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Analysis and Optimization of Long-Haul Transportation Problems

par
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Analysis and Optimization of Long-Haul Transportation Problems

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Résumé

Le transport occupe une place majeure dans l'économie mondiale et sous-tend autant les activités économiques que sociales. Néanmoins, le secteur du transport des pays développés se distingue considérablement de celui des pays en voie de développement. Dans cette thèse, nous nous concentrons sur le transport terrestre de marchandises de longue distance en Amérique du Nord et en Afrique de l'Est. Nous analysons des problèmes de transport à travers deux réalités bien différentes. En conséquence, la thèse est divisée en deux parties composées de deux chapitres chacune. Les problèmes sont traités en utilisant des approches basées sur la recherche opérationnelle et l'économétrie. Nos analyses permettent de répondre à des questions qui relèvent du domaine de la gestion des opérations et de celui des politiques publiques.

Dans la première partie de cette thèse, nous présentons et résolvons un problème riche de tournées de véhicules se posant dans l'industrie du transport en charges partielles. Cette étude est motivée par le cas du Groupe Robert Inc., mais notre contribution demeure d'application générale. Le problème à l'étude comprend deux composantes principales: une composante de routage qui consiste à déterminer la séquence des clients visités par chaque véhicule ainsi qu'une composante de planification d'horaires des chauffeurs qui consiste à déterminer leurs périodes de repos et les temps de service. La contribution majeure du premier chapitre de la première partie de cette thèse est le développement et l'intégration d'algorithmes d'ordonnancement qui traitent le problème de planification des horaires des chauffeurs à l'intérieur d'une heuristique de recherche avec tabous. Les résultats montrent que les solutions peuvent être considérablement améliorées en intégrant différentes possibilités pour la planification des périodes de repos et que les gains varient selon le niveau de sophistication de l'algorithme de planification des horaires implanté.

Dans le deuxième chapitre de cette partie, nous présentons une version améliorée de l'heuristique de recherche avec tabous décrit dans le chapitre précédent. Une méthode de résolution multicritère basée sur la distance avec un objectif de référence a été intégrée à l'algorithme de recherche avec tabous afin d'obtenir des ensembles de solutions non dominées permettant de réaliser un arbitrage entre le nombre de véhicules, les coûts d'opération du transporteur et les inconvénients pour les chauffeurs. Les ré-

sultats du deuxième chapitre montrent que la version multicritère de l'algorithme fournit de meilleures solutions en termes de nombre de véhicules, de coûts d'opération et d'inconvénients pour les chauffeurs par rapport à la solution appliquée par le Groupe Robert. Des analyses ont permis de confirmer l'efficacité de la pratique couramment appliquée par les répartiteurs qui cherchent à minimiser le nombre de véhicules utilisés. On constate aussi qu'une diminution des inconvénients pour les chauffeurs augmente les coûts d'opération du transporteur, mais ce dans une proportion moindre.

Dans la deuxième partie, nous abordons des problématiques de transport humanitaire liées à la distribution de denrées alimentaires en Afrique de l'Est. Notre étude est motivée, d'une part, par le cas du Programme Alimentaire Mondial en Éthiopie et, d'autre part, par le cas de tous les différents organismes impliqués dans la chaîne d'approvisionnement au niveau régional au Kenya. Dans le premier chapitre de cette partie de thèse, nous analysons le marché du transport en Éthiopie à l'aide de modèles économétriques. Nous avons développé des modèles de régression linéaire multiple pour déterminer quels facteurs expliquent significativement la structure des tarifs de transport. Les résultats révèlent que les principaux déterminants de tarifs pour les services de transport en Éthiopie sont à la fois l'état des routes et la structure du marché. Néanmoins, des analyses de dominances et des analyses contrefactuelles indiquent que l'augmentation du niveau de la concurrence a un impact plus important sur la réduction des tarifs de transport que l'amélioration des infrastructures. Nous montrons aussi comment les modèles de prédiction peuvent être utilisés pour soutenir les processus d'achat de services de transport et ainsi contribuer à améliorer les performances globales de la chaîne d'approvisionnement des expéditeurs en affinant l'estimation de leurs coûts de distribution.

Dans le dernier chapitre, nous présentons et résolvons un problème de conception de réseaux tactiques pour la distribution de denrées alimentaires au Kenya. Le Kenya, comme les autres pays de l'Afrique de l'Est, est sujet à des sécheresses périodiques, au début et à la fin de deux saisons des pluies irrégulières, lesquels ont un effet important sur les crises alimentaires saisonnières. Nous décrivons donc comment nous avons combiné l'information provenant de l'évaluation des besoins en aide alimentaire subséquente à la saison courte des pluies de 2012 avec des données démographiques maillées afin d'évaluer la répartition de la demande dans la région de Garissa et ses environs. Nous montrons aussi comment nous avons exploité des données provenant d'un système d'information géographique du réseau routier afin d'établir l'ensemble des centres de distribution potentiels, où la nourriture est directement distribuée aux bénéficiaires. Nous présentons un modèle de localisation pour déterminer l'ensemble des centres de distribution actifs et l'affectation de la population à ces centres de distribution. Notre modèle prend en compte les coûts rattachés au bien-être de tous les acteurs impliqués dans ce système de réponse: le gouvernement, le Programme Alimentaire Mondial, la Croix-Rouge et les

bénéficiaires. En plus des résultats obtenus grâce à la résolution de notre modèle principal, nous présentons les résultats provenant de diverses analyses de sensibilité, de comparaisons de solutions résultant de modèles de couverture classiques ainsi que des illustrations cartographiques de réseaux de distributions optimaux. Bien que notre analyse ait été effectuée sur un problème relatif à la région de Garissa, notre méthodologie s'applique à d'autres pays en développement dans un contexte de planification de la distribution de denrées alimentaires.

En résumé, nous résolvons différents problèmes appliqués liés au transport longue distance. Ces problèmes proviennent d'organisations évoluant dans des contextes économiques dont les niveaux de maturité se distinguent clairement. Les méthodes de résolution utilisées pour aborder chaque problème sont appropriées selon les contextes dans lesquels ces problèmes émergent. Elles constituent des outils d'aide à la décision qui peuvent faciliter la planification des opérations de transport.

Mots clés : Transport longue distance, problèmes riches de tournées de véhicules, heures de conduite, heuristiques, logistique humanitaire, régression linéaire multiple, tarifs de transport, distribution de denrées alimentaires, conception de réseaux, problèmes de localisation

Abstract

Transportation plays a major role in the global economy since it underlies all economic and social activities. However, the transportation sector in developed countries differs considerably from that of developing countries. In this thesis, we focus on long-haul freight transportation in North America and East Africa. We analyze transportation problems through two very different realities. Accordingly, this thesis is divided into two parts of two chapters each. The problems are treated through methodologies rooted in operations research and econometrics. Our analyses provide answers to questions falling within the area of operations management and public policies.

In the first part of this thesis, we present and solve a rich vehicle routing problem arising in the less-than-truckload transportation industry. This study is motivated by the case of Groupe Robert Inc., but our contribution remains of general applicability. The problem under study contains two dominant features: a routing component which consists in determining the sequence of customers visited by each vehicle, and a scheduling component which consists in planning the rest periods and the service time of each customer. The major contribution of the first chapter is the development and integration of different sophisticated scheduling algorithms, embedded within a tabu search heuristic tackling the vehicle routing component, defining truck driver schedules complying with the hour of service regulations in the United States. The results show that solutions can be greatly improved by integrating multiple possibilities for planning rest periods and the gains vary depending on the complexity of the implemented scheduling algorithm.

In the second chapter of the first part of this thesis, we present an improved version of the heuristic described in the previous chapter. A multicriteria solution approach based on the distance to a reference objective has been integrated into the tabu search heuristic to obtain non-dominated solution sets with the aim of achieving a balance between the number of vehicles, the carrier operating costs and the driver inconvenience. The multicriteria version of the algorithm provides better solutions in terms of the number of vehicles, operating costs and driver inconvenience compared with the Groupe Robert solution. Results of tradeoff analyses also show that decreasing driver inconvenience increases carrier operating costs in a smaller proportion. Experiments confirmed the efficacy of the

rule-of-thumb generally applied in the industry of focusing on minimizing the number of vehicles sent on the road. Overall, the interpretations of the computational results on artificial and real-life instances provide meaningful information to long-haul carriers.

In the second part of this thesis, we address issues related to long-haul transportation in the context of food distribution in East Africa. Our study is motivated, on the one hand, by the case of the World Food Programme (WFP) in Ethiopia and, on the other hand, by all the different organizations involved in the supply chain at a regional level in Kenya. To transport food aid, the WFP primarily contracts with third-party transport carriers in markets that are not well understood. In the first chapter of this part, we propose a methodology based on econometric models in order to study the international and domestic Ethiopian transportation markets. We analyse historical contracts between WFP and private carriers using multiple linear regression to gain insights about these markets and to determine which factors better explain transportation tariffs. The results show that the major determinants of the truckload pricing structure are both the road conditions and the market structure. However, dominance and counterfactual analyses indicate that improving competition intensity has a greater impact on reducing transportation tariffs than improving the infrastructure, at least in the short-term. We also show how predictive models can be used to support the transportation procurement process and thus contribute to improve the shipper supply chain overall performance and refine budgeting for transportation operations.

In the last chapter, we present a tactical network design problem for food aid distribution in Kenya, namely in and around Garissa. Like other countries in East Africa, Kenya is subjected to periodic droughts at the beginning and at the end of two rainy seasons, which have a significant effect on seasonal food crises. In order to estimate the demand distribution for the region of Garissa and its surroundings, we describe how we have combined the results of the 2012 short rain food assessment along with gridded demographic data. We also show how we have used GIS road network data to determine the set of potential distribution centers, where food is directly handed to the beneficiaries. We present and solve a model that determines the active distribution centers location as well as the population assignment to these distribution centers. Our model takes into account the welfare costs of all the stakeholders involved in this response system: the government, the WFP, the Red Cross and the beneficiaries. In addition to the results obtained by solving our main model, we present results from various sensitivity analyses, we compare solutions resulting from our main model with those resulting from classical covering models, and we illustrate optimal distribution network maps. Although our analysis was performed on an instance representing the region of Garissa, our methodology can be applied to other developing countries in the context of food distribution planning.

In summary, we solve different applied problems related to long-haul transportation planning. These problems arise in organizations operating in economic contexts where the levels of maturity are clearly distinctive. Solution approaches used to address each problem are suitable for their particular contexts. Decision tools, such as the one we have developed in this thesis, can help decision makers handle simultaneously various features when planning transportation operations and establish a suitable solution.

Keywords : long-haul transportation, rich vehicle routing problems, hours of service regulation, heuristics, humanitarian logistics, multiple linear regression, freight tariffs, food aid distribution, network design, location problems

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Liste des abréviations

CRC	Community Relief Committee
CSAE	Central Statistical Agency of Ethiopia
CVRP	Capacitated Vehicle Routing Problem
DARP	Dial-a-Ride Problem
DC	Distribution Center
DOT	Department of Transportation
EDP	Extended Delivery Point
EU	European Union
FDP	Final Delivery Point
GoK	Government of Kenya
HOS	Hours of Service
ILP	Integer Linear Programming
KRCS	Kenya Red Cross Society
LTL	Less-Than-Truckload
MOVRTDSP	Multi-Objective Vehicle Routing and Truck Driver Scheduling Problem
MW	Main Warehouse
NGO	Non-Governmental Organization
PAM	Programme Alimentaire Mondial
PIB	Produit Intérieur Brut
RFQ	Request for Quotation
SW	Satellite Warehouse
TDSP	Truck Driver Scheduling Problem
TL	Truckload
TSP	Traveling Salesman Problem
TTVRP	Truck and Trailer Vehicle Routing Problem
UN	United Nations
US	United States

VRP	Vehicle Routing Problem
VRPMTW	Vehicle Routing Problem with Multiple Time Windows
VRPRB	Vehicle Routing Problem with Route Balancing
VRPTW	Vehicle Routing Problem with Time Windows
VRTDSP	Vehicle Routing and Truck Driver Scheduling Problem
WFP	World Food Programme

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Chapitre 1

Introduction

Le transport constitue une activité indispensable aux échanges commerciaux et sociaux. Les cycles de production-consommation dépendent des systèmes permettant d'acheminer les matières premières, la main-d'œuvre et l'énergie aux manufactures ainsi que les produits manufacturés aux consommateurs. La mobilité des personnes est aussi indispensable à l'activité sociale. Des études montrent qu'elle est un indice du développement des sociétés et des individus (Mellor, 1966; Adams, 1981).

Au niveau macro-économique le transport compte pour une proportion se situant entre 6% et 12% du PIB des pays développés (Rodrigue et al., 2009). En 2010, le secteur du transport comptait pour 9% du PIB aux États-Unis et contribuait aussi à l'économie en fournissant 16% des emplois (Research and Administration, 2011). En Europe, l'industrie du transport représentait 5% du PIB et employait quelque dix millions de personnes (Commission européenne, 2011). Dans les pays en voie de développement, la productivité économique est freinée par l'inefficacité des systèmes de transport (Replogle, 1991) et le coût élevé de transport constitue un obstacle majeur aux échanges internationaux (Limão and Venables, 2001). Les coûts de transport des pays enclavés en Afrique compte pour 10 à 15% des coûts total d'importation, ce qui est de trois à quatre fois plus que pour la plupart des pays développés (Teravaninthorn and Raballand, 2010). Au niveau micro-économique, les ménages ont dépensé en moyenne autour de 13,5% de leurs dépenses totales en biens et services connexes au transport dans le pays de l'OCDE en 2005 (Kauppila, 2010). Diaz-Olvera et al. (2008) constatent que les dépenses en transport varient considérablement entre les pays d'Afrique subsaharienne et que le transport public y est souvent inabordable, ce qui inhibe considérablement la mobilité des populations pauvres. Néanmoins, le transport demeure une composante majeure des dépenses des ménages africains.

