{p} x_{ijkr}\right) \qquad j = 1, \dots, p; k = 1, \dots, K; r = 1, \dots, R \qquad (2.9)$$

$$u_{0kr} \geq u_{p+1,k,r-1} \qquad k = 1, \dots, K; r = 2, \dots, R \qquad (2.10)$$

$$u_{p+1kr} - u_{jkr} \leq T_{max}^{j} + T_k\left(1 - \sum_{i=0}^{p} x_{ijkr}\right) \qquad j = 1, \dots, p, k = 1, \dots, K; r = 1, \dots, R \qquad (2.11)$$

$$u_{p+1,kr} - u_{0,k1} \leq T_k \qquad k = 1, \dots, K; r = 1, \dots, R \qquad (2.12)$$

Objective (2.1) minimizes the traveled distance. Constraints (2.2) ensure that every pick-up p (every node of P) is performed by a vehicle route (r, k). Constraints (2.3) assure that a truck k on its route r visits at most one node of the original SCC n. Constraints (2.4) force the flow of each truck k for each of its routes r to be balanced for each node j of the network. Constraints (2.5) state that a truck k can start a route r or not but, (2.6) if the vehicle starts a route, it must come back to the depot (node $p + 1$). Constraints (2.7) order the routes; thus, route r is started if, and only if, a route $r - 1$ has already been done. Constraints (2.8) to (2.12) handle the time constraints. Their explanation is similar to constraints (1.9) to (1.13).

As in the case of BSTP-MR, the following constraints (2.13) and (2.14), aiming at breaking the symmetry of the problem, were added to the formulation.

$$\sum_{j=1}^{p} x_{0jk1} - \sum_{j=1}^{p} x_{0jk-1,1} \leq 0 \qquad k = 2, \dots, K \qquad (2.13)$$

$$\sum_{r=1}^{R} \sum_{i=1}^{p} x_{ijkr} - \sum_{l=1}^{j-1} \sum_{r=1}^{R} \sum_{i=1}^{p} x_{ilk-1,r} \leq 0 \qquad j = 1, \dots p; k = 2, \dots, K \qquad (2.14)$$

As explained in the previous section, constraints (2.13) break symmetry due to truck selection in the lab, and constraints (2.14) make the extension to SCC's, stating that a transportation request p can be satisfied by any route of vehicle k, only if a request with a smaller index ($l < p$) has been served by vehicle $k - 1$.

As will be discussed in Section 4.6, the two formulations presented here are only efficient in dealing with rather small instances of BSTP. Therefore, in order to provide a daily transportation plan for the MSSS, an alternative and faster approach needed to be developed. The next section presents some simple but efficient heuristics to solve the BSTP.

4.5. Solving approach

This section presents a two-stage heuristic to solve the BSTP. In the first stage, a pool of feasible solutions is generated using two different construction procedures named *H1* and *H2*. Then, a local improvement procedure is applied to all the generated solutions.

4.5.1. H1: route first and then schedule

The first construction heuristic is an iterative procedure composed of two steps that are executed sequentially until all the requests are assigned to routes. We note U_{jr} as the arrival time at node j (in minutes) with route r. We also define D_r and F_r as the starting and finishing time of route r, respectively. Transportation requests are sorted in ascending order of their earliest time window (a_j) in the ordered set TR. Since each transportation request j is associated to a specific SCC, *request* and *node* are used indistinctly.

Step 1 routes' construction

Let $r = 1$ the first route.

<u>Step 1.1 Route initialisation</u>: Selects a transportation request $i \in TR$. Starts route r with request i. The departure time of this route is set so that the vehicle arrives at i at

the beginning of its time window (a_i) (i.e. $D_r = a_i - t_{0i} - \tau_0$). The visit time of node i is set ($U_{ir} = a_i$). Deletes i from TR.

<u>Step 1.2 Adding visits to the current route:</u> Considers the next transportation request $j \in TR$ and verifies the three following conditions:

1. SCC stating the request j has not been visited in the current route r.
2. It is possible to arrive at j before the end of its time window ($U_{ir} + \tau_i + t_{ij} \leq b_j$).
3. After visiting j at time $U_{jr} = max\{U_{ir} + \tau_i + t_{ij}; a_j\}$, it is possible to return to the lab, respecting the maximal travel time T_{max}^k of all the requests k in the route.

If all three are satisfied, j is added to route r, U_{jr} is set as the earliest possible service time to point j ($U_{jr} = max\{U_{ir} + \tau_i + t_{ij}; a_j\}$), and j is erased from *TR*. Node *j* becomes the current position in route *r*, and the next potential visit is evaluated. When none of the transportation requests in *TR* are eligible, the route is closed, and the vehicle goes back to the lab. Then, we can calculate F_r as the finishing time of route r ($F_r = U_{jr} + \tau_j + t_{j0}$). If *TR* is not empty, go to Step 1.1 to create route $r = r + 1$; otherwise, the algorithm goes to Step 2.

Step 2 Vehicles' assignment

Let *R* be the set of feasible routes sorted in ascending order of their departure time D_r. The routes are assigned to vehicles in order to construct the carriers' schedule. This is done by assigning a subset of routes to a specific vehicle *k*. Vehicle *k's* departure and finishing times are U_k^d and U_k^f, respectively. To initialise this phase, we set $k = 1$. The first route $r \in R$ is selected, and we set $U_k^d = D_r$ and $U_k^f = F_r$. Route *r* is deleted from *R*.

Then we select the next route $r' \in R$ and evaluate the two following conditions:

1. The departure time of route r', $D_{r'}$, is later (greater) than U_k^f.
2. The schedule of vehicle k, $F_{r'} - U_k^d$, complies with the daily work shift limit T_k.

If the two conditions are respected, route r' is added to the schedule of vehicle k, we set $U_k^f = F_{r'}$, and we erase r' from the list R. Otherwise, the next route is considered. The process is repeated until no route in R can be assigned to vehicle k, in which case k's schedule is finished. If there are still routes not assigned to any vehicle, a new vehicle $k = k + 1$ is created, and Step 2 is repeated until all routes are assigned.

4.5.2. H2: Schedule construction

This heuristic produces the schedule of the vehicles directly. This means that vehicles are activated one at a time, and the transportation requests are assigned to them one by one in order to create its routes. Let $k = 1$ the first vehicle.

Step 1 Vehicle initialisation

Select a transportation request $i \in TR$. The vehicle k is started with request i and TR is updated. U_k^d is set in such a way that the vehicle collects empty boxes at the lab and leaves in time to be at the beginning of the time window i. The arrival time to node i is set ($U_{ik} = a_i$).

Step 2 Schedule construction

Let i be the last node visited in the current route. We define a subset J' of feasible destinations that could be visited from i. A feasible node satisfies all three of the conditions in Step 1.2 of H1 and allows the vehicle to visit node j and to go back to the lab without exceeding the daily shift's duration T_k. Then, a destination $j \in J'$ is selected according to a selection criterion (either the closest request to i, or the one having the earliest time window) and is added to the vehicle. U_{jk} is updated, j is erased from TR, and this step is re-executed. If none of the requests in TR can be added to J', the vehicle returns to lab and U_k^f is set. Then, a new route for vehicle k is initiated. The first visit j in this new route will be the first request in TR satisfying the next two conditions:

1. *Vehicle* k is able to arrive to j before the end of the node's time window (b_j).
2. *Vehicle* k is able to go to j and return to the lab before the end of the drivers' shift.

If the two conditions are guaranteed, j is added, TR is updated, and Step 2 is re-executed. Otherwise, a new vehicle $k = k + 1$ is activated, and the heuristic goes to Step 1. The procedure is repeated until TR is empty.

4.5.3. Multi-start versions of H1 and H2

In order to improve H1 and H2's robustness with respect to the requests' order in *TR*, we executed both heuristics H1 and H2 several times, choosing a different request in the initialisation process (independently of its order in *TR*) for each execution.

We also observed that, due to the maximum sample transportation time constraint, departure times have an important impact on the routes. Indeed, delaying a departure might reduce in some cases the waiting time at SCCs and thus the sample transportation time. However, it is not possible to predict when such a strategy might result in better solutions, nor how much it might delay the departure time. Therefore, we decided to modify H1 and H2 in such a way that for each considered initialization request *j*, the heuristics will set the departure time to a_j, b_j and at the middle of *j*'s time window ($(b_j - a_j)/2$).

4.5.4. Local improvement

An iterative local improvement procedure is applied to all the solutions obtained by the previously described heuristics. A feasible solution S is composed of K vehicles, each vehicle performing multiple routes. The neighborhood of a given solution is obtained by moving a request *v* assigned to a vehicle *k* to a later position in any of *k*'s routes. If the move leads to a distance reduction, the feasibility of the neighboring solution is verified. Starting with the first vehicle, its complete neighborhood is evaluated, and the best feasible move is implemented. The procedure is repeated until no improvement is found. Then the procedure is applied to the following vehicle, until all the other vehicles' schedules have been considered.

4.6. Computational results

This section presents the set of 38 real instances provided by the MSSS and compares the computational results produced for them by the two formulations and the developed heuristics.

4.6.1. Instances

We conducted, together with the MSSS, a detailed survey spanning from June to August 2013 to determine the transportation needs of SCCs. The 149 SCCs of four administrative regions[5] were required to provide their opening hours, the number of transportation requests and their associated time windows for each working period (a.m., p.m., night) of weekdays, weekends and holidays. Hence, each of the 149 SCCs provided the requested data concerning 18 different working periods. After a careful analysis of all demand patterns, and since some SCCs made the same demand in several periods, we obtained 38 different instances. For example, if the demands' pattern for Monday morning is the same as that of Wednesday afternoon, both periods were considered the same instance. The workload is higher Monday through Wednesday, leading to larger (more requests) instances. As fewer SCCs are opened on weekends and only a few are open on holidays, the related instances are rather small. We arbitrarily divided instances into *Small* (four SCCs for a total of around 10 requests), *Medium* (up to 10 SCCs, around 20 requests) and *Large* (up to 20 SCCs, up to 50 requests) sets. Experts in the MSSS set the loading and unloading time to 10 minutes ($\tau_i = 10$ minutes), and T^j_{max} was set to 180 minutes for any SCC j, which means that a sample will never travel more than 180 minutes. The working shift's maximal length was set to $T_k = 480$ minutes. All travel times and distances were calculated by using GoogleMaps.

4.6.2. Results produced by BSTP-MR and BSTP-EG

Both formulations were solved using the commercial software Gurobi v6.0, running on a PC with two Intel Xeon X5650 2.66GHz 6 Core and 72Go de RAM.

[5] Saguenay-Lac-Saint-Jean, Capitale-Nationale, Mauricie and Montérégie.

Computational time was initially limited to 3 600 sec. *Table 4.1* reports the distance of the best feasible solution (*Dist.*), its gap in percentage with respect to the best lower bound (*Gap*) and the computational time (*Sec.*). Column *k* reports the required number of vehicles which, in fact, happened to be the same for both models and for all cases. Lastly, *Table 4.1* also includes a column called *Dist (k-1)* which will be discussed later in this section. *Table 4.1* does not contain results for the larger instances because Gurobi was unable to find any integer feasible solution, except for one particular instance.

All the *Small* instances were solved to optimality in negligible time. Considering *Medium* instances, formulation BSTP-MR gave proof of optimality in 12 cases out of 13, while BSTP-EG reached all 13 optimal solutions. Moreover, BSTP-EG seems to be more efficient because on average, it only requires less than one-third of the computing time used by BSTP-MR.

Before moving to the experiments on the larger instances, it is worth to mentioning the results reported in column *Dist(k-1)*. If you will recall, formulations BSTP-MR and BSTP-EG both seek to minimize the total traveled distance, regardless of the required number of vehicles or routes. Although such approach seems right if a contract with external carriers is being considered, it is worth wondering if, in doing so, the solver neglected solutions using fewer vehicles but requiring slightly higher traveling distances. These non-optimal solutions could be extremely appealing from a practical standpoint. In order to explore the existence of such solutions, we observed for each instance the number of vehicles *k* in the optimal solution, and we ran the instances again, this time limiting the number of vehicles to *k-1*. These results are reported in column *Dist(k-1)*. In 12 out of 25 cases, the instances were "unfeasible" (UF). In eight cases, solutions having exactly the same total traveled distance (=) were produced by assigning the same set of routes to the new set of vehicles. Finally, in five cases, we observed that solutions using fewer vehicles are still possible requiring between 0.2% and 21.3 % additional kilometers.

As per the Large instances, we extended the limit on the computational time to 10 800 seconds but Gurobi was still unable to find any integer feasible solution other than for I-38, for which the gaps reported were of around 29%. Given the difficulty shown by Gurobi in finding an integer solution, we decided to provide the solver with an initial feasible solution.

Table 4.1 – Results produced by the two formulations (time limit = 3 600 sec.).

			BSTP-MR			BSTP-EG			
	Inst.	***k***	**Dist.**	**Gap**	**Sec.**	**Dist.**	**Gap**	**Sec.**	**Dist (*k*-1)**
Small	I-1	2	193.9	0.0	0.0	193.9	0.0	0.0	UF
	I-2	1	125.3	0.0	0.2	125.3	0.0	0.1	UF
	I-3	3	311.8	0.0	0.1	311.8	0.0	0.1	=
	I-4	3	235.8	0.0	0.2	235.8	0.0	0.1	UF
	I-5	3	324.2	0.0	0.1	324.2	0.0	0.2	=
	I-6	3	270.7	0.0	0.6	270.7	0.0	0.3	UF
	I-7	3	279.9	0.0	0.5	279.9	0.0	0.2	UF
	I-8	3	267.9	0.0	0.6	267.9	0.0	0.2	UF
	I-9	2	184.0	0.0	0.0	184.0	0.0	0.2	UF
	I-10	3	556.8	0.0	0.2	556.8	0.0	0.0	UF
	I-11	4	618.9	0.0	0.4	618.9	0.0	0.1	623.5
	I-12	3	199.4	0.0	0.3	199.4	0.0	0.2	=
	Avg. :		297.4	0.0	0.3	297.4	0.0	0.2	
Medium	I-13	7	754.4	0.0	0.0	754.4	0.0	0.1	=
	I-14	4	230.3	0.0	0.8	230.3	0.0	0.3	=
	I-15	3	234.0	0.0	0.2	234.0	0.0	0.3	UF
	I-16	2	126.0	0.0	0.5	126.0	0.0	0.6	152.8
	I-17	3	193.0	0.0	0.3	193.0	0.0	0.3	=
	I-18	3	193.0	0.0	0.5	193.0	0.0	0.4	=
	I-19	4	284.7	0.0	1.1	284.7	0.0	0.9	UF
	I-20	3	301.3	0.0	3.0	301.3	0.0	1.5	UF
	I-21	3	154.9	0.0	211.2	154.9	0.0	20.4	158.9
	I-22	3	230.1	0.0	8.7	230.1	0.0	14.2	253.7
	I-23	5	931.3	0.0	244.9	931.3	0.0	251.3	=
	I-24	5	995.3	0.0	1079.6	995.3	0.0	128.8	997.2
	I-25	7	991.3	3.4	3600.0	990.5	0.0	1012.2	UF
	Avg.:		432.3	0.3	396.2	432.2	0.0	110.1	

To this end, we used the best solutions found by the heuristics presented in Section 5. *Table 4.2* reports the results of these experiments, where column *Best Heuristic Dist.* gives the best solution found by the heuristics for each instance. We used these solutions as starting solutions for Gurobi, and we allotted 10 800 seconds of computational time, but the best results achieved after 3 600 seconds were also recorded.

Table 4.2 – Results produced for large instances using an initial heuristic solution.

			BSTP-MR				**BSTP-EG**				
			3 600 sec		**10 800 sec**		**3 600 sec**		**10 800 sec**		
Inst.	**Best Heuristic Dist.**	***k***	**Dist.**	**Gap**	**Dist.**	**Gap**	**Dist.**	**Gap**	**Dist.**	**Gap**	***k***
I-26	1229.3	6	1183.2	31.2	1183.2	27.0	1183.2	27.0	1183.2	26.8	6
I-27	1923.3	10	1923.3	8.6	1923.3	8.1	1923.3	7.0	1832.8	1.2	10
I-28	2108.9	9	2108.9	61.7	2108.9	60.6	2108.9	59.2	2108.9	56.2	9
I-29	497.0	6	497.0	7.6	497.0	7.4	497.0	8.4	497.0	8.3	6
I-30	523.7	6	523.7	11.2	523.7	10.9	523.7	10.2	523.7	10.1	6
I-31	636.8	6	636.8	15.9	636.8	15.6	636.8	13.8	636.8	13.7	6
I-32	1700.7	7	1700.7	36.9	1700.7	36.7	1700.7	23.3	1700.7	23.3	7
I-33	638.4	6	603.7	15.7	603.7	15.7	600.7	9.3	586.7	6.9	6
I-34	1787.0	9	1787.0	40.3	1787.0	40.1	1787.0	29.9	1787.0	29.7	9
I-35	1883.1	8	1883.1	39.4	1883.1	39.2	1883.1	29.6	1883.1	28.5	8
I-36	1888.3	8	1888.3	39.5	1888.3	39.0	1888.3	31.4	1888.3	29.6	8
I-37	2022.3	8	2022.3	40.0	2022.3	39.6	2022.3	29.9	2022.3	29.0	8
I-38	460.7	6	460.7	25.4	460.7	25.4	448.6	17.0	445.1	16.3	6
Avg:	1330.7		1324.5	28.7	1324.5	28.1	1323.3	22.8	1315.0	21.5	

After one hour, the average distance produced by the heuristics (1 330.7) was reduced to 1 324.5 and 1 323.3 by BSTP-MR and BSTP-EG, respectively. After two additional hours of computing, BSTP-MR reached no additional improvement, while BSTP-EG found better solutions for three instances out of 13. These improvements reduced the total distance slightly. In particular, we observed reductions ranging from 3.39 % up to 8.1 %. Still, the optimality gaps produced by both formulations remained quite high, 28.1% and 21.5% in average, which confirms their poor performance in closing the optimality gap. However, we can conclude that after 3 600 or 10 800 seconds of computing time, BSTP-EG produced slightly better solution in terms of distance and optimality gaps than BSTP-MR.

4.6.3. Results produced by the heuristics

Table 4.3 reports the results produced by H1 and H2 alone (under header *Without local improvement.*) or after applying the improvement procedure. For each instance, H1 was executed 3*$|TR|$ times, with each execution using a different request in the initialisation phase and, for each request, using the three arrival times strategies (at the beginning, at the middle and at the end of the time window). As per H2, each instance was executed 2*3*$|TR|$ times, because two options for the selection criterion were available (choose the closest request or the one having the earliest time window).

The left part of *Table 4.3* reports the results for H1, H2 and the best solution between H1 and H2 (column *Min*). The right part reports the same data but after applying the Local improvement procedure. An asterisk * beside the instance number indicates that a proven optimal solution is known for the given instance. Moreover, table cells are empty for these instances for which the heuristic methods reached a proven optimal solution (or the same value as the best known solution). The corresponding best distances are also reported. The rightmost column, *HDist*, reports the best heuristic's value, which consists of running both H1 and H2 with improvement and selecting the best outcome. Computational times were always under one second and are therefore not reported.

Concerning the *Small* instances, H1 and H2 produced eight optimal solutions, and the average gap for the remaining four small instances ranged from 5.4% up to 23.9%. The local improvement procedure reduced these gaps in three out of four cases. All in one, H1 and H2 alone produced solutions with an average gap of 3.5% with respect to optimal solutions, and the average gap was reduced to only 1.7% by the local improvement procedure.

Table 4.3 – Performance of the proposed heuristics.

	Without local improvement Deviation %			With local improvement Deviation%			
Inst.	**H1**	**H2**	**Min**	**H1**	**H2**	**Min**	**HDist**
I-1*							193.9
I-2*							125.3
I-3*							311.8
I-4*							235.8
I-5*							324.2
I-6*	8.1	8.6	8.1	5.6	8.6	5.6	285.8
I-7*	5.4	6.4	5.4	4.5	6.4	4.5	292.6
I-8*	10.2	7.1	7.1	8.5	7.1	7.1	286.8
I-9*	9.7						184.0
I-10*							556.8
I-11*							618.9
I-12*	23.9	21.7	21.7	5.5	3.5	3.5	206.4
Avg:	4.8	3.6	3.5	2.8	2.1	1.7	301.8
I-13*	2.2	2.6	2.2				754.4
I-14*	24.4	7.2	7.2	8.5	7.2	7.2	246.8
I-15*	37.2	37.2	37.2				234.0
I-16*	7.9	4.0	4.0	7.9	4.0	4.0	131.0
I-17*	17.2	17.2	17.2		15.7		193.0
I-18*	18.6	2.6	2.6		2.6		193.0
I-19*	23.7	23.7	23.7				284.7
I-20*	17.2	13.7	13.7	12.6	9.6	9.6	330.4
I-21*	13.7	11.8	11.8	7.3	3.3	3.3	160.0
I-22*	6.4	6.4	6.4	6.4	6.4	6.4	244.8
I-23*	3.4	2.0	2.0	2.0	2.0	2.0	949.6
I-24*	28.9	25.9	25.9	4.4	0.8	0.8	1003.2
I-25*	8.0	4.8	4.8	7.8	4.1	4.1	1031.2
Avg:	16.1	12.2	12.2	4.4	4.3	2.9	442.8
I-26	9.5	8.9	8.9	9.5	3.9	3.9	1229.3
I-27	12.0	5.3	5.3	4.9	5.2	4.9	1923.3
I-28	10.9	12.4	10.9		2.1		2108.9
I-29	4.0	2.1	2.1	2.6			497.0
I-30	7.0	3.8	3.8	2.6			523.7
I-31	4.0	3.4	3.4	0.7			636.8
I-32	11.0	7.8	7.8	4.0			1700.7
I-33	16.5	13.2	13.2	15.9	8.8	8.8	638.4
I-34	20.7	12.9	12.9	3.6			1787.0
I-35	21.6	14.2	14.2	1.2			1883.1
I-36	21.0	14.3	14.3	1.2			1888.3
I-37	23.2	14.2	14.2		2.6		2022.3
I-38	22.9	8.0	8.0	17.6	3.5	3.5	460.7
Avg:	14.2	9.3	9.2	4.9	2.0	1.6	1330.7

For *Medium* instances, H1 and H2 alone were unable to produce any optimal solution, the average optimality gap being of 16.1% and 12.2% for H1 and H2 respectively. However, the local improvement procedure produced five optimal solutions, and reduced those gaps to only 4.4% and 4.3% respectively. The combined heuristic (H1 + H2 + Local improvement) offers a very good performance, reaching five optimal solutions and an average gap of only 2.9%. Finally, it is not possible to refer to optimal solutions for *Large* instances and, for that reason we must refer to best known solutions. That being said, H1 and H2 alone produced solutions within 14.2% and 9.2% with respect to the best known solutions. The local improvement procedure succeeds again in reducing these gaps to 4.9% and 2.0% respectively. The complete heuristic performance is again excellent, producing nine best known solutions and an average gap with respect to the best known solution of only 1.6%.