De toute évidence, le transport occupe une place majeure dans l'économie mondiale et sous-tend autant les activités économiques que sociales. Néanmoins, le secteur du transport des pays développés se distingue considérablement de celui des pays en voie de développement. Dans cette thèse, nous analysons des problèmes de transport à travers ces deux réalités bien différentes. Nous nous concentrons sur le transport terrestre de marchandises de longue distance en Amérique du Nord et en Afrique de l'Est. Le transport soulève des questions qui touchent différentes sphères de l'économie, l'économétrie, de la politique et de la société. Les études en transport relèvent donc de plusieurs disciplines comme l'économie, la statistique, le génie, la gestion et la recherche opérationnelle. Dans cette thèse, les problèmes de transport sont traités en utilisant des approches basées sur la recherche opérationnelle et l'économétrie. Nos analyses permettent de répondre à des questions qui relèvent autant du domaine politique que de la gestion des opérations.

Cette thèse se penche principalement sur deux problématiques liées au transport de longue distance : le transport de marchandises en charges partielles en Amérique du Nord et la distribution de denrées alimentaires en Afrique de l'Est. Ces problèmes découlent de cas réels émergeant dans des contextes économiques et organisationnels complètement différents. Les outils nécessaires à l'analyse et à l'optimisation de ses problèmes nécessitent des méthodologies appropriées selon leur contexte. En conséquence, cette thèse est divisée en deux parties composées de deux chapitres chacune. La première partie porte sur la planification du transport de longue distance en Amérique du Nord et la deuxième sur des problèmes se posant en Afrique de l'Est.

1.1 Partie 1 : Planification de tournées de véhicules de longue durée avec contraintes d'heures de service. Le cas de l'Amérique du Nord

Le but de la première partie de cette thèse est de présenter, de modéliser et de résoudre un problème riche de tournées de véhicules se posant dans l'industrie du transport en charges partielles. Cette étude est motivée par le cas du Groupe Robert Inc., un important prestataire de services logistiques au Canada, mais notre contribution demeure d'application générale. Le problème traité est une extension du problème de tournées de véhicules avec fenêtres de temps dans lequel les exigences législatives sur les heures de service aux États-Unis sont prises en compte (Partie 395.2 des règles sur les heures de conduite du Département des Transports). En plus de la réglementation américaine, notre étude considère d'autres contraintes telles que des fenêtres de temps multiples et une flotte de véhicules hétérogène. Plusieurs fenêtres de temps sont affectées aux clients parce que le problème s'étend sur plusieurs jours et chaque client peut être visité à l'intérieur d'une

fenêtre par jour, bien qu'il ne doive être visité qu'une seule fois. Les contraintes considérées existent sous d'autres formes dans d'autres pays développés, dont le Canada (Goel and Rousseau, 2012; Goel and Vidal, 2012), l'Australie (Goel et al., 2012; Goel and Vidal, 2012) et les pays de l'Union Européenne (Goel, 2009; Kok et al., 2010; Prescott-Gagnon et al., 2010; Goel and Vidal, 2012).

Le problème à l'étude comprend deux composantes principales : une composante de routage qui consiste à déterminer la séquence des clients visités par chaque véhicule ainsi qu'une composante de planification d'horaires des chauffeurs qui consiste à déterminer les périodes de repos et les temps de service. Le problème consiste donc à créer des tournées de véhicules optimales tout en respectant les différentes contraintes. Trois objectifs différents définissent la notion d'une solution optimale dans ce cas. Le premier objectif est le nombre de véhicules utilisés alors que le deuxième objectif représente les coûts opérationnels du transporteur. Les coûts opérationnels sont les coûts variables proportionnels à la distance totale parcourue par les véhicules. Le troisième objectif représente les inconvénients pour les chauffeurs. Ce dernier objectif est le temps non rémunéré que les chauffeurs passent sur la route, c'est-à-dire le temps total d'attente et de repos. La méthodologie utilisée pour traiter ce problème est basée sur des techniques de la recherche opérationnelle.

Le premier chapitre de la première partie de cette thèse décrit une heuristique de recherche avec tabous pour le problème de tournées de véhicules ave contraintes d'heures de service au États-Unis. La contribution majeure de ce chapitre est le développement et l'intégration d'algorithmes d'ordonnancement qui traitent le problème de planification des horaires des chauffeurs à l'intérieur d'une heuristique de recherche avec tabous. Ces algorithmes sont des heuristiques qui exploitent les principes de la programmation dynamique pour générer des horaires de durée minimale. Dans ce chapitre, les différents objectifs du problème de tournées de véhicules ont été traités comme un seul objectif par le biais d'une somme pondérée de deux termes. L'objectif primaire est de minimiser le nombre de véhicules utilisés dans la solution, tandis que l'objectif secondaire est de minimiser la distance totale parcourue. Cet objectif est obtenu en multipliant le nombre de véhicules par un grand nombre M et en additionnant ce terme à la distance totale. Néanmoins, cet objectif ne tient pas compte des horaires des chauffeurs et peut mener à des solutions avec des temps d'attente ou de repos importants. Pour éviter de telles situations, la durée totale a aussi été considérée comme objectif secondaire. Le problème a été résolu deux fois, une fois pour chacun des deux objectifs secondaires tout en conservant l'objectif primaire de minimiser le nombre de véhicules. En d'autres termes, nous avons appliqué un processus lexicographique où le décideur peut prédéfinir une pondération des différents objectifs et les optimiser un à la fois dans les cas extrêmes.

Dans le deuxième chapitre de cette partie, nous présentons une version améliorée de l'heuristique de recherche avec tabous décrit dans le chapitre précédent. Une méthode de résolution multicritère basée sur la distance avec un objectif de référence a été intégrée à l'algorithme de recherche avec tabous afin d'obtenir des ensembles de solutions permettant de réaliser un arbitrage entre le nombre de véhicules, les coûts d'opération du transporteur et les inconvénients pour les chauffeurs. Ce cadre de résolution permet d'obtenir un ensemble diversifié de solutions non dominées qui peuvent être transmises au gestionnaire afin qu'il les traite selon ses propres critères d'arbitrage. Afin de traiter simultanément deux objectifs, soit les coûts d'opération du transporteur et les inconvénients pour les chauffeurs, nous avons utilisé une fonction objectif globale avec des poids qui changent dynamiquement tout au long de la recherche. Les poids associés à chacun des objectifs ont deux fonctions, soit de rendre les objectifs comparables entre eux en les rapportant sur une même échelle et d'orienter la recherche avec tabous vers des espaces de recherche diversifiés. Pour orienter la recherche, les poids varient dynamiquement de manière à mettre l'emphase sur l'objectif qui s'éloigne le plus du point de référence. Des mécanismes de diversification sont aussi activés pour éviter que la recherche ne stagne dans un espace de recherche non prometteur. Le nombre de véhicules est un objectif traité différemment. Des ensembles de solutions non dominées, en termes de coûts et d'inconvénients, ont été obtenues avec différentes tailles du parc de véhicules. Pour ce faire, l'algorithme bi-objectif a été exécuté quatre fois en ajoutant à chaque exécution un véhicule additionnel à la flotte de taille minimale. Cette procédure a permis d'obtenir quatre ensembles de solutions non dominées. Les solutions produites ont ensuite été comparées pour obtenir un seul ensemble de solutions heuristiquement Pareto optimales par rapport aux trois objectifs.

Tous les algorithmes ont été testés sur des instances modifiées de Solomon (1987) et sur un exemple typique de livraisons du Groupe Robert Inc. Les résultats du premier chapitre montrent que les solutions peuvent être considérablement améliorées en intégrant différentes possibilités pour planifier les périodes de repos et que les gains varient selon le niveau de sophistication de l'algorithme de planification des horaires implanté. Les tests montrent aussi que les meilleures procédures de planification d'horaires améliorent les résultats davantage lorsque les tournées de véhicules peuvent contenir un plus grand nombre de clients puisqu'il existe alors un plus grand nombre de solutions réalisables. La méthode de recherche avec tabous et les résultats présentés dans ce chapitre sont parus en 2013 dans la revue *Transportation Science* dans l'article intitulé "Long-haul Vehicle Routing and Scheduling with Working Hour Rules". Les résultats du deuxième chapitre montrent que la version multicritère de l'algorithme fournit de meilleures solutions en termes de nombre de véhicules, de coûts d'opération et d'inconvénients pour les chauffeurs par rapport à la solution appliquée par le Groupe Robert. Des analyses ont permis de confirmer

l'efficacité de la pratique couramment appliquée par les répartiteurs qui cherchent à minimiser le nombre de véhicules utilisés. Nous montrons que dans la plupart des cas, les coûts d'opération augmentent lorsque le nombre de véhicules utilisés est plus grand que la taille de la flotte minimale. On constate aussi qu'une diminution des inconvénients pour les chauffeurs augmente les coûts d'opération du transporteur dans une proportion moindre. L'article "Multicriteria Optimization of a Long-Haul Routing and Scheduling Problem" qui résulte de ce chapitre a est en processus de révision pour la revue *Journal of Multi-Criteria Decision Analysis*.

1.2 Partie 2 : Planification du transport de longue distance dans des pays en voie de développement. Le cas de l'Afrique de l'Est

En Afrique de l'Est, le transport de marchandises engendre des défis importants dans les chaînes d'approvisionnement des organismes humanitaires. Des problèmes liés aux mauvaises infrastructures, aux risques de sécurité, aux politiques instables et au manque de transparence rendent les opérations de transports complexes dans cette région du monde. Dans le transport commercial de produits de consommation, les coûts de transport sont compensés par les prix chargés aux consommateurs. Dans les chaînes d'approvisionnement humanitaires, les coûts de transport élevés peuvent réduire le nombre de bénéficiaires que les organisations peuvent atteindre avec le financement qu'elles reçoivent. Les organismes humanitaires accordent donc de plus en plus d'importance à la minimisation de leurs coûts. Dans la deuxième partie de cette thèse, nous nous penchons sur des problématiques liées à la distribution de denrées alimentaires en Éthiopie et au Kenya. Notre étude est principalement motivée par le cas du Programme Alimentaire Mondial (PAM), une division des Nations Unies qui vise à lutter contre la faim dans le monde.

Le problème de distribution de denrées alimentaires en Afrique de l'Est consiste d'abord à transporter les dons de nourriture des ports d'arriver jusqu'aux entrepôts principaux (phase 1) et ensuite des entrepôts principaux jusqu'aux entrepôts informels (phase 2). Les entrepôts principaux sont situés dans des régions stratégiques du pays où des infrastructures formelles de stockage sont disponibles ; ces entrepôts agissent comme centres d'entreposage et de transbordement avant la seconde phase de transport. L'Éthiopie est un pays enclavé, ce qui implique que le transport depuis les ports de Djibouti et de Berbera jusqu'aux entrepôts principaux consiste en des mouvements internationaux sur de longues distances. Après la deuxième phase de transport, les denrées alimentaires sont directement distribuées aux bénéficiaires à partir d'entrepôts informels. Ces entrepôts sont

des dépôts temporaires tels que des abris, des écoles et des cliniques médicales souvent situés dans des régions éloignées difficiles d'accès. Contrairement aux entrepôts principaux, les entrepôts informels peuvent changer de localisation en fonction des besoins des bénéficiaires dans le temps. Le PAM sous-traite ses opérations de transports, ce qui implique que des transporteurs commerciaux assurent les services de transport pour le PAM. Dans la deuxième partie de cette thèse, nous analysons d'abord le marché du transport en Éthiopie en nous basant sur des principes d'économétrie. Le premier chapitre de la deuxième partie de cette thèse propose un outil d'analyse pouvant supporter les processus d'achat de services de transport en Éthiopie. Dans le chapitre suivant, nous proposons une méthodologie basée sur les principes de la programmation mathématique pour la conception de réseaux tactiques pour la distribution de denrées alimentaires au Kenya.

Les marchés du transport des pays en développement restent mal compris encore à ce jour. Dans un contexte où l'information n'est pas transparente, déterminer si un expéditeur paie un juste prix pour un service de transport demeure une tâche complexe. En travaillant en collaboration avec le PAM, nous avons recueilli des données sur les taux offerts par différents transporteurs ainsi que sur les tarifs réalisés sur le marché en Éthiopie, ce qui nous a permis de développer un cadre général pour caractériser les marchés du transport dans un pays en voie de développement. Nous avons recueilli plus de 15 000 observations d'offres de plus de 75 transporteurs couvrant de nombreux segments origine-destination, autant pour les corridors internationaux (des ports aux entrepôts principaux) que pour les routes domestiques (des entrepôts principaux aux entrepôts informels ou d'échanges entre entrepôts principaux).

Nous avons développé des modèles de régression linéaire multiple pour déterminer quels facteurs expliquent significativement la structure des tarifs de transport. Nous avons considéré des paramètres spécifiques aux pays en voie de développement pour expliquer les marchés de transport international et domestique en Éthiopie. Dans ce cas, les tarifs de transport par tonne pour chaque segment (od) du réseau éthiopien sont donnés, où un segment correspond à la route d'un point d'origine o à un point de destination d. Nos modèles considèrent différentes variables indépendantes regroupées en trois catégories : les facteurs de coûts (C), les indices de structure du marché (M) et les facteurs socio-économiques (S). Ainsi, le modèle économétrique générique est le suivant :

$$\ln tarif = f(C, M, S) + \epsilon,$$

où $\ln tarif$ est le logarithme naturel de $tarif$ et ϵ est l'erreur aléatoire causée par les facteurs non observables.