Based on the previous results, we estimated the daily route distance and duration and the number of vehicles needed to perform the requests during the day and the evening shifts for each administrative region and for each laboratory (Renaud et al. 2013). Moreover, we also computed an estimation of the annual sample transportation effort for these four Quebec's administrative regions which rises up to 2 163 000 kilometers. These results were presented to the MSSS who positively validated our estimations. We are presently working on extending similar computations to the rest of Quebec's administrative regions.

4.7. Conclusions and research perspectives

This article presents and formalizes the biomedical sample transportation problem faced by Quebec's *Ministère de la santé et des services sociaux* (MSSS). Although this problem is similar to the multi-trip vehicle routing problem with time windows, it presents particular constraints related to the perishable nature of the samples and the organization of work in the network of sample collections centers in Quebec. We proposed two mathematical formulations and some fast heuristics to tackle this problem. Since commercial branch and bound software was proved unable to find integer solutions for several of our instances, we used the heuristic solutions as initial solutions for the solver. This strategy produced interesting results, but optimality gaps remained high.

Nonetheless, this first phase of the *Optilab* project has allowed the MSSS to get a precise idea of the needs for transportation and logistics related to the biomedical sample collection and analysis. Transportation schedules of good quality have been produced. These schedules can be used as references to evaluate the transportation "effort" required to adequately satisfy the requirements of the current biomedical analysis system in Quebec for a number of vehicles, driving time and traveling distance. In other words, the MSSS can now express its transportation requirements in a clear and detailed manner to interested 3PL or carriers willing to provide transportation services.

Optilab offers new and challenging perspectives. Among them, we aim to develop more efficient solving approaches. We also feel that the existing network needs to be reconsidered to include, for example, optimized opening hours at certain SCCs or the SCC-to-lab allocation.

4.8. References

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Chapitre 5

Une méthode itérative de recherche locale pour résoudre le problème de transport d'échantillons biomédicaux au Québec

Le but de cet article est de résoudre le problème de transport d'échantillons biomédicaux pour le réseau des laboratoires du Québec. Les prélèvements sont effectués dans divers établissements de soins de santé (ou centres de prélèvements – CPs). Ensuite, les échantillons doivent être analysés, dans la plupart des cas, dans un laboratoire externe (lab) où les prélèvements doivent être expédiés. La courte durée de vie des échantillons biomédicaux exige que plusieurs passages par journée soient faits aux CPs et impose une contrainte forte sur la durée maximale des routes. Suite à notre première collaboration avec le Ministère de Santé et de Services sociaux du Québec (MSSS) (Anaya-Arenas et al. 2015), le MSSS a réévalué ses besoins et remis en considération les hypothèses précédemment appliquées sur le nombre de cueillettes à faire à chaque CP et leur fenêtres de temps. Ceci est fait afin d'obtenir une meilleure planification centralisée et coordonnée sur les décisions de transport du réseau. Dans ce contexte, nous cherchons à définir une planification efficace des heures d'ouverture des CPs et un ensemble de routes pour effectuer le nombre optimal de collectes à chacun des centres. L'objectif est de minimiser le temps facturable (durée totale des routes) tout en garantissant qu'aucun échantillon ne périsse pendant le transport ni dans les CPs. Nous abordons le problème par une procédure itérative de recherche locale (ILS). L'idée principale est d'explorer à chaque itération le voisinage local d'une solution perturbée. Nous avons testé la méthode proposée sur les instances réelles, tirées du réseau de laboratoires au Québec.

Article 4: An ILS approach to solve the biomedical sample transportation problem in the province of Quebec

Ce chapitre fait l'objet d'un article accepté pour présentation dans une conférence internationale avec comité d'évaluation: Anaya-Arenas, A.M., Prodhon, C., Afsar, H.M. & Prins, C., 2015. An ILS approach to solve the biomedical sample transportation problem in the province of Quebec. *Acte de conférence de la 11ème édition du Congrès international de génie industriel CIGI 2015,* Organisé par l'Université Laval, 26-28 octobre 2015, Québec, Canada.

Abstract: The aim of this paper is to solve the biomedical sample transportation problem for the laboratory's network in the province of Québec. Biomedical tests are performed in a healthcare facility (or specimen collection center - SCC). Then, the collected specimens have to be analyzed, in most of the cases, at an external laboratory (lab) to which the samples have to be transported. The short lifespan of the specimens implies that CPs have to be visited several times in a day and imposes a strong constraint on the routes' maximal length. After our first collaboration with the Quebec's *Ministère de la Santé et des Services sociaux* (MSSS - Ministry of Health and Social Services) (Anaya-Arenas et al., 2015), the MSSS revaluated its needs and reconsider previous hypothesis for the number of visits to perform at each SCC and its time windows. This allows the MSSS to seek a better organized transportation plan that centralizes its decisions in a more coordinated way. In this context, we thus seek to define an efficient set of routes to perform the optimal number of pick-ups at each SCC, coordinating SCC's opening hours, to minimize billable time (total route duration) and to warrant that none of the samples perish, neither at the SCCs nor during transportation. We propose to approach the problem heuristically, through an iterated local search (ILS) procedure. The main idea is to explore at each iteration a different neighborhood of a perturbed solution. The obtained preliminary results are very promising, achieving in few seconds optimal solution for the small and medium-size instances, and good-quality solutions for the larger ones. Further analysis on the ILS performance is planned, seeking a better performance.

5.1. Introduction

The biomedical sample transportation problem (BSTP) rises in the context of healthcare logistics to support accurate and in time diagnosis. Specimens are collected in a healthcare facility (or SCC) that subsequently have to be analyzed. In most of the cases, the SCCs do not own the proper equipment to perform the analysis, thus the samples have to be sent to an external laboratory (lab). This analysis has to be made inside the samples' lifespan, or the specimens will perish and tests have to be performed again. Therefore, due to samples' lifespan, an SCC might request several pick-ups per day to preserve samples' quality. Evidently, this transportation task requires an efficient planning to ensure service quality, to avoid delays and loss of samples and to reduce operation costs. This research work is an extension of our partnership with the MSSS of the Canadian province of Quebec. The MSSS is responsible for supporting and overseeing Quebec's health network, and one of its current priorities in is the optimization of the laboratories' network services (embedded in a supply chain optimization project named Optilab). In a previous work, Anaya-Arenas et al., (2015) performed the formalization of the BSTP faced by the MSSS. The authors considered a first version of the problem where the SCCs state several transportation requests that have to be performed inside strict time windows, including also other time constraints related to the perishable nature of specimens and Quebec's laboratory network. The problem was modeled as a multi-trip vehicle routing problem with time windows (MTVRP-TW), two mathematical formulations were proposed, and MSSS's real instances were solved with a combination of fast heuristics and a commercial branch and bound software.

In the current phase of the project, some key aspects on the network's structure are reconsidered, and an efficient metaheuristic is proposed to develop more productive transportation plans for the MSSS. Two primary hypotheses are lifted to include in our problem the optimization of the SCCs' operation decisions. First of all, we include in our analysis the SCC's decisions concerning the number and frequency of the transportation requests. Until now, each SCC provided the number of pick-ups to be performed during the workday with strict time windows. However, these parameters represent a major restriction in the transportation planning, and can lead ultimately to inefficient use of resources, and there is no prove that the estimations of the SCCs are accurate. We thus include the SCC's capacity into our analysis seeking to find the optimal number of visits. We consider that SCCs have a limited stocking capacity, which must be respected in order to avoid that samples perish. In other words, we no longer talk about a fixed time window for a transportation request, but a maximum timespan between two consecutives pick-ups that must be respected. This creates interdependency between pick-ups, and requires a different treatment in the routing planning. *Figure 5.1* illustrates how the maximum timespan constraint creates an interdependency between pick-ups. Let us consider an SCC g. According to SCC's capacity and demand, a maximum timespan between visits is estimated (named Δ^g_{max}). Consider that SCC g opens at moment a_g. Then, a first pick-up must be performed anytime between a_g and $a_g + \Delta^g_{max}$, in order to respect SCC's capacity. Defining u_1 as the scheduled time for the first pick-up, one can say that $u_1 \leq a_g + \Delta^g_{max}$. Following this, once the first pick-up is scheduled, the second one (u_2) must be performed before another Δ^g_{max} minutes (i.e. $u_2 \leq u_1 + \Delta^g_{max}$) and so on, until a last pick-up is schedule after closing hour (b_g). Notice that a visit can be performed before the Δ^g_{max} limit, however, this will impose that the next visit is also advanced. Therefore, the latest hour to perform a visit i depends exclusively of the pick-up hour of visit $i-1$ and so on. In addition, once the visit i is scheduled in a route, it has a maximum of T^i_{max} units of time to arrive to the lab. Therefore, a route's schedule has now a direct influence on the feasibility of a given frequency of visits and, thus, on other routes planned in the current solution. On the other hand, due to the geographic disposition and the time-constraints of a network, an extra pick-up to a particular client can result in greater flexibility in the transportation plan and ultimately a better global solution.

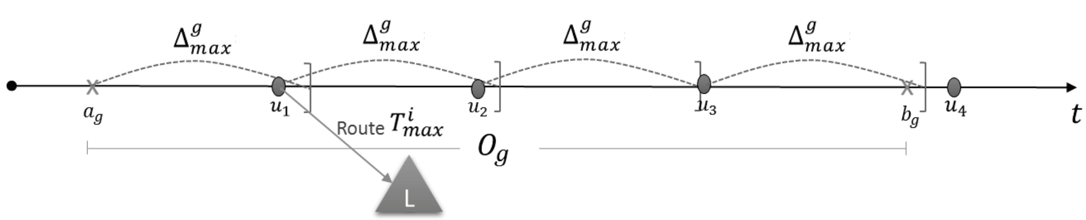

Figure 5.1 – Example of interdependency between pick-ups at SCC g.

Secondly, we take a deeper look in the opening hours of the SCCs. This is also motivated by the interdependency of pick-up decisions. Indeed, the opening hour decision (a_g) impacts the time limit of the first visit, and therefore all the schedule of the SCC. On the other hand, even if the collection periods are defined by the particular demand and workload of a SCC, in a crowed network, like the one in Montreal's downtown, many SCCs can have a similar (even the same) schedule. This fact can easily result in multiple and simultaneous transportations request at different locations and finally incompatibles SCCs for a transportation plan, increasing the transportation costs. A more interesting approach could be to define the right opening hours of the SCCs, keeping into account their demand and specific needs, in order to get a simpler and more synchronized schedule for the entire set of SCCs. To guide this decision inside the working schedule of the SCCs, a time window is set around its usual opening hour. Then, once it is opened, the SCC's collecting period (total collecting time) is respected.

Blood collection and clinical specimen collection were first addressed in the 1970s (McDonald, 1972). However, due to the specific constraints attached to the context, as well as the practical impact in social welfare, biomedical sample logistics has regained attention in recent years, and some related works had been added to the literature. Yi (2003) was one of the first to approach the blood transportation as a variant of the VRP with time windows (VRPTW). Their collection points need to be visited (once) inside its operation time window to bring blood back to a central depot to be treated. As there is only one pick-up that can be done to each center, the later the pick-up is done, more blood can be brought back to the depot. The objective is to maximize the quantity of blood that is collected and treated, respecting transportation's time constraints and minimizing logistics' cost. More recently, Sahinyazan et al. (2015) present a tour mobile collection system for the Red Cross in Turkey. Their main concern is to define the tours for the mobile collection units (vehicles) selecting the nodes to be used as base for the collection. Then, a second tour needs to be planned each day to pick-up collected blood through the planning horizon. As in the case of Yi (2003), there is only one pick-up to perform at each client per day. This is a different and simpler approach that the one stated in our problem because there is no interdependency between pick-ups. On their side, Yücel et al. (2013) present what they denominated as the collection for processing problem. Their contribution is including the laboratory's processing rate in the tour's planning.

Contrary to the BSTP, routes are not restricted by any time constraints, but are rather formed to seek balance between the number of samples processed in a day and the transportation costs. Finally, Doerner et al. (2008) present a problem from the blood collection process in the Austrian Red Cross, with the particularity that the SCCs' sites are temporal collection tends. This consideration implies that no proper samples' conservation can be assured, and represent multi-interdependent pick-ups for a single customer. The authors propose a complex MIP model to the problem (which demanded days to solve even small size instances), a construction heuristic and a branch-and-bound algorithm to find a schedule to a specific number of pick-ups. Notice that our work shares some common features with Doerner et al. (2008)'s work on the Red Cross case. However, there are at least two important differences. First, in their case the operation hours of each SCCs are given in advance. Second, in Doerner et al. (2008), the number of pick-ups for a given SCC is decided out of the model by executing an exhaustive search in a limited number of scenarios, resulting in a higher computational effort. We propose to embed these two aspects in the same resolution approach, seeking an integral solution to the global optimization of the BSTP.

The rest of this article is organized as follows. Section 2 describes the BSTP version approached in this work and Section 3 presents the resolution method proposed to solve it. Section 4 presents preliminary results from our numerical experiments, and Section 5 draws main conclusions and research perspectives of our work.

5.2. Problem statement

The biomedical sample collection network in Quebec province is composed by a set of SCCs and laboratories. Each SCC g has a specific operation timeframe in which samples are collected at a known and constant rate λ_g. This operation timeframe is denoted in the following as the SCC's *collection period* (O_g). Once collected, the specimens are pre-treated and prepared to be sent to the lab. In the current structure of the MSSS, SCCs are assigned to a specific lab, according to their geographical position, having thus a single-depot (single-lab) network for our transportation problem. Now, a SCC can collect hundreds of different specimens, and pre-treatment operations vary from a sample type to another. Even so, after preparation, all the samples are consolidated and stocked in standard refrigerated sample boxes, which are transported. A typical box can content up to 80 different samples. Due to the size of the boxes, and the small number of boxes send by SCCs at each pick-up, we consider that each SCC states a number of *transportation requests* during their work day and it will never overpass vehicles' capacity. A major determinant of the samples' lifespan is the capacity of the SCC to pre-treat the samples and stock them in optimal conditions before sending them to the lab. In fact, we can assume that as long as samples are kept at SCCs, their deterioration is slowed down. However, each SCC g has limited conservation capacity C_g that in many cases is smaller than the capacity required for the entire operation day. This means that, inside its operation hours, an SCC g might need to call several transportation requests to liberate its stocking capacity. We can therefore estimate a maximal timespan inter-pick-ups to ensure that SCC's capacity is always respected as follows: $\Delta_{max}^{g} = C_g/\lambda_g$. This is the first particularity of the BSTP and a major challenge in transportation planning. The second one is the travel time limit. In fact, once the boxes leave the SCC, the optimal conditions of temperature cannot be warranted, so deterioration process is accelerated. Therefore, as soon as samples are out of the SCC facility, they must arrive to the lab within a *maximal transportation time*. This time limit can vary from a sample to another. Hence, each transportation request p has a particular time limit for transportation, noted T_{max}^{p}, deduced by the most urgent sample transported in it. To summarize, a vehicle must visit the SCCs and recover the samples' boxes (completely full or not) before a maximum time from its last visit, and return to the lab in time to avoid that any of transported samples (in the route) perish.

In addition to the time-constraints described before, the BSTP has other particularities related to the SCCs. First of all, SCCs opening time can be modified, inside a small window, in order to contribute to a better global transportation plan. Let us thus define a_g as the opening time for SCC g, which is inside its opening time window $[e_g, l_g]$. Let e_g and l_g be the earliest and latest hour that SCC g can open (respectively). However, remember that the collection period is fixed for each SCC, so once a_g has been decided, the collection period start and last exactly O_g hours. In that moment ($b_g = a_g + O_g$) the center closes its service to patients so no more samples are collected. Moreover, all samples collected must be treated in the same day (the length of the time horizon). Therefore, once the collection period has passed (at b_g), a last pick-up must be scheduled within the next φ_g minutes to transport the last collected samples before the SCC's employees leave. *Figure 5.2* illustrates how the opening decision and the other parameters interrelate. It also shows how once a pick-up decision has been made (here noted u_1), Δ_{max}^g fixes a limit in time to revisit the SCC.

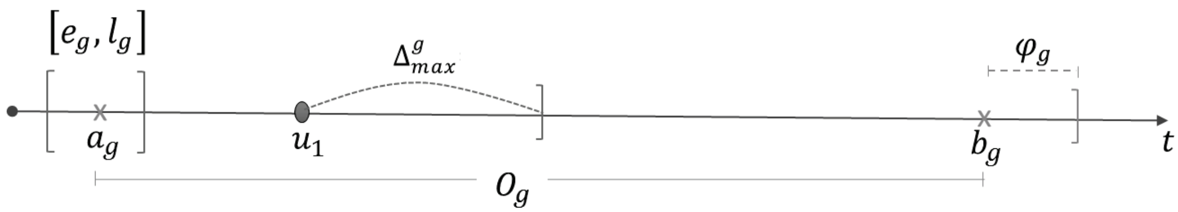

Figure 5.2 – Example of opening decision and collection period at SCC g.

Finally, the collection period and the maximum timespan between pick-ups, allow us to fix for SCC g, a minimum number of transportation requests $P_g = \lceil O_g/\Delta_{max}^g \rceil$. However, there is no guarantee that this minimum number of pick-ups is optimal, and thus it needs to be included as a decision in the BSTP. *Figure 5.3* gives an example of the BSTP network as well as a feasible solution to the problem. Two routes (R1 and R2) that start and end at the lab visit the nine SCCs. Notice that SCC 2 and SCC 6 requested two pick-ups and are thus visited by both R1 and R2.

It is worth to mention that the interdependency between the pick-ups also implies that pick-ups have to be sufficiently separated in time to ensure an efficient use of resources. Otherwise, a SCC might be visited an excessive number of times. This efficiency principle might lead to create waiting times at an SCC node.

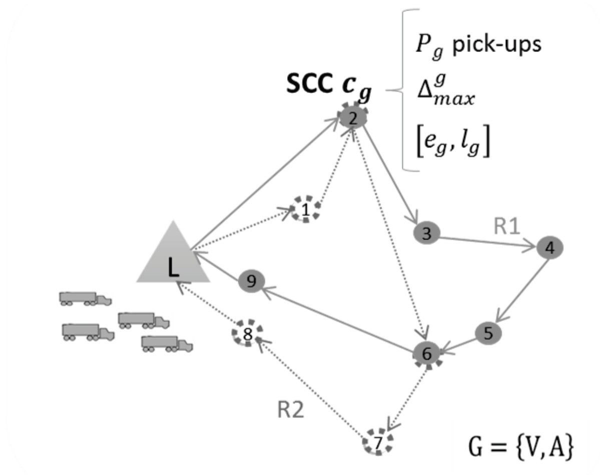

Figure 5.3 – Example of a BSTP network configuration.

Consider, for instance, an SCC g that has a collect period from $7{:}00$ to $10{:}00$ a.m. and a maximum timespan of $1{:}30$. If a vehicle arrives at $8{:}20$ a.m and makes the first pick-up immediately, a second pick-up has to be done before $9{:}50$ a.m to respect the SCC's capacity. This means that SCC g has to request a third pick-up after closing in order to send the samples collected in the last five minutes of operation. It might be more interesting to ask the vehicle to wait before performing the first pick-up (respecting still the Δ^g_{max}), get the samples at $8{:}30$ a.m. and then a last pick-up is requested at $10{:}00$. Hence, even if there are no time windows fixed to the transportation requests, a vehicle might have to wait at a SCC before the pick-up to assure than the next pick-up will not exceed Δ^g_{max}. This is illustrated in *Figure 5.4*.