Les résultats révèlent que les principaux déterminants de tarifs pour les services de transport en Éthiopie sont à la fois l'état des routes et la structure du marché. Néanmoins,

des analyses contrefactuelles indiquent que l'augmentation du niveau de la concurrence a un impact plus important sur la réduction des tarifs de transport que l'amélioration des infrastructures. Ce résultat est cohérent avec les conclusions de Teravaninthorn and Raballand (2010) à l'effet que le faible niveau de concurrence est l'un des principaux obstacles à la réduction des prix de transport en Afrique. Il semble donc qu'investir massivement dans les infrastructures n'est pas une condition suffisante pour réduire les tarifs de transport, car l'absence de concurrence peut inciter les transporteurs à introduire des marges de profits importantes dans leurs structures de prix. Nous montrons aussi comment les modèles de prédiction peuvent être utilisés pour soutenir les processus d'achat de services de transport et ainsi contribuer à améliorer les performances globales de la chaîne d'approvisionnement des expéditeurs en affinant l'estimation de leurs coûts de distribution. L'article "Market Analysis and Transportation Procurement for Food Aid in Ethiopia" résultant de ce chapitre sera soumis sous peu à la revue *Transportation Research Part A*.

Le dernier chapitre de cette thèse porte sur un problème de gestion de la chaîne d'approvisionnement dans le secteur humanitaire. Un des grands défis de la logistique humanitaire est l'allocation efficace de ressources rares dans un contexte opérationnel complexe. L'application de méthodes basées sur la recherche opérationnelle dans ce domaine est de plus en plus populaire (voir Van Wassenhove and Martinez, 2012, et Naji-Azimia et al., 2012, pour des exemples récents). Dans ce dernier chapitre, nous présentons et résolvons un problème de conception de réseaux tactiques pour la distribution de denrées alimentaires au Kenya. La distribution de l'aide alimentaire en Afrique de l'Est s'affecte principalement dans une perspective de développement à long terme puisque l'insécurité alimentaire, caractérisée par des chocs périodiques, persiste depuis plusieurs années. Le Kenya, comme les autres pays de l'Afrique sub-saharienne, est sujet à des sécheresses au début et à la fin de deux saisons des pluies irrégulières, lesquels ont un impact important sur la capacité des populations à se nourrir sans le soutien d'organismes humanitaires. Nous présentons un modèle de localisation pour déterminer l'ensemble des centres de distribution actifs et l'affectation de la population à ses centres de distribution. Le défi de ce projet réside davantage dans la modélisation du problème, incluant la collecte et le traitement des données pour l'étude d'un cas réel, que dans le développement algorithmique. En effet, l'accès aux des données est limitée dans les pays en développement comme le Kenya. Pour cette étude, nous avons recueilli des données sur l'évaluation des besoins en aide alimentaire subséquente à la saison courte des pluies de 2012, ainsi que des données démographiques maillées et des données relatives aux infrastructures routières avec des systèmes d'information géographique. Cette collecte de données été facilitée par une observation directe sur le terrain et par la collaboration d'organismes impliqués dans la distribution de denrées alimentaires. Ce projet a été réalisé en collaboration avec la Croix-Rouge du Kenya et avec Kimetrica, un prestataire de services conseils et de logiciels

spécialisés dans la gestion de projets appliqués au secteur humanitaire, ainsi qu'avec la participation du PAM.

Dans le dernier chapitre de cette thèse, nous expliquons dans un premier temps les principales opérations dans le contexte de distribution d'aide alimentaire et nous présentons la chaîne d'approvisionnement qui en résulte. Dans un deuxième temps, nous présentons notre modèle principal localisation d'entrepôts dans lequel on prend en compte les coûts rattachés au bien-être de tous les acteurs impliqués dans ce système de réponse : le gouvernement, le Programme Alimentaire Mondial, la Croix-Rouge et les bénéficiaires. En incorporant des coûts d'opportunité associés à la collecte de denrées alimentaire, nous cherchons à démontrer et à quantifier l'importance de valoriser le temps des bénéficiaires, qui constitue une contribution intéressante pour la conception de réseaux de distribution. Afin de résoudre ce problème, nous décrivons comment nous avons combiné l'information provenant de l'évaluation des besoins en aide alimentaire avec des données démographiques maillées pour évaluer la répartition de la demande dans la région de Garissa et ses environs. Nous montrons aussi comment nous avons exploité de l'information géographique sur le réseau routier afin de déterminer l'ensemble des centres de distribution potentiels, où la nourriture est directement distribuée aux bénéficiaires. En plus des résultats obtenus grâce à la résolution de notre modèle principal, nous présentons les résultats provenant de diverses analyses de sensibilité, de comparaisons de solutions résultant de modèles de couverture classiques ainsi que des illustrations cartographiques de réseaux de distributions optimaux. Bien que notre analyse ait été effectuée sur un problème relatif à la région de Garissa, notre méthodologie s'applique à d'autres pays en développement dans un contexte de planification de la distribution de denrées alimentaires. L'article "Tactical Network Planning for Food Aid Distribution in Kenya" résultant de ce chapitre sera soumis sous peu à la revue *Production and Operations Management*.

Première partie

Planification de tournées de véhicules de longue durée avec contraintes d'heures de service. Le cas de l'Amérique du Nord

Chapitre 2

Long-Haul Vehicle Routing and Scheduling with Working Hour Rules

Chapter information

An article based on this chapter was published in *Transportation Science*: M.-È. Rancourt, J.-F. Cordeau and G. Laporte. Long-haul vehicle routing and scheduling with working hour rules. *Transportation Science*, 47(1): 81–107, 2013.

Abstract

Long-haul carriers must comply with various safety rules which are rarely taken into account in models and algorithms for vehicle routing problems. In this paper, we consider the rules on truck driver safety during long-haul trips in the United States. The problem under study has two dominant features: a routing component that consists in determining the sequence of customers visited by each vehicle, and a scheduling component that consists in planning the rest periods and the service time of each customer. We have developed different scheduling algorithms embedded within a tabu search heuristic. The overall solution methods were tested on modified Solomon instances, and the computational results confirm the benefits of using a sophisticated scheduling procedure when planning long-haul transportation.

Keywords: Vehicle routing, trip scheduling, multiple time windows, driver rules, HOS regulation, enumeration procedure, tabu search heuristic.

2.1 Introduction

In long-haul transportation, the distances traveled by truck drivers during a journey can be considerable and drivers often have to be on the road for several consecutive days. This is in contrast with classical vehicle routing problems (VRPs) in which all requirements are typically fulfilled within the same day. As a result, truck driver fatigue is often a contributing factor to serious accidents in long-haul transportation. To reduce fatigue and improve safety, several western countries have adopted legislations which regulate the amount of time long-haul truck drivers can drive without a rest over a given period. Trucking companies are monitored, and non-compliance with the legislation can result in substantial fines. Accordingly, legislative requirements should be considered when planning long-haul vehicle routes. However, these requirements are rarely considered in the vehicle routing literature or in routing and scheduling software.

The aim of this paper is to present, model and solve a rich vehicle routing problem arising in the less-than-truckload industry, and which takes into account the legislative requirements on work and rest hours in the United States (US). We solve the problem by means of scheduling algorithms embedded within a tabu search heuristic. Our study is motivated by the case of Groupe Robert Inc., one of the largest and best known Canadian third-party logistics providers, but our contribution is of general applicability. In addition to the US regulations, our study also takes into account other constraints sometimes considered in VRPs, such as multiple time windows and heterogeneous fleet constraints. Multiple time windows are assigned to each customer since the problem extends over several days, but customers are visited only once.

The legislation stipulates for how long commercial vehicle drivers may drive without resting during long-haul trips and three restrictions are generally imposed. First, a driver can only cumulate a certain number of driving hours between two consecutive rest periods. Second, a driver may not drive beyond a given number of consecutive hours after resuming duty following a rest. These two restrictions are meant to ensure that a driver does not work over a prescribed limit within a certain time interval. Third, a driver may not drive after being on-duty for a maximum cumulated time within a certain number of consecutive days following an off-duty period of more than a prescribed time.

Similar legislations are also enforced in several other countries. For example, the European Union (EU) has adopted regulation No 561/2006 (the EU regulation) which sets restrictions on driving hours and limits the working hours of drivers. Although similar in objective, the provisions of the American regulations are different from those of Europe. The main differences stem from the more restrictive nature of the EU regulation which requires additional breaks after specified working time periods. In fact, in addition to

daily rest periods, the EU regulation stipulates that short breaks must be scheduled after certain driving time intervals. Other rules and alternative provisions also apply.

2.1.1 Literature review

Several solution approaches have been proposed to deal with working hour restrictions and driver break scheduling requirements within the VRP. Rochat and Semet (1994) model rest breaks as fictitious customers, whereas Cordeau et al. (2002) treat them as arcs in a multi-stage network. Desaulniers et al. (1999) have shown that maximum working time constraints can be handled within constrained shortest path algorithms by means of resource constraints like those used for time and load variables. Campbell and Savelsbergh (2004) have presented a modified insertion heuristic to handle maximum shift time limits for drivers. Savelsbergh and Sol (1998) incorporate breaks and daily rests into a branch-and-price algorithm for a general pickup and delivery problem. Kok et al. (2011) have proposed a sequential insertion heuristic for the VRP with time windows (VRPTW) and time-dependent travel times. They have developed an integer linear programming (ILP) model for the vehicle departure time optimization problem in which the EU regulations are considered in a one-day planning horizon and where drivers may only take a break at specified locations. Dealing with legislation on working hours for several days cannot be treated as a basic break scheduling problem because these problems are defined over a multi-day horizon and there are interactions between days. The authors have extended their ILP formulation to a multi-day planning horizon but have not tested it numerically.

A number of authors have developed algorithms incorporating the EU or US regulations. Goel and Gruhn (2006) consider the maximum driving time restriction imposed by the EU regulation within a VRPTW and solve the problem by means of a large neighbourhood search algorithm. Goel (2009) subsequently improved this methodology, although his research is focused on the basic provisions of the EU regulation and does not consider some of the alternative provisions of this regulation. The author has applied a large neighbourhood search algorithm to modified Solomon (1987) test instances for the VRPTW. In their consideration of the EU regulation within a VRPTW, Kok et al. (2010) present a basic break scheduling method embedded within a dynamic programming framework. Prescott-Gagnon et al. (2010) have proposed a large neighbourhood search algorithm based on a column generation heuristic to solve the problem. This method relies on a tabu search for generating routes (columns) and a labeling algorithm to check their feasibility. Kok et al. (2010) and Prescott-Gagnon et al. (2010) have introduced in their algorithms the alternative EU provisions that were not considered by Goel (2009). The algorithm developed by Prescott-Gagnon et al. (2010) outperforms those of Goel (2009)

and Kok et al. (2010) on VRP benchmark instances. However, these methods may not consider some routes within the optimization process because the truck driver scheduling algorithm they use is sometimes unable to find a feasible solution. Goel (2010) presents a procedure that always identifies a feasible schedule satisfying the EU regulation whenever one exists but, to our knowledge, this method has not yet been embedded within an overall algorithm for the combined VRP and truck driver scheduling problem.

Zäpfel and Bögl (2008) and Bartodziej et al. (2009) have worked on vehicle routing problems stemming from real case studies and incorporating rest constraints specified by the EU regulation. Zäpfel and Bögl (2008) have presented a two-phase heuristic for a complex combined vehicle routing and personnel assignment problem, including outsourcing decisions. A VRP is solved during the first phase by a tabu search or by a genetic algorithm. An assignment problem is solved heuristically during the second phase. Bartodziej et al. (2009) have studied a block planning problem that deals with time windows, rest regulations and a heterogeneous fleet. They have combined a column generation heuristic and a large neighbourhood search with two types of neighbourhoods.

To our knowledge, the only North Americain regulations considered in a routing context are those of the US Department of Transportation (DOT). These were first considered by Powell (1996) who presented a hybrid model that takes into account forecast demands to perform dynamic routing and driver scheduling. The simulator used to test Powell's model integrated the version of the DOT regulations that were then in force. The first paper that explicitly integrates DOT regulation driver restrictions in a VRP is due to Xu et al. (2003). These authors have proposed a column generation algorithm in which DOT regulations are handled in the subproblem which is solved by means of a fast heuristic. Ceselli et al. (2009) have worked on a rich problem embodying several operational difficulties arising in real-world applications, among which they consider a working time limit before a rest. They have developed a column generation algorithm in which the pricing problem is a particular resource-constrained elementary shortest-path problem solved by a bounded bidirectional dynamic program. However, the scheme used to schedule rest periods is rather basic. A rest is inserted only when no more driving time is available, so that the possibility of resting before the allowable driving time is depleted is not considered. As shown by Archetti and Salvelsbergh (2009), not using early rests means that some feasible customer sequences are considered to be infeasible.

More recently, some authors have focused their attention on the difficulty of constructing a feasible schedule for a given sequence of customers in conformity with a country legislation, a problem called the truck driver scheduling problem (TDSP). The two following studies take into account the Federal Motor Carrier Safety Administration's Hours of Service (HOS) regulations for commercial vehicle drivers (49 Part 395), the latest DOT

working hour rules, and concentrate on the trip scheduling problem rather than on the VRP. Archetti and Salvelsbergh (2009) have considered the problem of determining how a sequence of full truckload transportation requests, each with a dispatch window at the origin, can be executed by a driver in conformity with the HOS regulations. They have developed an algorithm, called SMARTRIP, to schedule the working and driving hours of a driver. It finds a feasible schedule in polynomial time, if one exists. Goel and Kok (2012) have also studied a TDSP in which each location must be visited within one of several time windows, and have presented a scheduling method capable of finding a feasible schedule in polynomial time if one exists. They have shown that the complexity of their algorithm for the case of single time windows remains the same in the case of multiple time windows when there is a gap of at least ten hours between them. Goel (2011) has proposed a mixed integer programming formulation which can handle different sets of rules, as well as a dynamic programming algorithm for a variant of the truck driver scheduling problem in which truck drivers may only rest at customer locations or at prespecified parking lots. Like Kok et al. (2011), the objective is to find a schedule of minimal duration. The dynamic approach have been tested for the US and EU regulations on a multi-day planning horizon. Goel and Rousseau (2012) have studied the TDSP under the Canadian Commercial Vehicle Driver Hours of Service Regulations, and Goel et al. (2012) have analyzed this problem under the Australian Heavy Vehicle Driver Fatigue Law.

2.1.2 Scientific contribution

The problem considered in this paper differs from those addressed by the above mentioned authors. First, the US regulations and the EU regulations are different. The EU regulations are more restrictive than the US regulations and several alternative provisions can be applied. This being said, in the problem considered by Goel (2009), Kok et al. (2010), and Prescott-Gagnon et al. (2010), a single wide time window is associated with each customer and only one vehicle type is used. In the present paper, we consider multiple time windows for each customer and a heterogeneous fleet of vehicles. In addition, we analyze the impact of considering the total schedule duration as opposed to only minimizing the total distance traveled. We integrate the labor costs of drivers in the routing and scheduling processes to better represent the cost of operating a vehicle in practice. Second, we extend the ideas of the authors who have considered the HOS regulations by including, in the scheduling process, the possibility for the driver to split a rest into two shorter periods spent in the sleeper berth. We also embed sophisticated trip scheduling modules that can deal with multiple time windows for the combined vehicle routing and driver scheduling problem, an alternative not yet treated in the papers that have dealt with the HOS regulations. Third, in the scheduling process, we heuristically

minimize the duration of the planned trips rather than only trying to find a feasible schedule. Goel (2011) has solved a variant of the TDSP under this objective, but not in conjuction with routing optimization. Kok et al. (2011) have also minimized route durations in the context of single time windows under the EU regulations with a one-day planning horizon. Recently, Goel and Rousseau (2012) and Goel et al. (2012) have studied the TDSP under the Canadian and Australian regulations, respectively. In this paper, we solve the VRP with multiple time windows under the US regulations with a multi-day planning horizon and we consider a heterogeneous fleet of vehicles for a practical case. Table 2.I summarizes these contributions.

The remainder of the paper is organized as follows. In Section 2, we provide a description of the constraints and objectives of the problem. The algorithms we have developed are described in Section 3. The computational results obtained on artificial and real-life instances are presented in Section 4, followed by conclusions in Section 5.

2.2 Constraints and objectives

We consider a VRP with multiple time windows (VRPMTW) that combines scheduling rest periods for drivers in conformity with the US regulations, as well as other typical VRP constraints. We begin by describing the VRP and its constraints. We then elaborate on the work regulations in greater detail. Finally, we introduce three alternative objective functions for the problem.

2.2.1 Vehicle routing and scheduling constraints

We first describe the basic concepts of the VRPMTW. Given a set of vehicles based at a depot, the problem consists in determining a set of feasible routes to serve a set V of customers in order to minimize a given objective. The depot is denoted by 0 and we define $V_0 = V \cup \{0\}$. Let c_{ij} be the travel distance between i and j, where $i, j \in V_0$, and let d_{ij} be the driving time to reach j from i. The problem is solved over a planning horizon of length H. A unique time window $[\tau_{1,0}^{\min}, \tau_{1,0}^{\max}]$ of length H is associated with the depot, where $\tau_{1,0}^{\min}$ and $\tau_{1,0}^{\max}$ represent the earliest possible departure from the depot and the latest admissible arrival at the depot, respectively.

Many companies provide customized transportation services to meet their customer requirements, which may lead to the use of a heterogeneous fleet of vehicles suited to various functions (e.g. refrigerated vehicles, tank-trucks, livestock transportation vehicles, etc.). Consequently, we consider a heterogeneous vehicle fleet in this study. Every customer $i \in V_0$ has a non-negative demand q_i and can be served only by a subset of the

Table 2.I: Summary of the main references related to our problem

Article	Problem		Regulations				Time Windows		Objectives					Horizon	
									Routing			Scheduling			
	Routing & scheduling	Scheduling	EU	US	CAN	AUS	Multiple	Single	Dist.	Dur.	Cost	None	Time cost	Several days	One day
Archetti and Salvelsbergh (2009)		✓		✓				✓				✓		✓	
Ceselli et al. (2009)	✓			✓[a]				✓			✓	✓		✓	
Goel (2009)	✓		✓					✓	✓			✓		✓	
Goel (2011)		✓	✓	✓			✓						✓	✓	
Goel and Kok (2012)		✓		✓			✓					✓		✓	
Goel and Rousseau (2012)		✓			✓			✓				✓		✓	
Goel et al. (2012)		✓				✓		✓				✓		✓	
Kok et al. (2011)	✓		✓					✓	✓			✓		✓	
Kok et al. (2010)	✓		✓					✓		✓			✓		✓
Prescott-Gagnon et al. (2010)	✓		✓					✓	✓			✓		✓	
Xu et al. (2003)	✓			✓			✓				✓		✓	✓	
This paper	✓			✓			✓		✓	✓	✓		✓	✓	

[a]The legislation considered in this study is not specified, but the applied rules are very similar to the US regulations.

vehicle fleet. Every vehicle type has a given load capacity which cannot be exceeded by the total demand it carries. Moreover, a restriction on on-duty time has to be imposed to prevent overloaded work schedules for drivers. A driver can be on-duty for a maximum of h^{total_duty} hours during the planning horizon and this restriction translates into a duration constraint on the vehicle routes.

An ordered set of time windows $T_i = \{[\tau_{ti}^{\min}, \tau_{ti}^{\max}], t = 1, \ldots, \bar{t_i}\}$, with $\tau_{t-1,i}^{\max} \leq \tau_{ti}^{\max}$ $(t = 2, \ldots, \bar{t_i})$, is associated with each customer i to determine the time intervals within which delivery is allowed. Each customer $i \in V_0$ must be visited once by a vehicle during w_i time units, without service interruption. Consequently, a single time window has to be chosen for each customer delivery. If a vehicle arrives before the opening of this time window, it has to wait. It must also arrive before the closing of the selected time window, for otherwise the driver will have to wait until the opening of the next available time window, if one exists.

2.2.2 Working hour constraints

In this paper, we consider the HOS regulations for commercial vehicle drivers (Part 395 of the Federal Carrier Safety Regulations) which have been in force in the US since January 2009. By law, every driver operating a commercial vehicle during a long-haul trip in America is required to record his duty status for each 24-hour period on a specific grid in a log book (Figure 2.1). A change of duty status has to be registered as one of the following four possible states: driving, on-duty, off-duty, or sleeper berth. These states, as defined in Section 395.2 of the HOS regulation, can be described as follows.

Driving: Driving time is the total time spent at the driving controls of a commercial vehicle in operation, even when the vehicle is stuck in a traffic jam.

On-duty: On-duty time means all the time a driver is performing work for any employer or is required to be available for work. Accordingly, this time is computed from the moment a driver begins work until he is relieved from work. On-duty time includes the following activities: 1) driving time; 2) time spent at a property of a carrier or a shipper, unless the driver has been relieved from duty; 3) time remaining in readiness to operate a commercial vehicle; 4) time spent inspecting, servicing, or conditioning any commercial vehicle; 5) time spent in or upon any commercial vehicle, except time spent resting in the sleeper berth; 6) time spent loading, unloading, supervising or attending a commercial vehicle; 7) time spent handling paperwork for shipments; 8) time spent repairing or remaining in attendance upon a disabled commercial vehicle; 9) time spent performing any compensated work for a person who is not a carrier.

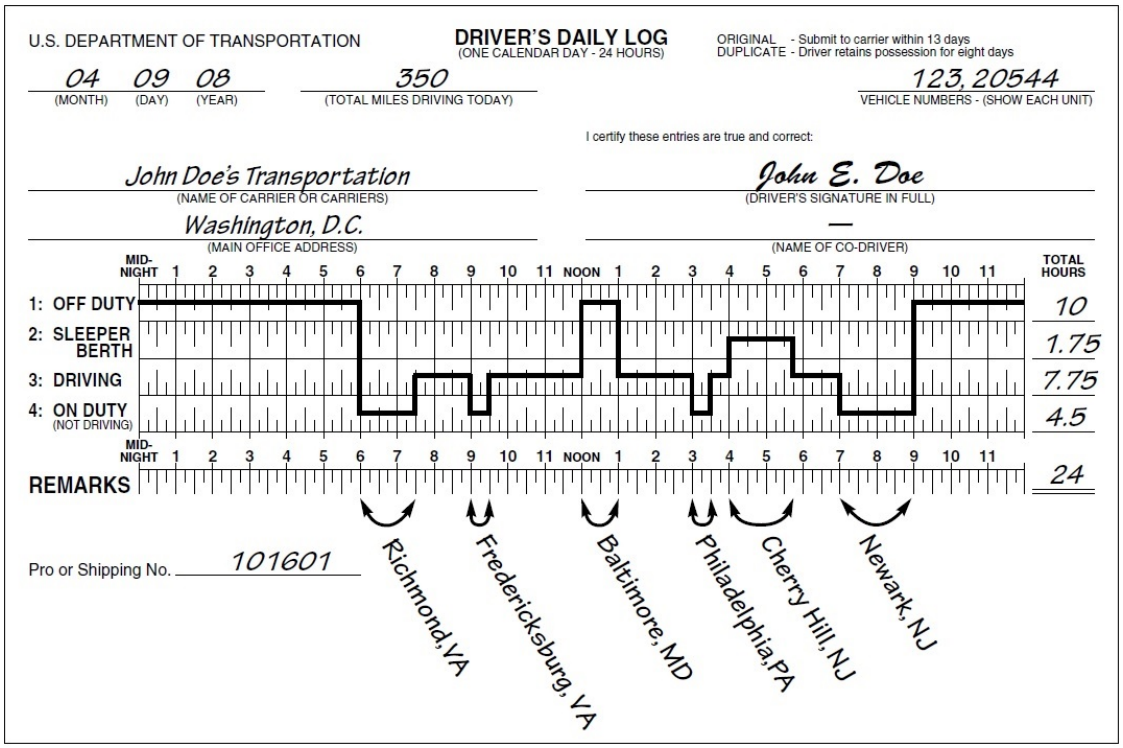

Figure 2.1: Illustration of a completed driver's log for one working day (Federal Motor Carrier Safety Administration, 2010).

Off-duty: When off-duty, drivers have no obligation to perform any work. They are free to pursue any activity and are allowed to leave the place where the vehicle is parked.

Sleeper berth: The time the driver is in the sleeper berth of a commercial vehicle in conformity with specific requirements.

The HOS restrictions on driving periods (Part 365.3) are summarized in Tables 2.II and 2.III. These regulations place specific limits on driving and on-duty time before the driver of a commercial motor vehicle is no longer permitted to drive without resting. Table 2.II describes the three fundamental rules: the 60/70-hour on-duty limit, the 11-hour driving limit and the 14-hour limit. The first rule enforces a limit on on-duty time during a specific number of consecutive days. In this case, we use the 70-hour on-duty limit to be consistent with the policy applied by Groupe Robert. The idea would have remained the same if, instead of applying the 70-hour on-duty limit rule, the restriction with a limit of 60 working hours during a period of seven consecutive days had been applied. The second rule limits to 11 hours the driving time after an off-duty period of 10 hours. The third rule forbids driving after an on-duty period of 14 hours beginning at the end of an off-duty period of 10 hours. A driver can also use the sleeper berth provision to

get the equivalent of 10 consecutive off-duty hours with two separated split rest periods, see Table 2.III.

Table 2.II: Hours of service rules

60/70-hour on-duty limit	A driver cannot drive after 70 hours on-duty in seven/eight consecutive days. He may restart an eight consecutive day period after 34 or more consecutive hours off-duty.
11-hour driving limit	A driver may only drive a maximum of 11 hours after 10 consecutive hours off-duty.
14-hour limit	A driver cannot drive beyond the 14^{th} consecutive hour after coming on-duty, following 10 consecutive hours off-duty. Off duty time does not expand the 14-hour period.

The benefit of using the sleeper berth provision is to extend the 14-hour limit. Any period of at least eight consecutive hours spent in a sleeper berth will not be included in the 14-hour horizon. This allows a driver to extend the time during which he can use the 11 hours of driving as long as the conditions described in Table 2.III are respected. Two separate split rest periods of less than 10 hours are required: at least eight consecutive hours spent in the sleeper berth (long split rest) and at least two consecutive hours spent in the sleeper berth or off-duty (short split rest). Any of these two periods can be taken first. When the second required rest split period is completed, a new calculation point starting at the end of the first rest split period initiates the 14-hour limit. As in the basic rules, it is prohibited to drive after 14 hours from this point. However, a long split rest is not counted as part of the 14-hour limit, but the short one is.

Table 2.III: Sleeper berth provision

Sleeper berth partial rest periods	Drivers using the sleeper berth provision must spend: 1) at least eight consecutive hours (but less than 10 consecutive hours) in the sleeper berth; 2) a separate period of at least two consecutive hours (but less than 10 consecutive hours) either in the sleeper berth, off-duty, or in any combination of the two.
Driving and duty limits with partial rest periods	After the second required rest period is completed, a new calculation point for the 14-hour limit, starting at the end of the previous rest period, will have to be considered to determine the available on-duty and driving hours. In this calculation, only the period in the sleeper berth of at least eight consecutive hours will not be counted as part of the 14-hour limit; a period of less than eight hours will. The sleeper berth provision can be used continually until 10 consecutive hours off duty are taken. After 10 consecutive hours off duty, a driver has 11 hours of driving time and 14 hours of duty time available again.