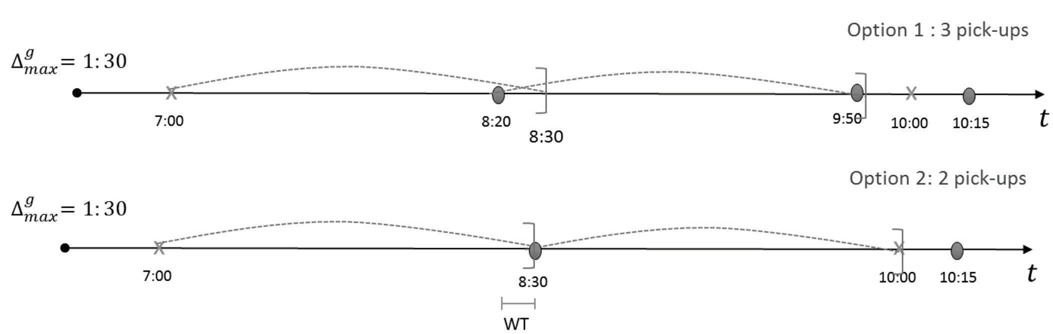

Figure 5.4 – Example of a reason to create waiting time in a solution.

Following the MSSS objectives, an external carrier will be selected to perform the samples transportation; hence, there are no limits in the available fleet of vehicles. In addition, as time constraints play a major role in the transportation planning for the BSTP, it will also be considered as the optimization objective, considering that carrier services are charged by total service time. This consideration allows us to avoid (minimize) waiting time for service, and it adapts to the MSSS operations context. Notice that there are no practical constraints forbidding that a given SCC is served more than once by the same route, even if this could rarely happen in practice.

We thus seek to define a set of routes to perform the optimal number of pick-ups at each SCC, minimizing billable time (total routes duration) and warranting that none of the samples perish, neither in the SCCs nor during transportation.

5.3. An iterated local search for the BSTP

Previous results on the BSTP (Anaya-Arenas et al. 2005) and the VRP with interdependent time windows (Doerner et al. 2008) proved the complexity of our problem and how commercial solver are incapable of finding good quality solutions in short computational time. We thus propose to approach the problem heuristically through an iterated local search (ILS) procedure. Among the numerous algorithms existing in the literature to solve the VRP, a recent literature review by Vidal et al. (2013) confirm the pertinence of ILS algorithms to solve multi-attributes VRPs, specially the VRPs with time depending features. The main idea is to explore at each iteration a different neighborhood through the local search (LS) of a perturbed solution, generated by removing a set of SCCs and reinserting them in the incumbent solution, until a stopping criterion is reached. In addition, this perturbation process allows us to explore neighborhoods where the SCCs are visited more times than the minimum number requested. In this section we present the three main stages of our ILS, and *Figure 5.5* depicts them in a general schema.

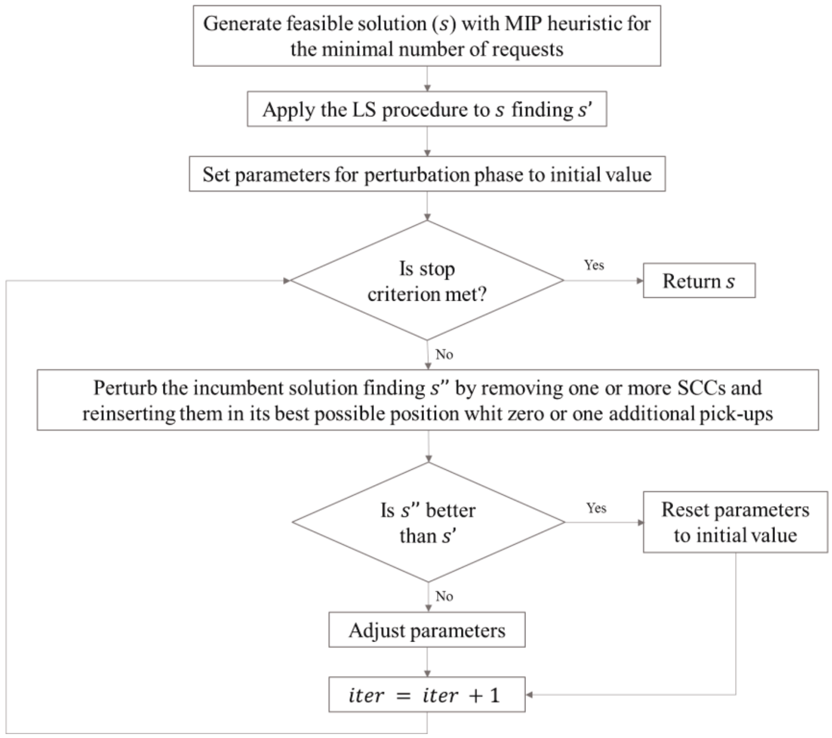

Figure 5.5 – Basic structure our ILS approach.

5.3.1. Initialisation

To initialize the ILS, a first feasible solution is obtained routing the minimum number of transportation requests stated by each SCC. Due to the multiple time constraints and the interdependency between the pick-ups, construct a valid solution of good quality is quite challenging. Therefore, we propose a mixed integer program that includes all the practical constraints of the BSTP to be solved for a given number of transportation requests. The model proposed is formalized as follows:

MIP for a fixed number of pick-ups

We define $N = \{c_1, c_2, \dots, c_n\}$ as the set of the n SCCs assigned to the lab. We consider that each SCC c_g (with $g = \{1, \dots n\}$) requires a fixed number of transportation requests (set P_g), and all the transportation requests of all SCCs form a set P ($P = \cup_g P_g$). The BSTP can be modeled over a complete digraph $G = \{V, A\}$, where the set of nodes $V = \{v_0, v_1, v_2, \dots, v_{|P|}\}$ is composed by the $|P|$ transportation requests of all SCCs, and the laboratory ($\{v_0\}$) where the routes must start and end. We consider and unlimited fleet of vehicles available at the lab to perform the routes. Without loss of generality, we label the pick-ups so that $\{v_1, v_2, \dots v_{|P_1|}\}$ are the transportation requests of SCC 1, $\{v_{|P_1|+1}, \dots, v_{|P_1|+|P_2|}\}$ are requests of SCC 2 and so on. More precisely, we define I_g as the set of index for the requests of a center c_g where $I_g = \{\sum_{h=1}^{g-1}|P_h| + 1, \dots, \sum_{h=1}^{g}|P_h|\}$.

In addition, we define an arc set $A = \{(v_i, v_j): v_i, v_j \in V, i \neq j, i, j = 0, \dots, |P|\}$ and for each arc (v_i, v_j) a fixed transportation time (t_{ij}) is known. Evidently, t_{ij} is fixed to zero to all v_i and v_j belonging to the same SCC ($v_i, v_j \in P_g$). In addition to the notation defined in Section 2, we need to consider the loading time at c_g (τ_g) and the unloading time of the vehicle at the lab before a new route can be started (τ_0). The objective is to define a transportation plan (set of routes) defining the service time for each one of the transportation request of each SCC, as well as the opening hours of the SCCs, in order to warrant that none of the samples perish and to minimize total route duration. The BSTP can be modeled as a MIP as follows:

Decisions variables

x_{ij}	binary variable equal to one if node i is visited before node j.
u_i	continuous variable that indicates the time when pick-up i is performed.
d_i	continuous variable that indicates the duration of the route that starts at node i.
a_g	continuous variable that indicates the opening hour of SCC g.
b_g	continuous variable that indicates the end of collection period hour of SCC g.
f_i^p	the maximum remaining time at node i, to bring request p to the lab before perishing.

BSTP for a fixed number of pick-ups

$$Min \sum_{i=1}^{|P|} d_i \tag{1}$$

Subject to:

$\sum_{i=0}^{\|P\|} x_{ij} - \sum_{i=0}^{\|P\|} x_{ji} = 0$	$j = 0, \dots, \|P\|$	(2)
$\sum_{i=0}^{\|P\|} x_{ij} = 1$	$j = 1, \dots, \|P\|$	(3)
$u_j \geq u_i + t_{ij} + \tau_i - M(1 - x_{ij})$	$i = 0, \dots, \|P\|;\ j = 1, \dots \|P\|;\ (i \neq j)$	(4)
$e_g \leq a_g \leq l_g$	$g = 1, \dots, n$	(5)
$a_g + O_g = b_g$	$g = 1, \dots, n$	(6)
$u_k - a_g \leq \Delta_{max}^g$	$g = 1, \dots, n$ where $\|P_g\| > 1;\ k = \sum_{h=1}^{g-1} \|P_h\| + 1$	(7)
$u_k - u_{k-1} \leq \Delta_{max}^g$	$g = 1, \dots, n$ where $\|P_g\| > 2; k = \sum_{h=1}^{g-1} \|P_h\| + 2, \dots, \sum_{h=1}^{g} \|P_h\| - 1$	(8)
$b_g - u_k \leq \Delta_{max}^g$	$g = 1, \dots, n$ where $\|P_g\| > 1; k = \sum_{h=1}^{g-1} \|P_h\| - 1$	(9)
$b_g \leq u_k \leq b_g + \varphi_g$	$g = 1, \dots n; k = \sum_{h=1}^{g} \|P_h\|$	(10)
$f_j^p - f_i^p + M(1 - x_{ij}) \geq u_j - u_i$	$i = 1, \dots, \|P\|;\ j = 0, \dots, \|P\|;\ p = 1, \dots, \|P\|$	(11)
$f_0^i = T_{max}^i$	$i = 1, \dots, \|P\|$	(12)
$f_i^i \geq 0$	$i = 1, \dots, \|P\|$	(13)
$d_i \geq T_{max}^i - f_i^i + t_{0i} + \tau_0 - M(1 - x_{0i})$	$i = 1, \dots, \|P\|$	(14)
$u_i, a_g, b_g, d_i \geq 0$	$i = 0, \dots, \|P\|;\ g = 1, \dots, n$	(15)
$x_{ij} = \{0,1\}$	$i \neq j = 0, \dots, \|P\|$	(16)

The objective (1) is to define a transportation plan that minimizes the total routes' duration. Constraints (2) ensure flow conservation on every node of the graph, while constraints (3) ensure that every transportation request j is satisfied. Constraints (4)-(10) are time constraints. Constraints (4) estimates the service time at request j (time in which pick-up j is performed) and eliminates the subtours between pick-ups. Constraints (5) assure that SCC g opens inside its given time window and constraints (6) fixes the end of the collecting period. Constraints (7) assure that the first pick-up of SCC g (pick-up $k = \sum_{h=1}^{g-1} |P_h| + 1$) is performed before Δ_{max}^g units of time after the SCC g opens. Constraints (8) check that all pair of consecutives pick-ups of SCC

g (k and $k-1$, with $k=\sum_{h=1}^{g-1}|P_h|+2,\ldots,\sum_{h=1}^{g}|P_h|-1$) respect as well the maximum timespan Δ_{max}^{g}, and constraints (9) ensure that the SCC g'collection period ends before Δ_{max}^{g} minutes after penultimate pick-up. Evidently, constraints (7) and (9) are imposed exclusively over the SCCs demanding more than a single pick-up during its collection period, and constraints (8) is only needed if the SCC request more than two pick-ups. In addition, constraints (10) state that the last pick-up of SCC g ($k=\sum_{h=1}^{g}|P_h|$) is performed after the end of the collection period but before the center closes. Constraints (11) to (13) control the flow of time restriction over all pick-ups. Please notice that our problem fixes for pick-up i a limited time to return to the lab (T_{max}^{i}) from the moment the pick-up is done (no from the moment the truck start a route). That is why our "time left" resource is consumed from lab to customers in the opposite direction of the route. This time consumption is directly related to the service time at each request. Therefore, constraints (11) ensure the coherence between the time resource variables and the service time variables for any pair of nodes (i,j), saying that if the arc (i,j) is included in the route, the difference between its respective service time variables must match the resource consumption difference. Then, constraints (12) state the available time at the lab for pick-up i at its limit T_{max}^{i}. Constraints (13) force the time resource to return pick-up i to be non-negative at i. Finally, constraints (14) estimate the duration of routes, saying that if the route start with transportation request i, its duration is greater or equal to the time consumed from i to be back to the depot, plus the travel time of arc $(0,i)$ and the loading time at the depot. If the route does not start with pick-up i, the duration will be fixed to 0. Constraints (15) and (16) define the decision variables' domain.