In summary, a driver can drive at most h^{drive} hours and can be on-duty at most h^{on_duty} hours before a prescribed rest of at least h^{rest} hours has to be taken to gain the right to drive again. In fact, a rest period has to start at the latest when the driving

limit or the on-duty limit is reached. Duty time consists primarily of driving, waiting and service time. When a driver makes use of the sleeper berth provision, he has to take a rest of at least h^{long_berth} consecutive hours and another one of at least h^{short_berth} consecutive hours. In such a case, the driving limit and the on-duty limit remain. Moreover, a driver can be on-duty for at most h^{total_duty} during a horizon of H consecutive unit of time. According to the HOS regulations, we can set the parameters as follows:

- $h^{total_duty} = 70$ hours, the maximal cumulated on-duty hours during eight consecutive days;
- $h^{rest} = 10$ hours, the minimal duration of a rest period to regain driving time;
- $h^{drive} = 11$ hours, the maximal cumulated driving hours between two rest periods;
- $h^{on_duty} = 14$ hours, the maximal cumulated on-duty hours after which it is illegal to drive before resting;
- h^{long_berth} = eight hours, the minimal duration of a long rest split period when a rest is split in conformity with the sleeper berth provision;
- h^{short_berth} = two hours, the minimal duration of a short rest split period when a rest is split in conformity with the sleeper berth provision;
- H = eight days, the number of consecutive days during a planning horizon.

2.2.3 Objective functions

In studies in which driver working hours are considered (see Section 2.1.1), the primary objective is typically to minimize the number of vehicles used in the solution, and the secondary objective is to minimize the total distance traveled. However, minimizing this objective without considering driver schedules may yield unacceptable solutions such as long routes with significant resting times. To avoid such situations we consider the total trip duration as a secondary objective. For the artificial instances, the problem is solved twice, with each of the two different objectives. The solutions obtained can then be compared and the selection of the best compromise solution is left to the decision maker. In other words, we apply a lexicographic process by which the decision maker can predefine an order between the different objectives and then optimize these one at the time.

To solve the problem of Groupe Robert, we minimize the number of vehicles used in the solution, and then the real routing cost. This cost is in fact a weighted sum of the total traveled distance and total duration. In this case, we optimize a unique objective

function reflecting the real routing cost since the unit costs for a driver per hour and for the truck per kilometer are known.

2.2.4 Illustrations

Figure 2.2 depicts a feasible solution for a VRPMTW with working rules. Each horizontal line represents either a time line for the depot (the top and the bottom lines) or for a customer. The demand of each customer is indicated on the left-hand side of their time line and the capacity of each vehicle is equal to 10 units. The square brackets and associated values on a time line represent the time windows associated with the corresponding customer. The numbers in the middle of the double arrows on the right-hand side show the driving times between locations. A vehicle trip is represented by a path that reads from the top left corner to the bottom right corner. More precisely, a path between the two depot time lines represents a driver's schedule. An inclined black segment means that the driver is driving, whereas a horizontal segment represents working time (dark dotted line) or resting time (light grey line). A dotted light grey line shows that the rest period is longer than the prescribed resting time h^{rest}. A customer is served by a driver when a dark dotted line appears in a time window. In Figure 2.2, a first vehicle serves customers 1, 2 and 3, and a second one serves customers 4 and 5.

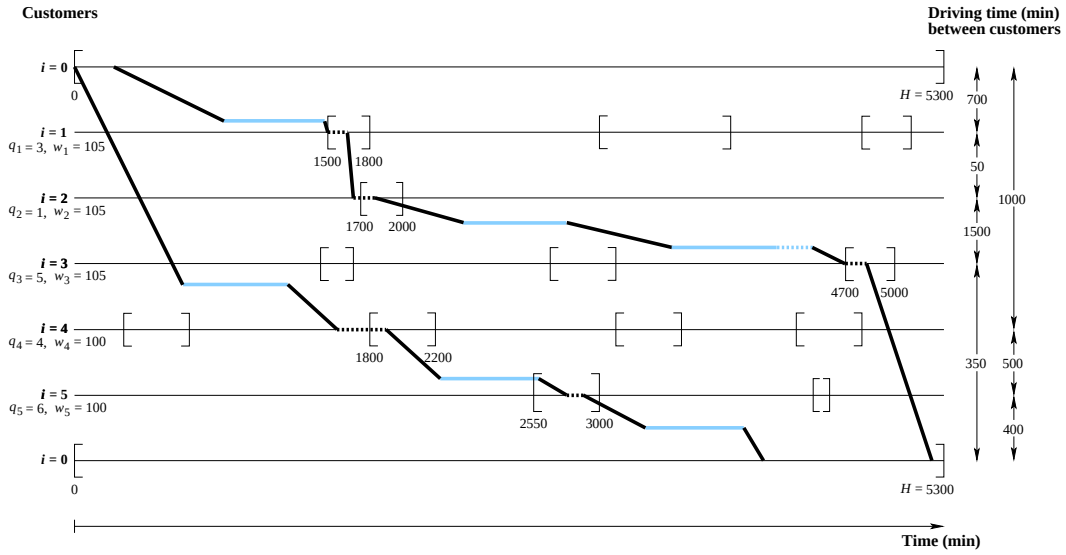

Figure 2.2: Illustration of a feasible solution for a VRPMTW with working hour rules. An inclined black segment represents driving time, whereas a horizontal segment represents working time (dark dotted line) or resting time (light grey line). A customer is served by a driver when a dark dotted line appears in a time window.

Figures 2.3, 2.4 and 2.5 illustrate different scheduling possibilities to serve a sequence of three customers with the following characteristics:

- $i = 1$, $w_1 = 120$ min., and $T_1 = \{[0, 90], [1500, 1700]\}$;
- $i = 2$, $w_2 = 60$ min., and $T_2 = \{[40, 250], [780, 1260]\}$;
- $i = 3$, $w_3 = 60$ min., and $T_3 = \{[150, 650], [1150, 1440]\}$;
- $d_{01} = 90$ min., $d_{12} = 540$ min., and $d_{23} = 30$ min.

Figures 2.3 and 2.4 depict the two possible schedules to serve the customers when taking into account the basic HOS rules, and Figure 2.5 illustrates a schedule respecting the sleeper berth provision. This example also illustrates the computation of the 11-hour driving limit and the 14-hour limit, and shows that a feasible schedule can only be found when making use of the sleeper berth provision. We suppose that before leaving the depot, the driver has completed a rest of at least 34 hours so that the previous on-duty activities do not have an influence on the subsequent ones.

The only way to serve customers 1 and 2 in time is to leave the depot at time zero, drive and serve customer 1 directly, which implies that a calculation point (cp_1) for the 14-hour limit starts at time zero so the driver cannot drive after time 840 without resting. There are then two ways of serving customer 2 considering the basic HOS rules. The first, shown in Figure 2.3, is to wait before serving customer 2 until the opening of its second time window. In this case, the driver must take a rest before driving to customer 3 because the 14-hour limit is reached, this even if there remain 30 minutes of driving time according to the 11-hour driving limit. The driver drives to customer 3 after taking a rest, but customer 3 is reached too late to be served on time. The second possibility, shown in Figure 2.4, is to rest before serving customer 2. However, customer 2 cannot be served on time in this case since the driver finishes his rest after the closing of all time windows. This shows that there is no feasible schedule for the sequence of customers 1, 2 and 3 when only considering the basic HOS rules.

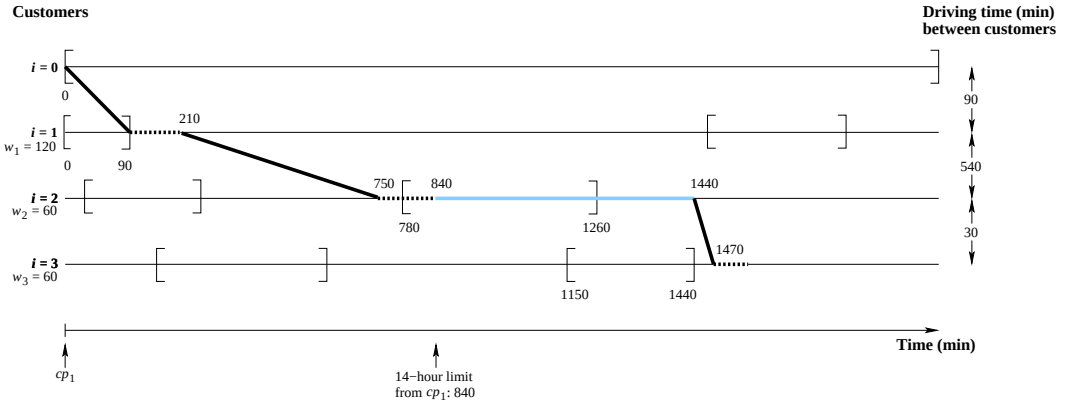

Figure 2.3: Illustration of a non-feasible solution by using the basic rules and serving customer 2 directly without resting.

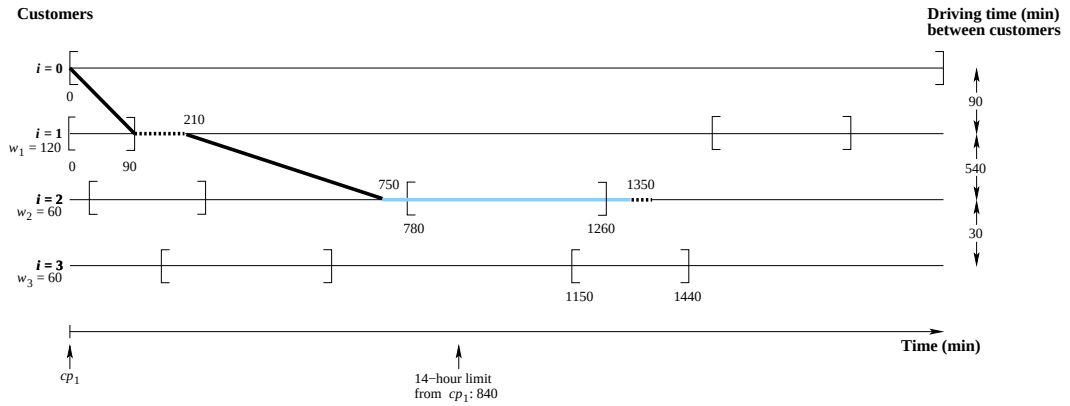

Figure 2.4: Illustration of a non-feasible solution by using the basic rules and serving customer 2 after resting.

Figure 2.5 illustrates how the sleeper berth provision can be exploited to find a feasible schedule for the sequence of customers 1, 2 and 3. The driver schedule is the same as in Figure 2.4 until customer 2 is reached, but the driver takes a rest period of eight hours in the sleeper berth instead of taking a complete rest. Consequently, the 14-hour limit is pushed forward at time 1320 because rest periods of at least eight hours in the sleeper berth are not taken in consideration in the 14-hour limit calculation. After a long split rest in the sleeper berth, customer 2 can be served on time and the driver immediately continues his route to customer 3, and reaches this customer before the closing of its time window. This shows that a feasible schedule can be determined for serving the sequence of customers 1, 2 and 3 when considering the HOS rules and using the sleeper berth provision.

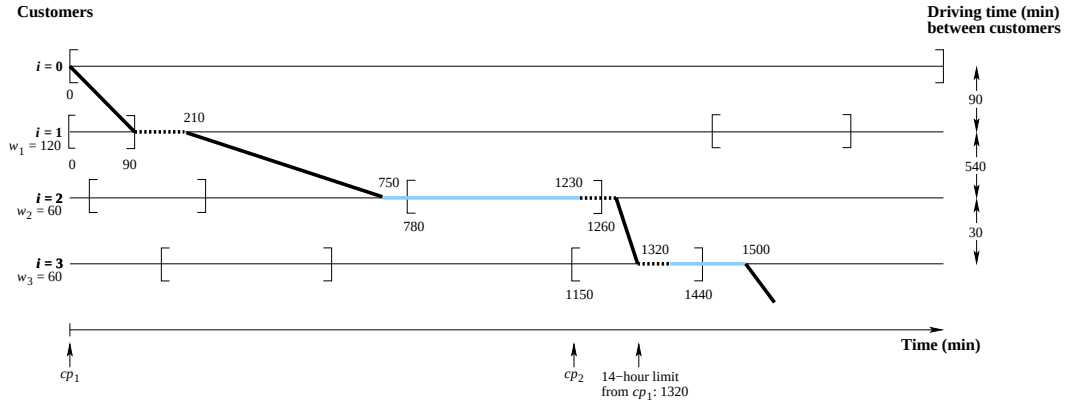

Figure 2.5: Illustration of a feasible solution by using the sleeper berth provision and serving customer 2 after taking a resting period of eight hours.

To illustrate the apparition of the new calculation point when the sleeper berth provision is used, we suppose that customer 3 is served as soon as this customer is reached as illustrated in Figure 2.5. After customer 3 has been served, the driver takes a two-hour rest in the sleeper berth. This is necessary since the 11-hour driving limit and the

14-hour limit are reached at this point, which implies that driving is prohibited without completing the rest periods in the sleeper berth. Another possibility, not illustrated in the figure, would have been to take the short split rest of two hours (off-duty or in the sleeper berth) before performing the service. After completing the two-hour period, the calculation point for the 14-hour limit moves to the end of the eight-hour period spent in the sleeper berth to form the new calculation point (cp_2) for the remaining activities. Note that for the following resting period, the driver can end the rest splits in the sleeper berth by taking a complete rest or continue the rest splits by taking a long split rest of at least eight hours, but no more than ten hours, in the sleeper berth.