This model was implemented in Gurobi (v.6.0) and the solver provides feasible solutions in less than a second for all the proposed instances. This is already an encouraging and interesting result compared to other modeling approaches previously proposed for related problems (Anaya-Arenas et al., 2014 and Doerner et al., 2008). Indeed, eliminate the vehicle index to define routes as we propose proves to be very efficient finding a feasible solution. Seeking to start our heuristic with a high-quality solution, we set a time limit which depends on the size of the instance to solve before stopping Gurobi and calling the LS procedure.

5.3.2. Local search procedure (LS)

In this phase we explore two basic neighbourhoods of the best solution produced by Gurobi. The major challenge in this case is to handle the interdependency between the transportation requests of a single SCC. Consider for instance a SCC g that has a total collection period of four hours and a half, but its capacity limit forces a pick-up every hour and a quarter ($\Delta_{max}^{g}= 1:15$). In addition, let us assume that SCC g has an opening time window between $[7:00 - 7:30]$ a.m. Then, SCC g have to be visited at least four times and no more than $1:15$ later than the last visit or the opening period. Suppose a feasible solution where SCC g have a collection period from $7:00$ to $11:30$ a.m. and a first route (R1) visits SCC g at $8:10$, a second route (R2) at $9:25$, R3 at $10:40$, and finally, R4 at $11:30$ to get any remaining samples. A possible neighbour of this solution could be to modify route two in such a way that the arrival time at SCC g would be advanced to $9:15$. In order to check if this change leads to a feasible solution, vehicle three has to visit SCC g before $10:30$, which might lead to change the pick-up schedule for all pick-ups (and thus all the SCCs) that are included in R3. In other words, the whole solution should then be almost completely inspected to assure that the desired modification produces a feasible solution. Evidently, a complete inspection is not computationally efficient.

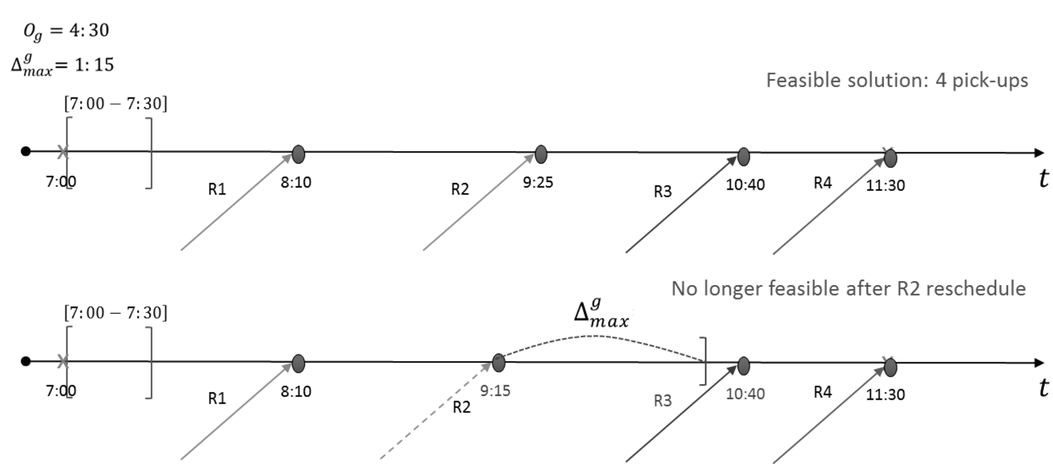

Figure 5.6 – Impact of the interdependency in the LS phase.

To cope this difficulty, we introduce time windows to each transportation request that depend exclusively on the current solution (service time for each request) in order to reduce this interdependency. In addition, we implement concatenation techniques from Vidal et al., (2014) to evaluate efficiently cost and feasibility of the movement explored. This two aspects are explained in the two following sub-sections.

Interdependency reduction

Notice that the time window of the opening decision, together with the maximum timespan between pick-ups, define an initial approximation for the time windows for each transportation request. This first rough calculation of the possible service time can be very large and it might lead to infeasibility for the SCC's capacity. However, once a service time decision is made, time windows are shrunk and reflect the "real flexibility" of the pick-ups, without affecting the other request of that center. Hence, to reduce the interdependency between pick-ups during the local search evaluation process, we estimate time windows for each transportation request based on the current solution. For index notation simplicity, we present an example of the time window computation for SCC c_1. We define $[\alpha_k - \beta_k]$ as the earliest and latest possible time at which pick-up k can be done without affecting the other pick-ups of SCC c_1. Let u_k (with $k = 1, \dots, |P_1|$) be the service time of the transportation requests of SCC c_1 in a solution s. First, the opening and closing time windows are reduced by the service time of the first and penultimate requests. The service time for the first requested pick-up of an SCC (i.e. u_1) might delay the earliest opening hour (to find a new limit, named e'_1) and service time of penultimate pick-up ($u_{|P_1|-1}$) might advance the latest possible closing (thus opening) hour defining l'_1. Precisely, for SCC c_1 one can define $e'_1 = max\{e_1; u_1 - \Delta^1_{max}\}$ (17) and $l'_1 = min\{l_1; u_{|P_1|-1} + \Delta^1_{max} - O_1\}$ (18). The new time windows for opening and closing of SCC c_1, affects the time windows for the first, penultimate and last pick-up as follows:

$$\beta_1 = l'_1 + \Delta^1_{max} \quad (19)$$

$$\alpha_{|P_1|-1} = e'_1 + O_1 - \Delta^1_{max} \quad (20)$$

$$\alpha_{|P_1|} = e'_1 + O_1 \quad (21)$$

$$\beta_{|P_1|} = l'_1 + O_1 + \varphi_1 \quad (22)$$

Needless to say, the service time of pick-up j (u_j) sets the latest possible service time for $j + 1$ and the earliest possible service time for $j - 1$, i.e. $\alpha_{j-1} = u_j - \Delta^1_{max}$ (23) and $\beta_{j+1} = u_j + \Delta^1_{max}$ (24). For an SCC that requests only one pick-up, time windows are always the same (see equations 21 and 22). This approach eliminates the interdependency for any two consecutives pick-ups during the evaluation of moves. These calculations are illustrated in *Figure 5.7*.

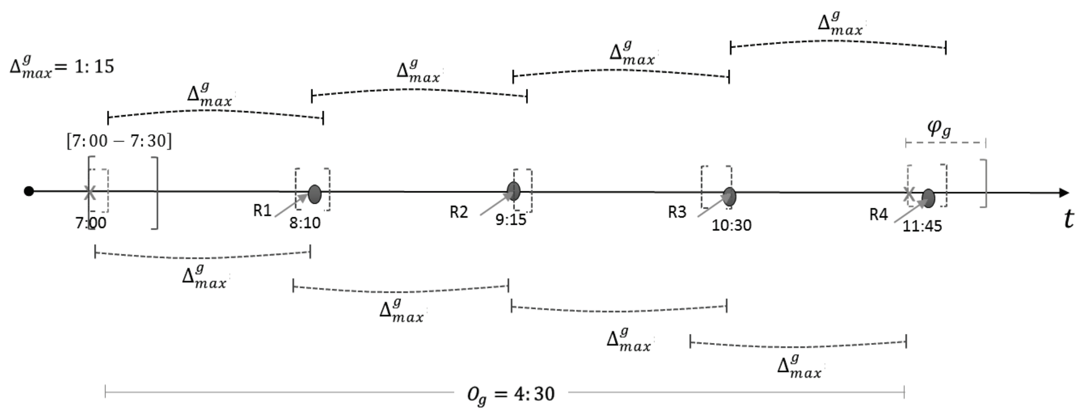

Figure 5.7 – Time windows estimation for a solution s.

However, due to the fact that the opening and closing times are also flexible inside a window, there is still interdependency between the first, penultimate and last pick-up of each client. Consider again the example of SCC g, but this time, a move in R1 could delay the arrival to SCC g to 8:45. In order to validate if this delay still leads to a feasible solution, the earliest opening hour must be delayed to 7:30 (to respect the Δ^g_{max}). However, this will imply that the last pick-up is no longer feasible, because it is performed before the end of the collection period (as illustrated in *Figure 5.8*). Likewise, an advance in service time of penultimate pick-up might result in infeasibility for the first pick-up.

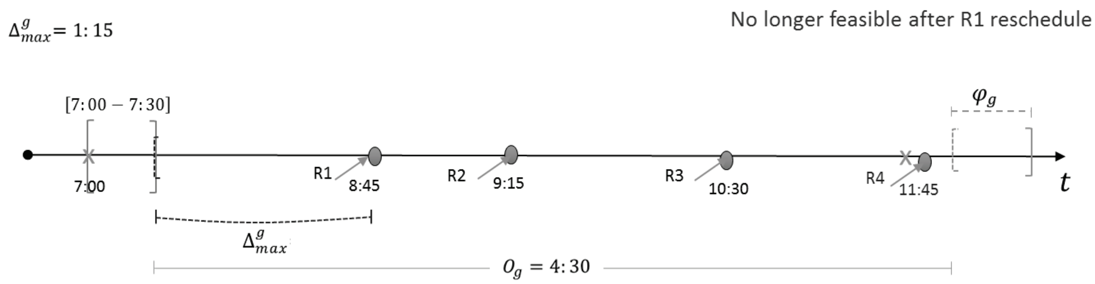

Figure 5.8 – Movement in R1 leading to an unfeasible solution.

This last dependency cannot be avoided and it is checked for every move considered that affects any of those three requests (for every SCC). If infeasible, the movement will be refused.

Cost and feasibility check

It is well known that a key component of any efficient LS is the cost and feasibility check procedure. In order to evaluate efficiently a move we implement the sequence concatenation technique proposed by Vidal et al., (2014). The basic idea is to define any solution (i.e. set of routes) as the combination of different sequence of visits. Moreover, edge exchanges and node relocations are finally a recombination of known sequences. Estimating significant information to describe the sequences and evaluate its concatenation allows us to evaluate all moves in constant time. However, once a move is implemented, the entire solution information has to be updated. The significant information that is used to characterize any sub-sequence of the BSTP are:

- the total service time $T(\sigma)$, i.e. the sum of travel and service time,
- the earliest finish time of a sequence $E(\sigma)$,
- the latest start time $L(\sigma)$,
- the minimal duration of the sequence $D(\sigma)$,
- and the feasibility statement $F(\sigma)$.