2.3 Tabu search heuristic

The problem under study contains two dominant features: a routing component consisting of determining the sequence of customers visited by each vehicle, and a scheduling component consisting of planning the rest periods and the service time of each customer. Therefore, we have developed several scheduling algorithms embedded within a routing heuristic. Our algorithm for the VRPTW with HOS regulations is based on an updated version of the Cordeau et al. (2001) unified tabu search algorithm (UTSA). This heuristic has been proven to be effective and flexible for a variety of VRPs. In the following, we will summarize the main features of the tabu search and detail the scheduling algorithms that can handle the HOS regulations.

2.3.1 Outline of the tabu search heuristic

The algorithm starts with an initial solution x_0, obtained with a simple constructive procedure, and moves at each iteration from a solution x of value $f(x)$ to another solution in the neighbourhood $N(x)$ of x. The neighbourhood $N(x)$ consists of all solutions that can be obtained by applying a given type of transformation to x. An attribute set $B(x) = \{(i,k) : i \in V, k = 1, ..., m\}$ is associated with solution x and indicates on which route k each customer i is visited. A neighbour solution is obtained by replacing a pair $(i,k) \in B(x)$ by another non-tabu pair $(i,k') \notin B(x)$. The attribute (i,k) is then declared tabu for a fixed number of iterations. However, an aspiration criterion allows the search process to accept a solution x containing a tabu attribute (i,k) if this solution is the best known solution with this attribute. The search can be broadened by accepting intermediate infeasible solutions. This is achieved through the use of a penalized objective functions with self-adjusting penalties. Let $q(x)$ be the violation of capacity constraints, $d(x)$ the violation of on-duty constraints emerging from the 70-hour limit, $v(x)$ the violation of time window constraints, $c_0(x)$ the fleet cost equal to a large

constant M multiplied by the number of vehicles used in the solution x and $c_z(x)$ the cost of the solution x with $z = 1, 2,$ and 3. Three cost evaluations of a solution have been separately considered in this study: $c_1(x)$ being the total traveled distance, $c_2(x)$ the total trip duration, and $c_3(x)$ a weighted sum of $c_1(x)$ and $c_2(x)$ representing the routing cost of Groupe Robert. The global cost functions are:

$$f_z(x) = c_0(x) + c_z(x) + \alpha q(x) + \beta d(x) + \gamma v(x), \quad z = 1, 2, \text{ and } 3,$$

where the parameters α, β and γ are dynamically updated throughout the search. After each iteration, the values of these parameters are modified by a factor of $1+\delta$, where δ is chosen randomly in the interval $[0, 1]$ at each iteration. If the current solution is feasible with respect to a constraint, the value of the parameter associated to this constraint is divided by $1 + \delta$, and it is multiplied by $1 + \delta$ otherwise. We note that f_1 and f_2 are separately optimized to solve the artificial instances with multiple time windows, f_3 is optimized when solving the real-life problem of Groupe Robert and f_1 is optimized to solve the artificial instances with single time windows. Diversification and intensification mechanisms are also used to improve the search. The goal of the diversification is to penalize solutions containing frequently encountered attributes, whereas intensification is a process aimed at deepening the search around good solutions.

In our problem, multiple time windows and the HOS regulations are integrated during route construction. To evaluate on-duty and time window violations of a route, a schedule complying with the HOS regulations is first determined. Before calculating the cost of a solution $x' \in N(x)$, a rest scheduling algorithm generates a schedule for the given modified sequence of nodes in x' in order to assess the cost impact of the modification.

In addition, operators favouring the minimization of the number of vehicles in the solution have also been implemented within the tabu search. Every time a feasible solution with m' vehicles is found and this value is smaller than the least known number of vehicles in any feasible solution, the upper bound on the number of vehicles available is fixed to $m' + 1$. This way, the possibility of moving customers to an empty trip remains, which ensures a certain flexibility in the search. A trip destruction operator has also been added to the tabu search procedure, but only when the secondary objective is to minimize the total distance. Every 100 iterations within the first 500 iterations, and every 500 iterations thereafter, the trip with the shortest duration is destroyed and its customers are moved sequentially into another route. This procedure is not applied when the secondary objective is to minimize the total duration because destroying the trip of shorter duration conflicts with this objective.

The trip destruction mechanism is applied more often early during the search process, i.e. during the first 500 iterations, since the best found solution is more often improved at

the beginning of the tabu search. The disturbances are initially spaced by 100 iterations to allow the process to perform a deeper search around the perturbed solution with the aim of identifying a feasible solution with one fewer vehicle. Subsequently, the solution is less often disturbed because it then becomes harder to reduce the number of vehicles.

2.3.2 Scheduling heuristics

Goel and Kok (2012) have presented a search scheme for an algorithm that generates all non-dominated feasible driver schedules for an ordered sequence of λ customers under the assumption of non-splittable rest periods. This algorithm solves the single time window US truck driver scheduling problem (US-TDSP) in $O(\lambda^2)$ time and it is shown that the same complexity can be achieved when the gap between subsequent time windows is at least ten hours. Empirical results indicate that the computational effort does not increase considerably in the case of multiple time windows. We have modified this procedure to develop two fast scheduling heuristics embedded within our tabu search heuristic. Algorithm 2.1 only considers complete rest whereas, in contrast to Algorithm 2.1 and the one of Goel and Kok (2012), Algorithm 2.2 allows split rests in accordance with the sleeper berth provision. These methods are heuristics that perform a less exhaustive search than that of Goel and Kok (2012) because they do not generate all Pareto-optimal solutions.

The main differences between the procedure developped by Goel and Kok (2012) and our implementations is that the search is restricted to schedules in which services are performed in the earliest possible time window and stricter heuristic dominance rules are used, which means that our heuristic cannot be slower. Because the scheduling procedures are executed each time the cost of a route is evaluated during the tabu search, restricting the search was thus necessary, especially when implementing the sleeper berth provision. In the following sections, we will explain the trip scheduling algorithms we have developed and embedded within the tabu search heuristic in more detail. We will first introduce the necessary terminology related to the scheduling problems before describing Algorithms 2.1 and 2.2.

2.3.2.1 Truck driver scheduling problem

The multiple time windows US-TDSP consists in deciding when a driver will drive, work and rest in order to comply with the HOS regulations, in such a way that all customers are visited within one of their time windows. Consider a route $(i_0 = 0, i_1, ..., i_p, i_{p+1}, ..., i_\lambda = 0)$. The driving time between two consecutive customers $i = i_p$ and $j = i_{p+1}$ is denoted by d_{ij}, and the service duration at customer i is equal to w_i. We will designate by *drive* any period of continuous driving, by *rest* an off-duty period of at least h^{rest}

hours, by *work* any period of service time at a customer and by *idle* the waiting time at a customer. Work and idle time are on-duty periods not regarded as driving time. Note that in practice, idle time is only considered as such when the driver is relieved of all responsibilities for the custody of the vehicle and is free to leave the premises where the vehicle is parked. Here, we adopt a conservative definition of idle time: we consider that idle time is on-duty time since the driver is not fully relieved of his duties. A schedule $s = (a_0, a_1, ..., a_u, ..., a_\kappa)$ is a sequence of activities performed by the driver along the route. Let $A := \{a_u = (a_u^{type}, a_u^{length}) \mid a_u^{type} \in \{drive, work, rest, idle\} \text{ and } a_u^{length} \geq 0\}$ denote the set of driver activities. A partial schedule from a_u to $a_{u'}$ is denoted by $s_{u,u'}$. We suppose that the driver has been off-duty for a period of at least 34 consecutive hours before leaving the depot.

To present the algorithm that constructs schedules in compliance with HOS regulations, we define the following values and show how they can be recursively computed:

- starting time of schedule s:

$$l_s^{start} := \begin{cases} \tau_{1,0}^{\min} + a_0^{length} & \text{, if } a_0^{type} = idle \\ \tau_{1,0}^{\min} & \text{, otherwise ;} \end{cases}$$

- completion time of schedule s:

$$l_{s_{0,0}}^{end} := a_0^{length} \quad \text{and} \quad l_{(s,a)}^{end} := l_s^{end} + a^{length} ;$$

- index of the last rest period activity in schedule s:

$$\mu := \max \{u \mid (a_u^{type} = rest) \text{ or } (u = 0)\} ;$$

- end time of the 14-hour limit from the last rest period in schedule s:

$$l_{s_{0,0}}^{calculation} := l_{s_{0,0}}^{end} + h^{on_duty} \quad \text{and}$$

$$l_{(s,a)}^{calculation} := \begin{cases} l_{(s,a)}^{end} + a^{length} + h^{on_duty} & \text{, if } a^{type} = rest \\ l_s^{calculation} & \text{, otherwise ;} \end{cases}$$

- cumulated driving time since the last rest period in schedule s:

$$l^{drive}_{s_{0,0}} := 0 \quad \text{and} \quad l^{drive}_{(s,a)} := \begin{cases} 0 & \text{, if } a^{type} = rest \\ l^{drive}_s + a^{length} & \text{, else if } a^{type} = drive \\ l^{drive}_s & \text{, otherwise ;} \end{cases}$$

- cumulated slack time of partial schedule s_{ij}:

$$l^{slack}_{s_{0,0}} := 0 \quad \text{and} \quad l^{slack}_{(s,a)} := \begin{cases} 0 & \text{, if } a^{type} = rest \\ l^{slack}_s + a^{length} & \text{, else if } a^{type} = idle \\ l^{slack}_s & \text{, otherwise .} \end{cases}$$

In the classical VRPTW, in order to reduce a partial route duration and unnecessary waiting time, it may be advantageous to delay departure from the depot and the beginning of service at a customer. Similarly, in the context of long-haul transportation, it may also be beneficial to expand the length of a rest period in order to reduce waiting time and to increase driver flexibility by delaying the end of the 14-hour limit. Goel and Kok (2012) apply these ideas by taking into account the time by which the last rest period may be postponed in a schedule. This time is denoted by l^{push}_s. We have adapted the computation of this value since when several time windows are feasible we only consider the first possible one, and infeasible solutions are allowed during the search.

The forward time slack is defined by Savelsbergh (1992) as the largest margin by which one can postpone the beginning of service at a customer without causing any time window violation. For a given route, this value is recursively evaluated starting from the depot up to the last customer. In our problem, which deals with several rests and allows temporary time window violations, we compute the "forward time slack since the last rest", which represents the latest time at which service can begin at a customer without increasing time window violations and is recursively evaluated starting from the previous rest to the following rest. In this evaluation, for every customer i of a route, we consider the time window $[\tau^{\min}_{t^*i}, \tau^{\max}_{t^*i}]$ that allows the earliest possible service or generates the least delay when there is no admissible time window. Suppose that customer i is reached at the end of the last activity of a schedule s. Thus, the value t^* that determines the selected time window for a customer i is the value of t yielding $\min\{\tau^{\max}_{ti} \mid l^{end}_s \leq \tau^{\max}_{ti} \text{ or } \tau^{\max}_{ti} = \tau^{\max}_{t_i i}\}$. Let $\sigma(a_u)$, with $a^{type}_u = work$, be the index of the customer served during activity a_u. The forward time slack since the last rest in schedule s is reccursively defined by

$$
\begin{aligned}
l^{push}_{s_{0,0}} &:= 0 \qquad \text{and} \\
l^{push}_{(s,a)} &:= \begin{cases} \tau^{max}_{1,0} - l^{end}_s & \text{, if } a^{type} = rest \\ \min\left\{ l^{push}_s, l^{slack}_s + \left(\tau^{\max}_{t^*\sigma(a)} - l^{end}_s \right)^+ \right\} & \text{, else if } a^{type} = work \\ l^{push}_s & \text{, otherwise ;} \end{cases}
\end{aligned}
$$

where $(y)^+ = \max\{0, y\}$. Then, the time by which the end of the last rest period in the work plan s may be extended corresponds to

$$
l^{extend}_s := \min\left\{ l^{slack}_s, l^{push}_s \right\} .
$$

A rest extension is implemented whenever a new rest is inserted and when the depot is reached at the end of a route. To this end, the departure from the depot is delayed when this is possible, and the previous rest is lengthened otherwise. The value by which the departure from the depot or the last rest (activity a_μ) will be brought forward or extended is equal to l^{extend}_s. In fact, a^{length}_μ will be increased by a value equal to l^{extend}_s whenever a new rest is inserted.

2.3.2.2 Trip scheduling procedure

This section presents our version of the method developed by Goel and Kok (2012) for determining driver schedules. The main idea of this procedure is to take a partial schedule and complete it by sequentially adding activities, such as driving and rest periods, until the following customer is reached. Given a partial route in which the last customer is i, the remaining driving time required to reach the next customer j in the trip is denoted by

$$
\delta_s := d_{ij} - \sum_{\substack{\omega \le u \le \kappa \\ a^{type}_u = drive}} a^{length}_u ,
$$

with $\omega = \max\{u \mid a^{type}_u = work\}$ and $\sigma(a_\omega) = i$. From a partial schedule s, the trip scheduling method illustrated in Algorithm 2.1 can be used to determine the sequence of activities to be performed by a driver from customer i to the subsequent customer j. Before describing our first scheduling algorithm, we present the procedures used to generate the schedules representing the two strategies that could be adopted before serving a customer. The first possibility, described by Procedure 2.1, is to execute the service directly without resting. The second possibility is to take a full rest before the service, which is described by Procedure 2.2.