In addition, in order to control the return of all the samples to the lab before they perish, we compute $Tlim(\sigma)$ as the maximum transportation time available when the vehicle leaves the last SCC in the sequence σ, so all its samples arrive to lab on time. For a sequence of a single visit i ($\sigma_0 = p_i$) we define:

$$T(\sigma_0) = D(\sigma_0) = \tau_i \quad (25)$$

$$E(\sigma_0) = \alpha_i + \tau_i \quad (26)$$

$$L(\sigma_0) = \beta_i \quad (27)$$

$$Tlim(\sigma_0) = T^i_{max} - \tau_i \quad (28)$$

$$F(\sigma_0) = true \quad (29)$$

We refer the interested reader on the equations used to compute the information for a concatenation of sequence for $T(\sigma), E(\sigma)$, $L(\sigma)$ to Vidal et al., (2014). Now, remember that waiting time is allowed before serving a customer. Its estimation (ΔWT), as well as the one for its minimum duration $D(\sigma)$, are defined in Vidal et al., (2013). On its side, (30) and (31) show how $Tlim(\sigma_1 \oplus \sigma_2)$ and $F(\sigma_1 \oplus \sigma_2)$ are computed.

$$Tlim(\sigma_1 \oplus \sigma_2) = Min\{Tlim(\sigma_1) - \Delta WT - t_{\sigma_1(|\sigma_1|),\sigma_2(1)} - D(\sigma_2), Tlim(\sigma_2)\} \quad (30)$$

$$F(\sigma_1 \oplus \sigma_2) \equiv F(\sigma_1) \wedge F(\sigma_2) \wedge \quad (E(\sigma_1) + t_{\sigma_1(|\sigma_1|)\sigma_2(1)} \leq L(\sigma_2)) \quad \wedge \quad (Tlim(\sigma_1) - \Delta WT - t_{\sigma_1(|\sigma_1|),\sigma_2(1)} - D(\sigma_2) \geq t_{\sigma_2(|\sigma_2|),0}) \quad (31)$$

Well-known neighbourhoods designed for the VRP, like 2-opt, have a high chance of leading to infeasibility solutions when applied to the BSTP, due to the time constraints in service and transportation. We thus limit our current application to two basic *relocate* neighbourhoods, incorporated in a variable neighborhood descent (VND) scheme. First, we explore the possibility of relocate a visit inside its route (**N1 :** intra-route). As our objective is to find the minimal duration for a route, for every neighbor solution explored, its feasibility is checked and then, if feasible, its minimal duration is computed and compared to the current solution. **N1** is explored completely to find the best possible improvement. Then, if an improvement is found, the movement is implemented, time windows and sequence information are updated, and we restart the LS of the incumbent solution. If no improvement is found, an inter-route relocate neighborhood is explored (**N2**: inter-route) and we proceed as done in **N1**. When a move is performed in **N2**, the LS goes back to **N1** to explore the intra-route of the routes affected by the inter-route. The procedure is repeated until no further improvement can be found.

5.3.3. Perturbation

The LS procedure seeks to improve the routing decisions based on the estimated time windows calculated for a given solution. However, as it was explained before, this procedure ignores the flexibility that is added by the time window of the opening decisions, or the possibility of making extra visits to one or several SCCs. Indeed, considering the operation decisions for the SCC has a great complexity that can hardly be coped directly with the time windows estimation and relocate neighbourhoods. Hence, we propose to explore this upper-level decision through a perturbation of the current solution. The basic idea of the perturbation stage is to remove all the transportation requests of one or several SCCs from the solution, and then to reinsert them in the best possible position. Removing an SCC from the routes gives us the opportunity to reset the opening decisions and the service time decisions at the same time. Different criteria can be defined to select the SCCs to remove. However, seeking to guide the search, we limit the selection criterion to remove the SCC with the pick-up that produces the highest increase on total duration. Once the selected SCCs have been removed, the remaining routes are improved by LS, seeking to shake the solution. On its side, the time windows on the transportation request removed from the solution are reset to the first approximation and reinserted one by one. Evidently, at each request insertion, the time windows must be properly updated in order to avoid infeasibilities. Once all the requests have been reinserted, a new solution is obtained and its basic neighbourhoods are explored by the LS. Nonetheless, nothing can ensure that the solution will be improved. In this case, the solution found is still accepted (implanted), but no improvement successive iterations are limited to a small number (*Fails'*) before a diversification is applied, defining a farther neighborhood.

There are two main diversification parameters in our ILS. First, we define ϑ_1 as the number of SCCs that are removed from the incumbent solution. Second, when an SCC is removed, it can be reinserted requesting the same numbers of pick-ups as before, or more. Although in a particular configuration making more than the minimum pick-up can result in a better result, it would not probably be the case for all the SCCs and for no more than one pick-up per SCC (Doerner et al., 2008). The objective is thus to find the right set of customers (if any) that by adding one pick-up, lead to a better solution. To handle this aspect, let us define ϑ_2 as the number of additional pick-ups inserted to the request of the removed SCC. These two parameters are initially set to $\vartheta_1 = 1$ and $\vartheta_2 = 0$, and are increased gradually through the ILS if no improvement is reached. In addition, when an SCC has been removed during the perturbation procedure, it is tagged as *forbidden* to guide the search to a new part of the solution space. At the beginning, a single SCC is removed and reinserted (the same number of pick-ups as requested before). Then, if no improvement is found for a certain number of iterations, ϑ_1 is increased, and the process is repeated until a certain limit ϑ_1'. Finally, if no improvement is possible by removing ϑ_1' SCCs, we restart ϑ_1=1 and the SCCs removed will now be reinserted but with an additional pick-up (each). The forbidden list is restarted when ϑ_1 or ϑ_2 are incremented. Pseudo-code of the ILS is summarized by *Algorithm 5.1*

Algorithm 5.1 – ILS for the BSTP.

1. $s \leftarrow$ MIP heuristic for minimum number of transportation request.
2. $s \leftarrow LS(s)$
3. Fix ϑ_1=1; $\vartheta_2 = 0$; *nbFails* = 0; *forbidden* = $\emptyset$; $iter = 0$
4. $s' \leftarrow s$
5. **Do until** *iter*= $iter'$ ***or*** all the SCCs are tagged as forbidden.

   5.1. Remove ϑ_1 SCCs from s' producing a partial solution $\hat{s}$ and tagged them as forbidden.

   5.2. $\hat{s} \leftarrow LS(\hat{s})$

   5.3. Reinsert the $|P_g| + \vartheta_2$ pick-ups of the removed SCCs to $\hat{s}$ obtaining s''.

   5.4. $s'' \leftarrow LS(s'')$

5.5. **If** s'' isNot better than s' **then**

5.5.1. *nbFails*= *nbFails* +1

5.5.2. **If** *nbFails* = *Fails'* **then**

If $\vartheta_1 < \vartheta_1'$ andAlso $\vartheta_2 = 0$ **then**

forbidden=∅; *nbFails*=0; $\vartheta_1 = \vartheta_1 + 1$

elseIf $\vartheta_2 = 0$ **then**

forbidden=∅; *nbFails*=0; $\vartheta_1 = 1$; $\vartheta_2 = \vartheta_2 + 1$

elseIf $\vartheta_1 < \vartheta_1''$ **then**

forbidden=∅; *nbFails*=0; $\vartheta_1 = \vartheta_1 + 1$

else

nbFails=0; $\vartheta_1 = 1$; $\vartheta_2 = 0$

else

nbFails=0; $\vartheta_1 = 1$; $\vartheta_2 = 0$

$s' \leftarrow s''$

5.6. $iter = iter + 1$

5.7. **If** s' is better than s **then** $s \leftarrow s'$

6. **return** s

5.4. Numerical experiments

In order to assess the efficiency of the proposed approach, we solved the set of 38 instances proposed in Anaya-Arenas et al., (2015). Instances are arbitrarily divided into 12 *small instances* (four SCCs for a total of around a total of 10 "minimum request" to schedule), 13 m*edium* (up to 10 SCCs, around 20 "minimum requests") and 13 l*arge* (up to 20 SCCs, up to 50 "minimum requests") sets. In this section, we present the preliminary results obtained with our ILS and compare its performance to the best-known solutions (BKS), obtained by Gurobi after 30 minutes of computing (1800 sec.).

All the tests were run on a 64 bits Intel Core i7-4770 CPU @3.4 GHz. PC with 32 Gb. of RAM. For the initialization stage, the MIP was solved by Gurobi v6.0, allowing $\lceil |P|/4 \rceil$ seconds to solve small and medium size instances and $\lceil |P|/2 \rceil$ seconds for the larger ones. On the other side, we allowed the perturbation to remove up to 10% of the SCCs (i.e. $\vartheta_1' = \lfloor 10\% |N| \rfloor$), if there is no improvement found we explore to add up to one pick-up per SCC removed, and this to a maximum of two SCCs ($\vartheta_2' = 1; \vartheta_1'' = 2$). Finally, the maximum number of iterations was set to the double of the number of SCCs in the instance ($iter' = 2 \times |N|$) and the number of iterations allowed without improvement was set at each iteration between four and one, according to the number of removed SCCs ($Fails' = \lceil 4/\vartheta_1 \rceil$).

Table 5.1 presents the preliminary results of our ILS. Column *BKS Avg.* gives, for each set of instances, the average value of the objective function. Column *ILS Avg.* reports the average results produced by the ILS. Notice that (*) symbol in column *BKS Avg.* indicates that Gurobi was able to prove optimality of the solution reported for all the instances in the set. Column *%ToBKS* gives the average gap of our method with respect to BKS (in percentage). Finally, columns *Gurobi sec.* and *ILS sec.* reports the average CPU time of Gurobi and the ILS procedure (respectively) to solve an instance of each group.

Table 5.1 – Average results over the three set of instances.

Instance set	BKS Avg.	ILS Avg.	%ToBKS	BKS sec.	ILS sec.
Avg. Small (12)	389*	389	0.0	0.2	0.3
Avg. Medium (13)	606*	606	0.1	7.2	1.6
Avg. Large (13)	1586	1615	1.5	1547.7	39.7

These first computational results are quite encouraging. Our ILS achieves optimal solutions for all small and medium instances. Solutions for these two set of instances were obtained in less than two seconds. For the set of large instances, ILS produced good-quality solutions (only 1.5% to BKS) in less than 40 seconds in average, which is very good compared to the average of 26 minutes reported by Gurobi. High quality solutions are obtained at the very first stage of the ILS, proving the quality and efficiency of our new mathematical formulation. A deeper analysis of the larger instances has revealed that the perturbation phase plays an important role in improving solutions. In fact, the main difference between the BKS and the ILS solution is related to the opening decisions. This supports and encourages our methodology to optimize these tactical aspects of the problem within the unified approach. In addition, the small computational times prove how a metaheuristic approach is suitable to solve the BSTP.

To explore the quality of the transportation plan defined by this new approach, we compare the solutions obtained with our ILS procedure (in terms of total distance) to the ones reported by Anaya-Arenas et al. (2015). To this end, we used the network of SCCs and Labs and the requests proposed in Anaya-Arenas et al. (2015). Notice that Anaya-Arenas et al. (2015) also includes time windows and aims at minimizing the total distance. Therefore, comparing the results produced by these two different models allows us to illustrate how the rigid time windows in Anaya-Arenas et al. (2015) lead in most of the cases to higher total distances. The results are presented in *Table 5.2*. Please note that in all the instances tested the number of transportation request are the same for the two approaches.

Table 5.2 – Average distances produced by ILS and the methods proposed in Anaya-Arenas et al. (2015).

Instance set	**Total distance (Km)**			**CPU time (sec.)**		
	BSTP-MR	**BSTP-EG**	**ILS**	**BSTP-MR**	**BSTP-EG**	**ILS**
Avg. Small (12)	297.4	297.4	294.7	0.3	0.2	0.3
Avg. Medium (13)	432.3	432.2	435.1	396.2	110.1	1.6
Avg. Large (13)	1324.5	1323.3	1199.3	3600.1	3600.3	39.7

As it can be seen in *Table 5.2*, the approach proposed in this paper leads, in average, to solutions (transportation plans) with smaller total traveled distance. For small instances, the distances are reduced by 1% in average and for the larger ones by 9.3% (BSTP-EG vs. ILS). On the other hand, on medium size instances the ILS needed 0.5% more km. (in average) than the solution reported in Anaya-Arenas et al. (2015). This shows a relative advantage in the transportation costs to the fact of eliminating the time windows constraints and including the SCC opening hour in the optimization decisions.

Based on our empirical study, a deeper analysis is currently being held to improve the perturbation procedure. In addition, different parameters tuning (on the maximum number of SCCs to remove, additional visits to reinsert, or number of iterations) and other selection criteria for the removed SCCs are presently being tested to perform a greater shake of the solution and hopefully obtain optimal solutions for all of our instances.

5.5. Conclusion and research perspectives

We present in this paper an efficient ILS to solve the biomedical sample transportation problem for Quebec's network of laboratories. This paper extends the version of the problem that was presented in Anaya-Arenas et al., (2014) to cope with some key tactical decisions on the operation of SCCs. In fact, the problem approached in this paper aligns with the objectives of the MSSS to continue the analysis and improvement of their laboratories' network. More precisely, the version of the problem here described encompasses decisions on the number and the frequency of the SCCs' pick-ups, as well as their opening hours. We propose a mathematical formulation for the BSTP with a fixed number of transportation request that proved to be efficient in finding a feasible solution in a less than a second with a commercial solver. We develop an ILS procedure that aims at improving the initial solution produced by the MIP. The ILS explores routing decisions through relocate moves, and then a perturbation phase of the incumbent solution. The perturbation procedure seeks to adjust the SCCs' operation and pick-ups schedule to minimize total route's duration. Preliminary results are very promising. Our ILS achieves optimal solutions for the small and medium-size instances, and a solution in average around 1.5% behind the best known solutions for the larger ones, and this in 3% of the computational time required by the solver. Further analysis on the ILS performance is planned, seeking a better parameters' tuning and thus a better performance.

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Conclusion générale et perspectives de recherche future

En appliquant les techniques issues de la recherche opérationnelle, nous avons développé des outils pour optimiser la distribution dans le contexte du déploiement en situation d'urgence et du transport d'échantillons biomédicaux.

Dans le domaine du déploiement en situation d'urgence, nous avons fait une revue systématique de la littérature. En utilisant une procédure de compilation et de synthèse transparente et reproductible, nous avons exploré plus de 170 références et 87 articles ont finalement été retenus et analysés. Nous avons classifié les contributions en quatre groupes : 1) le problème de localisation de centres de distribution d'aide humanitaire, 2) le problème de transport à l'intérieure d'un réseau, 3) le problème de localisation et routage, et 4) autres problématiques. Les attributs plus importants dans la modélisation, les hypothèses de base et les objectifs poursuivis ont été identifiés. Cette analyse a permis de faire ressortir les besoins de recherche dans le domaine. Des modèles plus réalistes avec des objectifs et des contraintes de capacité adaptés sont toujours nécessaires. De plus, nous soulevons un besoin d'harmonisation dans les étapes de design et d'exploitation du réseau, ainsi qu'un besoin pour des méthodes de résolution efficaces pouvant être intégrées dans des outils d'aide à la décision.

Parmi les différentes pistes de recherche identifiées au Chapitre 2, et grâce à notre collaboration avec notre partenaire Fujitsu Canada, une inquiétude sur la justesse dans la distribution lors d'un déploiement d'urgence est la base de notre deuxième contribution. Nous avons traité, dans le Chapitre 3, trois modèles d'optimisation multipériode pour le design d'un réseau de distribution d'aide après une catastrophe. Ces modèles, qui sont très détaillés, priorisent la minimisation de la non-satisfaction de la demande et mettent de l'avant le principe de justice. Afin de mieux analyser et d'incorporer le principe de justice dans la planification logistique, des mesures de performance, qui reflètent l'équité et la stabilité dans la distribution d'aide, ont été proposées. Ces modèles ont été testés sur des instances réalistes et il en ressort que la fonction linéaire par morceaux développée s'est avérée la plus adéquate pour garantir une distribution équitable et stable dans le temps. De plus, notre formulation considère les arrérages de la demande. Les modèles gèrent donc la rationalisation des ressources mais également la compensation des besoins lorsque l'offre est rétablie. L'aspect multipériode des modèles développés permet au réseau de s'adapter aux variations dynamiques de la demande.

En ce qui concerne des recherches futures, nous pensons qu'une utilisation intéressante des formulations proposées serait de simuler la migration des sinistrés. De plus, une étude empirique détaillée sur des instances plus complexes serait pertinente pour bien analyser les possibilités des modèles proposés. Une belle perspective de recherche qui s'ouvre à ce sujet est de penser à l'intégration de ces propositions dans une procédure de planification en horizon roulant. Ceci permettrait au décideur d'actualiser les données entrantes pour le système (comme la localisation des sinistrés et les prévisions de la capacité réelle disponible et de la demande) au fur et à mesure qu'elles se rendent disponibles, et d'optimiser les décisions de distribution de façon dynamique. De la même façon, l'intégration de ce modèle d'optimisation avec un modèle de simulation serait une prolongation qui permettrait de fournir un outil de préparation et d'entrainement complet pour les gestionnaires de crises.

Aux Chapitres 4 et 5 de la thèse, nous avons étudié le problème de transport d'échantillons biomédicaux. Une présentation de ce problème complexe dans le réseau des laboratoires d'analyse de la province de Québec est faite au Chapitre 4. Nous avons formalisé cette problématique comme un problème de tournées de véhicules avec plusieurs fenêtres de temps par client et des camions qui peuvent faire plusieurs routes. Nous avons proposé deux modèles d'optimisation et ils ont été testés sur un ensemble de problèmes provenant du réseau de santé québécois. Nous avons comparé les deux modèles en utilisant un logiciel commercial d'optimisation (Gurobi v.6.0) et nous en avons conclu que, en moyenne, la formulation sur le graphe étendu semble plus efficiente au niveau des temps de résolution et de la qualité de la solution. Cependant, le problème est toujours très difficile à résoudre et nécessite des temps de calcul élevés. Pour contourner ce problème, nous avons présenté une méthode de résolution composite, basée sur l'utilisation d'heuristiques simples afin de fournir une solution initiale au solveur et diminuer grandement le temps de résolution nécessaire. Le travail que nous avons présenté au Chapitre 4 est la première étape dans le processus d'optimisation du réseau des laboratoires dans la province de Québec. Lors de cette collaboration, nous avons déposé divers rapports techniques qui ont permis au MSSS de mieux exprimer leurs besoins en matière de transport.

Suite à ces travaux, le MSSS a continué ses réflexions et envisage de modifier les heures d'ouvertures des centres de prélèvement ainsi que le nombre de passage à ceux-ci afin de donner de la souplesse au réseau. C'est cette nouvelle problématique que nous étudions dans le Chapitre 5 où nous développons une métaheuristique pour résoudre ce cas qui peut être vu comme une extension du problème de base décrit au Chapitre 4. Tout d'abord, nous avons inclus dans la problématique la capacité des centres de prélèvements (CPs). Ceci nous a permis de remettre en question le nombre et la fréquence de ramassages demandés par un CP donné. Nous avons aussi remplacé les fenêtres de temps par un temps maximal entre les passages. De plus, nous avons considéré la synchronisation des horaires d'ouverture des CPs. Il en résulte une problématique de transport plus complexe et nouvelle dans la littérature du transport d'échantillons biomédicaux. Nous avons présenté une nouvelle formulation pour ce problème avec un nombre fixe de requêtes qui s'est avéré efficace pour trouver rapidement des solutions de bonne qualité. Finalement, une procédure itérative de recherche locale (ILS) a été proposée et elle s'est avérée également efficace. La méthode a trouvé des solutions de très bonne qualité, souvent optimales, en moins de 20 secondes pour les plus grandes instances, ce qui est moins que 1 % du temps requis par un solveur commercial.

Ce travail sert de base pour continuer l'optimisation des processus dans le système de transport des échantillons dans les laboratoires au Québec. Nous croyons qu'une analyse plus avancée sur la configuration du réseau est toujours pertinente pour le cas québécois. Plusieurs extensions de ce travail s'avèrent intéressantes. Par exemple, l'inclusion d'une analyse de la capacité de traitement des échantillons au laboratoire. Jusqu'à maintenant, le MSSS fixe un temps maximal de transport pour éviter la perte des échantillons, en considérant qu'une fois rendu au laboratoire les échantillons sont aussitôt traités. Cependant, il n'y a pas vraiment de garantie du temps d'attente réel d'un échantillon à l'intérieur du laboratoire. Une analyse détaillée des processus de réception et des charges de travail des laboratoires permettrait au décideur d'en tenir compte pour une estimation plus réelle du temps maximal de transport. D'autre part, on pourrait aussi reconsidérer l'affectation des CPs aux laboratoires et réévaluer la configuration du réseau dans une extension du problème de type « *Location-Routing* ». Finalement, une approche toujours intéressante serait d'inclure la planification des tournées dans un outil dynamique, qui permettrait d'intégrer une analyse de la capacité des CPs en temps réel en fonction de la demande observée. Ceci permettrait au décideur d'ajuster la programmation des visites à l'intérieur d'une journée. Des études futures s'avèrent nécessaires pour analyser ce sujet.

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