In Procedure 2.1, the time window $t^{\bar{r}}$ that allows the earliest service at customer j according to the current time l_s^{end} is first determined. The current time corresponds to the arrival time at customer j. If l_s^{end} is after the opening of the selected time window, the schedule $s^{\bar{r}}$ in which the service $(work, w_j)$ is directly performed is generated. If l_s^{end} is before the opening of the time window, a period of idle time starting at the arrival time and ending at the opening of the time window $(idle, \tau_{t^{\bar{r}},j}^{\min} - l_s^{end})$ is added before performing the service in schedule $s^{\bar{r}}$. In Procedure 2.2, these same scheduling principles are followed after adding a rest activity $(rest, h^{rest})$ prior to the service in order to generate a schedule s^r. However, in Procedure 2.2, the schedule with a prior rest is created only when this schedule is feasible $(l_s^{end} + h^{rest} \leq \tau_{\bar{t}_j,j}^{\max})$ or if the schedule with the direct service is also infeasible $(l_s^{end} > \tau_{\bar{t}_j,j}^{\max})$.

Procedure 2.1 Schedule service without resting

Determine the index $t^{\bar{r}}$ of the time window allowing the earliest service at customer j without resting:
$t^{\bar{r}}$ the value of t yielding $\min \left\{ \tau_{tj}^{\max} \mid l_s^{end} \leq \tau_{tj}^{\max} \text{ or } \tau_{tj}^{\max} = \tau_{\bar{t}_j,j}^{\max} \right\}$.
Concatenate the current schedule to create $s^{\bar{r}}$:
if $l_s^{end} \geq \tau_{t^{\bar{r}},j}^{\min}$ **then**
$s^{\bar{r}} = (s, (work, w_j))$
else
$s^{\bar{r}} = \left(s, (idle, \tau_{t^{\bar{r}},j}^{\min} - l_s^{end}), (work, w_j)\right)$
end if

Procedure 2.2 Schedule a rest before service

Determine the index t^r of the time window allowing the earliest service at customer j with a previous rest:
t^r the value of t yielding $\min \left\{ \tau_{tj}^{\max} \mid l_s^{end} + h^{rest} \leq \tau_{tj}^{\max} \text{ or } \tau_{tj}^{\max} = \tau_{\bar{t}_j,j}^{\max} \right\}$.
Concatenate the current schedule to create s^r:
if $l_s^{end} + h^{rest} \leq \tau_{\bar{t}_j,j}^{\max}$ or $l_s^{end} > \tau_{\bar{t}_j,j}^{\max}$ **then**
if $l_s^{end} + h^{rest} \geq \tau_{t^r,j}^{\min}$ **then**
$s^r = \left(s, (rest, h^{rest}), (work, w_j)\right)$
else
$s^r = \left(s, (rest, h^{rest}), (idle, \tau_{t^r,j}^{\min} - l_s^{end} - h^{rest}), (work, w_j)\right\}$
end if
end if

First, Algorithm 2.1 sets the remaining driving time to reach j from i equal to d_{ij} and initiates the departure of the depot at the opening of its time window. Afterward, the trip scheduling procedure computes Δ, the maximal legal driving time until either the next customer is reached or it is necessary to plan a rest period. A driving activity of length Δ is then added to the current schedule. At this point, if the next customer is not yet reached, a full rest period is included after extending the last rest period or by delaying the departure from the depot. This process continues until the next customer j is reached, at which point two time windows are determined: $\left[\tau_{t^{\bar{r}},j}^{\min}, \tau_{t^{\bar{r}},j}^{\max}\right]$ allows the earliest direct service and $\left[\tau_{t^r,j}^{\min}, \tau_{t^r,j}^{\max}\right]$ allows the earliest service after a full rest period. A first potential schedule $s^{\bar{r}}$ is then obtained by directly serving the customer with a minimum

idle time, and another schedule s^r is defined by resting before serving the customer. The set S_j of all identified schedules that comply with HOS regulations is then augmented.

Algorithm 2.1 Trip scheduling procedure

$\delta \leftarrow d_{ij}$
if $i = 0$ **then**
  $a_0 = (idle, 0)$
end if
1. Schedule driving and rest periods on the route from customer i to j:
while $\delta > 0$ **do**
  $\Delta \leftarrow \left(\min \left\{ \delta, h^{drive} - l_s^{drive}, l_s^{calculation} + l_s^{extend} - l_s^{end} \right\} \right)^+$
  $\delta \leftarrow \delta - \Delta$
  $s \leftarrow (s, (drive, \Delta))$
  if $\delta > 0$ **then**
    Extend the last rest: $a_\mu^{length} \leftarrow a_\mu^{length} + l_s^{extend}$
    Include a rest: $s \leftarrow (s, (rest, h^{rest}))$
  end if
end while
2. Schedule service without resting: Execute Procedure 2.1 to generate schedule $s^{\bar{r}}$
3. Schedule service with a previous rest:
  Extend the last rest: $a_\mu^{length} \leftarrow a_\mu^{length} + l_s^{extend}$
  Execute Procedure 2.2 to generate schedule s^r
4. Update set of possible schedules to reach customer j: $S_j \leftarrow S_j \cup \{s^r, s^{\bar{r}}\}$

By applying this process sequentially from the depot to the succeeding nodes in a route, multiple schedules are generated to reach each customer. The best schedule is the one that completes a trip within the shortest time. To reduce the number of possibilities and to speed up the process, some schedules are pruned during the enumeration by using a heuristic principle of dominance. The dominance rule works as follows. Consider two possible schedules s and s' obtained after serving the last customer of a sequence. The remaining driving time before resting in schedule s corresponds to $\Delta_s = \left(\min \left\{ h^{drive} - l_s^{drive},\ l_s^{calculation} + l_s^{extend} - l_s^{end} \right\} \right)^+$. In order to restrict the search and only expand schedules of shorter duration with more allowable remaining driving time, we consider that schedule s heuristically dominates schedule s' if

$$l_s^{end} - l_s^{start} \leq l_{s'}^{end} - l_{s'}^{start} \text{ and } \Delta_s \geq \Delta_{s'} .$$

These conditions mean that in schedule s the driver spends less time to perform the same duties as in schedule s' and still has more allowable driving time. Moreover, schedule s dominates schedule s' if $l_s^{end} - l_s^{start} + h^{rest} \leq l_{s'}^{end} - l_{s'}^{start}$. This is the case since the driver in schedule s can take a complete rest, enabling a maximum driving time, while still allowing the completion of all activities earlier than in schedule s'. By using these rules we might prune some solutions that are Pareto-dominant since all schedule characteristics of s and s' are not compared between each other. For example, if $\Delta_s = l_s^{calculation} + l_s^{extend} - l_s^{end}$

and $\Delta_{s'} = l_{s'}^{calculation} + l_{s'}^{extend} - l_{s'}^{end}$, we have no indication on the relation between l_s^{drive} and $l_{s'}^{drive}$.

To effectively implement the enumeration procedure, we have used a breadth-first search algorithm which can briefly be described as follows. Consider the route ($i_0 = 0, i_1, ..., i_p, i_{p+1}, ..., i_\lambda = 0$) and let S_{i_p} be a set of feasible schedules obtained at node i_p. To determine the set $S_{i_{p+1}}$, the schedules in S_{i_p} that are completed the earliest are successively considered and extended within the trip scheduling algorithm. Then, prior to extending the next schedule in S_{i_p}, all dominated schedules in $S_{i_{p+1}}$ are removed. When all schedules of S_{i_p} have been generated, the same steps are repeated for $S_{i_{p+1}}$. We can determine a set of feasible schedules for the route starting at i_0 and apply the same process up to i_λ. In our case, the feasible schedule retained for the trip, $s^* \in S_{i_\lambda}$, will always be the one with $l_{s^*}^{end} - l_{s^*}^{start} \leq l_s^{end} - l_s^{start}$ for all $s \in S_{i_\lambda}$.

2.3.2.3 Inclusion of the sleeper berth provision in the trip scheduling procedure

We now describe how to include the possibility of splitting a rest into two periods in compliance with the sleeper berth provision. We first establish a new set of states composed of two driver states, $sleeper_berth = \{long_berth, short_berth\}$, which represents partial rest periods spent in the sleeper berth in accordance with the provision described in Table 2.III. The states *long_ berth* and *short_ berth* are the periods of at least eight and two consecutive hours spent in the sleeper berth, respectively. Note that a *short_ berth* can also be an off-duty period and not necessarely time spent in the sleeper-berth. When rests are split in partial rest periods spent in the sleeper berth, the computation of the cumulated driving time and the 14-hour limit are modified. Accordingly, some values linked to a schedule have to be defined or adjusted:

- index of the last rest period or time spent in the sleeper berth in schedule s:

$$\mu := \max \{u \mid (a_u^{type} = rest) \text{ or } (a_u^{type} \in sleeper_berth) \text{ or } (u = 0)\} ;$$

- difference between h^{on_duty} and the cumulated on-duty time in schedule s:

$$l_{s_{0,0}}^{total_duty} := h^{on_duty} \quad \text{and}$$

$$l_{(s,a)}^{total_duty} := \begin{cases} l_s^{total_duty} - a^{length} & \text{, if } a^{type} \in \{drive,\ work,\ idle\} \\ l_s^{total_duty} & \text{, otherwise ;} \end{cases}$$

- number of partial rest periods during the last use of the sleeper berth provision in schedule s:

$$
\begin{aligned}
l_{s_{0,0}}^{split_length} &:= 0 \qquad \text{and} \\
l_{(s,a)}^{split_length} &:= \begin{cases} 0 & \text{, if } a^{type} = rest \\ l_s^{split_length} + 1 & \text{, else if } a^{type} \in sleeper_berth \\ l_s^{split_length} & \text{, otherwise ;} \end{cases}
\end{aligned}
$$

- time spent driving before the last rest split in the sleeper berth in schedule s:

$$
\begin{aligned}
l_{s_{0,0}}^{drive_berth} &:= 0 \qquad \text{and} \\
l_{(s,a)}^{drive_berth} &:= \begin{cases} 0 & \text{, if } a^{type} = rest \\ l_s^{drive} & \text{, else if } a^{type} = drive \text{ or} \\ & \quad a^{type} \in sleeper_berth \text{ and } l_s^{sleeper_berth} \geq 1 \\ l_s^{drive_berth} & \text{, otherwise ;} \end{cases}
\end{aligned}
$$

- cumulated driving time since the last calculation point in schedule s:

$$
\begin{aligned}
l_{s_{0,0}}^{drive} &:= 0 \qquad \text{and} \\
l_{(s,a)}^{drive} &:= \begin{cases} 0 & \text{, if } a^{type} = rest \\ l_s^{drive} + a^{length} & \text{, else if } a^{type} = drive \\ l_s^{drive} - l_s^{drive_berth} & \text{, else if } a^{type} \in sleeper_berth \\ l_s^{drive} & \text{, otherwise ;} \end{cases}
\end{aligned}
$$

- end time of the 14-hour limit from the last calculation point in schedule s:

$$
\begin{aligned}
l_{s_{0,0}}^{calculation} &:= l_{s_{0,0}}^{start} + h^{on_duty} \qquad \text{and} \\
l_{(s,a)}^{calculation} &:= \begin{cases} l_s^{end} + a^{length} + h^{on_duty} & \text{, if } a^{type} = rest \\ l_s^{calculation} + a^{length} & \text{, else if } a^{type} = long_berth \\ l_s^{calculation} & \text{, otherwise ;} \end{cases}
\end{aligned}
$$

- minimal resting time required to regain the right to drive when the on-duty limit or the driving limit will be reached when expanding schedule s:

$$l_{s_{0,0}}^{rest_required} := h^{rest} \quad \text{and}$$

$$l_{(s,a)}^{rest_required} := \begin{cases} h^{rest} & \text{, if } a^{type} = rest \\ h^{short_berth} & \text{, if } a^{type} = long_berth \\ h^{long_berth} & \text{, if } a^{type} = short_berth \\ l_s^{rest_required} & \text{, otherwise ;} \end{cases}$$

- cumulated slack time since last rest or period spent in sleeper berth in schedule s:

$$l_{s_{0,0}}^{slack} := 0 \quad \text{and}$$

$$l_{(s,a)}^{slack} := \begin{cases} 0 & \text{, if } a^{type} \in \{\ rest\ \} \cup sleeper_berth \\ l_s^{slack} + a^{length} & \text{, else if } a^{type} = idle \\ l_s^{slack} & \text{, otherwise ;} \end{cases}$$

- forward time slack since last rest or period spent in the sleeper berth in schedule s:

$$l_{s_{0,0}}^{push} := 0 \quad \text{and}$$

$$l_{(s,a)}^{push} := \begin{cases} \tau_{1,0}^{max} - l_s^{end} & \text{, if } a^{type} \in \{\ rest\ \} \cup sleeper_berth \\ \min\left\{l_s^{push}, l_s^{slack} + \left(\tau_{t^*\sigma(a)}^{\max} - l_s^{end}\right)^+\right\} & \text{, else if } a^{type} = work \\ l_s^{push} & \text{, otherwise ;} \end{cases}$$

- time by which the end of the last rest period or time spent in the sleeper berth may be extended without violating time window constraints and the sleeper berth provision requirements in the schedule s :

$$l_s^{extend} := \begin{cases} \min\left\{l_s^{slack}, l_s^{push}, l_s^{rest_required} - \epsilon\right\} & \text{, if } l_s^{split_length} > 0 \\ \min\left\{l_s^{slack}, l_s^{push}\right\} & \text{, otherwise ;} \end{cases}$$

with ϵ being a small value.

For a given route $\theta = (i_0 = 0, i_1, ..., i_p, ..., i_\lambda = 0)$ and a schedule $s = (a_0, ..., a_u, ..., a_\kappa)$, let us denote by $\bar{\sigma}(i)$ the index in s corresponding to the work activity performed at customer i, i.e. $a_{\bar{\sigma}(i)}$ is the service completed at location i. Let us also denote by $\rho(a_u)$ the index in s of the first rest period or partial rest period spent in the sleeper berth that precedes activity a_u. The US-TDSP that considers the sleeper berth provision is the problem of determining for a given route θ, where the driver has been off-duty for at least

34 consecutive hours before leaving the depot, a schedule s that satisfies the following constraints:

$$\sum_{\substack{\bar{\sigma}(i_0)\le u\le\bar{\sigma}(i_\lambda)\\ a_u^{type}=drive}} a_u^{length} = \sum_{\substack{0\le u\le\kappa\\ a_u^{type}=drive}} a_u^{length} \tag{2.1}$$

$$a_{\bar{\sigma}(i)}^{length} = w_i \quad \text{for each } i \in \theta \tag{2.2}$$

$$l_{s_{0,\bar{\sigma}(i)-1}}^{end} \in T_i \quad \text{for each } i \in \theta \tag{2.3}$$

$$\sum_{\substack{\bar{\sigma}(i)\le u\le\bar{\sigma}(j)\\ a_u^{type}=drive}} a_u^{length} = d_{ij} \quad \text{for each } \left\{ i,j \in \theta \mid i = i_p \text{ and } j = i_{p+1},\ 0 \le p \le \kappa - 1 \right\} \tag{2.4}$$

$$l_{s_{0,u}}^{drive} \le t^{drive} \quad \text{for each } 0 < u \le \kappa \tag{2.5}$$

$$a_u^{length} \ge h^{rest} \quad \text{for each } 0 < u \le \kappa \text{ with } a_u^{type} = rest \tag{2.6}$$

$$h^{long_berth} \le a_u^{length} < h^{rest} \quad \text{for each } 0 < u \le \kappa \text{ with } a_u^{type} = long_berth \tag{2.7}$$

$$h^{short_berth} \le a_u^{length} < h^{rest} \quad \text{for each } 0 < u \le \kappa \text{ with } a_u^{type} = short_berth \tag{2.8}$$

$$a_u^{length} \ge l_{0,\rho(u)}^{rest_required} \text{for each } 0 < u \le \kappa \text{ with } a_u^{type} \in sleeper_berth \text{ and } l_{s_{0,u}}^{split_length} > 1 \tag{2.9}$$

$$l_{s_{0,u}}^{split_length} \bmod 2 = 0 \quad \text{for each } 0 < u \le \kappa \text{ with } a_u^{type} = rest \tag{2.10}$$

$$l_{s_{0,u}}^{end} \le l_s^{calculation} \quad \text{for each } 0 < u \le \kappa \text{ with } a_u^{type} = drive \tag{2.11}$$

$$l_s^{total_duty} \ge 0 \quad \text{for each } 0 < u \le \kappa \text{ with } a_u^{type} = drive \tag{2.12}$$

$$l_s^{end} - l_s^{start} \le H\ . \tag{2.13}$$

Constraint (1) imposes that all driving is conducted between the first and the last work activity. For each customer, constraints (2) ensure that the duration of the work activity is equal to the service time and constraints (3) force these work activities to start within one of the corresponding time windows. Constraints (4) mean that the cumulated driving time between two work activities is equal to the driving time required to move from one location to the other. Constraints (5) state that the cumulated driving time does not exceed the limit given by the regulation. Constraints (6), (7), (8) and (9) ensure that the rest periods and the split rest periods in the sleeper berth are of legal duration. Constraints (10) force the completion of two partial rest periods when making use of the sleeper berth provision. Constraint (11) impose the condition that no driving can take place after 14 hours have elapsed from the last calculation point. Finally, constraints (12) and (13) enforce the 70-hour on-duty limit over an eight-day horizon.

Note that a solution respecting constraints (1) – (13) complies with the regulation, but the converse is not necessarily true because some solutions allowed by the HOS regulations are not taken into account by the model. For example, incorporating 34-hour rests during the planning horizon, which would reset the weekly on-duty time to zero, is not considered. Therefore, even if constraint (12) is violated, it could be possible to determine a schedule complying with the regulation by inserting such a rest period. Moreover, always considering idle time as being on-duty time may be viewed as overly restrictive since this is not always how this happens in practice.

2.3.2.4 Trip scheduling procedure that considers the sleeper berth provision

Before describing our second scheduling algorithm that exploits the sleeper berth provision, we present the procedures used to generate the schedules representing the four strategies that could be adopted before serving customer j. The first two possibilities, described by Procedures 2.1 and 2.2 as for Algorithm 2.1, is to execute the service directly without resting and to take a full rest before the service. Procedures 2.3 and 2.4 outline the two possibilities of partial rest periods according to the sleeper berth provision: taking a long rest or a short rest. Each of these procedures are similar to Procedure 2.2. The time window selected is the one that allows the earliest service when adding a partial rest period in the sleeper berth prior to the service. Note that, unless the arrival time at customer j is already above the latest time allowable to start performing the service, the partial rest periods spent in the sleeper berth are added to schedule s only if adding that partial rest period does not expand the schedule beyond the latest time window of customer j. Idle time is added to the schedule if necessary.

Procedure 2.3 Schedule a long split rest in the sleeper berth before service

Determine the index t^b of the time window allowing the earliest service at customer j with a previous long split rest:

t^b the value of t yielding $\min \left\{ \tau_{tj}^{\max} \mid l_s^{end} + h^{long_berth} \leq \tau_{tj}^{\max} \text{ or } \tau_{tj}^{\max} = \tau_{\bar{t}_j,j}^{\max} \right\}$.

Concatenate the current schedule to create s^b:

if $l_s^{end} + h^{long_berth} \leq \tau_{\bar{t}_j,j}^{\max}$ or $l_s^{end} > \tau_{\bar{t}_j,j}^{\max}$ **then**

  if $l_s^{end} + h^{long_berth} \geq \tau_{t^b,j}^{\min}$ **then**

    $s^b = \left(s, (long_berth, h^{long_berth}), (work, w_j)\right)$

  else

    $s^b = \left(s, (long_berth, h^{long_berth}), (idle, \tau_{t^b,j}^{\min} - l_s^{end} - h^{long_berth}), (work, w_j)\right\}$

  end if

end if

Algorithm 2.2 is similar to Algorithm 2.1, but more rest period possibilities are considered as it makes use of the sleeper berth provision. First, Algorithm 2.2 sets the remaining driving time to reach j from i equal to d_{ij} and initiates the departure of the depot at the opening of its time window. Afterward, the maximum legal driving time Δ is determined.

Procedure 2.4 Schedule a short split rest in the sleeper berth before service

Determine the index $t^{\bar{b}}$ of the time window allowing the earliest service at customer j with a previous short split rest:
$t^{\bar{b}}$ the value of t yielding $\min\left\{\tau_{tj}^{\max} \mid l_s^{end} + h^{short_berth} \leq \tau_{tj}^{\max} \text{ or } \tau_{tj}^{\max} = \tau_{\bar{t}_j,j}^{\max}\right\}$.
Concatenate the current schedule to create $s^{\bar{b}}$:
if $l_s^{end} + h^{short_berth} \leq \tau_{\bar{t}_j,j}^{\max}$ or $l_s^{end} > \tau_{\bar{t}_j,j}^{\max}$ **then**
  if $l_s^{end} + h^{short_berth} \geq \tau_{t^{\bar{b}},j}^{\min}$ **then**
    $s^{\bar{b}} = \left(s, (short_berth, h^{short_berth}), (work, w_j)\right)$
  else
    $s^{\bar{b}} = \left(s, (short_berth, h^{short_berth}), (idle, \tau_{t^{\bar{b}},j}^{\min} - l_s^{end} - h^{short_berth}), (work, w_j)\right)$
  end if
end if

Then, a driving activity of length Δ is added to the current schedule. If customer j is not yet reached, a rest period will be included after extending the previous rest, or by delaying the departure from the depot. Depending on the state of the driver, a rest split in the sleeper berth will be continued only if a complete rest cannot be included. This process is repeated until the next customer is reached, at which point the possibility of a direct service is considered in a first schedule and all eligible type of rest periods are then considered in different schedules. Accordingly, if the driver is already making use of the sleeper berth provision, the schedule with the appropriate split rest spent in the sleeper berth will be created. Another schedule including a complete rest will also be created if it is allowed to end splitting the rest periods. When the driver is not making use of the sleeper berth provision, then all the rest possibilities are considered by creating the corresponding schedules. Finally, the set S_j of schedules that comply with the regulations is augmented. In the tabu search heuristic, this procedure is implemented in the same way as Algorithm 2.1, but the heuristic dominance criterion is modified. In this case, schedule s heuristically dominates schedule s' if

$$l_s^{end} - l_s^{start} \leq l_{s'}^{end} - l_{s'}^{start} \ , \ \Delta_s \geq \Delta_{s'} \text{ and } \ l_s^{rest_required} \leq l_{s'}^{rest_required} \ .$$

The first two conditions mean that in schedule s the driver has spent less time to perform the same duties of schedule s' and still has more allowable driving time to continue his journey without resting. The last condition means that the resting time required to regain the right to drive, when the on-duty limit or the driving limit will be reached, is not more in schedule s than in schedule s'. Moreover, schedule s dominates schedule s' if the driver in schedule s is not making use of the sleeper berth provision or the use of the sleeper berth provision can be ended by including a complete rest ($l_s^{split_length} \mod 2 = 0$) and $l_s^{end} - l_s^{start} + h^{rest} \leq l_{s'}^{end} - l_{s'}^{start}$.

Algorithm 2.2 Trip scheduling procedure including sleeper berth provision

$\delta \leftarrow d_{ij}$
if $i = 0$ **then**
  $a_0 = (idle, 0)$
end if
1. Schedule driving and rest periods on the route from customer i to j
while $\delta > 0$ **do**
  $\Delta \leftarrow \left(\min \left\{ \delta, h^{drive} - l_s^{drive}, l_s^{calculation} + l_s^{extend} - l_s^{end} \right\} \right)^+$
  $\delta \leftarrow \delta - \Delta$
  $s \leftarrow (s, (drive\ ,\ \Delta))$
  if $\delta > 0$ **then**
    Extend the last rest period or time spent in the sleeper berth: $a_\mu^{length} \leftarrow a_\mu^{length} + l_s^{extend}$
    Include a rest or a split rest period:
    if $l_s^{split_length} > 0$ and $l_s^{split_length} \mod 2 \neq 0$ **then**
      if $l_s^{rest_required} = h^{long_berth}$ **then**
        $s \leftarrow \left(s, (long_\ berth\ ,\ l_s^{rest_required}) \right)$
      else
        $s \leftarrow \left(s, (short_\ berth\ ,\ l_s^{rest_required}) \right)$
      end if
    else
      $s \leftarrow \left(s, (rest\ ,\ h^{rest}) \right)$
    end if
  end if
end while
2. Schedule service without resting: Execute Procedure 2.1 to generate schedule $s^{\bar{r}}$
3. Schedule rest periods before service
Extend the last rest period or time spent in the sleeper berth: $a_\mu^{length} \leftarrow a_\mu^{length} + l_s^{extend}$
if $l_s^{split_length} > 0$ **then**
  if $l_s^{rest_required} = h^{long_berth}$ **then**
    Schedule a long split rest before service: Execute Procedure 2.3 to generate schedule s^b
    $s^{\bar{b}} \leftarrow \emptyset$
  else
    Schedule a short split rest before service: Execute Procedure 2.4 to generate schedule $s^{\bar{b}}$
    $s^b \leftarrow \emptyset$
  end if
  if $l_s^{split_length} \mod 2 \neq 0$ **then**
    $s^r \leftarrow \emptyset$
  else
    Schedule a complete rest before service: Execute Procedure 2.2 to generate schedule s^r
  end if
else
  Schedule a complete rest before service: Execute Procedure 2.2 to generate schedule s^r
  Schedule a long split rest before service: Execute Procedure 2.3 to generate schedule s^b
  Schedule a short split rest before service: Execute Procedure 2.4 to generate schedule $s^{\bar{b}}$
end if
4. Update set of possible schedules to reach customer j
  $S_j \leftarrow S_j \cup \left\{ s^{\bar{r}}, s^r, s^b, s^{\bar{b}} \right\}$

2.3.2.5 Basic trip scheduling procedure

To evaluate the benefits of a sophisticated trip scheduling procedure, we compare in Section 2.4.4.1 the Algorithm 2.1 with the basic trip scheduling procedure used by Xu et al. (2003) and Ceselli et al. (2009) to solve rich VRPs by column generation. In this procedure, a rest is always inserted as late as possible, i.e. when the driving or the on-duty limit has been reached. The departure time from the depot corresponds to the earliest possible time that will not create any waiting time before serving the first customer in a route, while departing as early as possible. Algorithm 2.3 determines the sequence of activities to be fulfilled by a driver from customer i to customer j according to the basic trip scheduling procedure. In this procedure, the current schedule s is sequentially extended so that a unique schedule is established for any sequence of customers.

Algorithm 2.3 Basic trip scheduling procedure

$\delta \leftarrow d_{ij}$
if $i = 0$ **then**
  $a_0 = (idle, 0)$
end if
1. Schedule driving and rest periods on the route from customer i to j:
while $\delta > 0$ **do**
  $\Delta \leftarrow \left(\min \left\{ \delta, h^{drive} - l_s^{drive}, l_s^{last_rest} + h^{on-duty} - l_s^{end} \right\} \right)^+$
  $\delta \leftarrow \delta - \Delta$
  $s \leftarrow (s, (drive, \Delta))$
  if $\delta > 0$ **then**
    Include a rest:
    $s \leftarrow (s, (rest, h^{rest}))$
  end if
end while
2. Schedule service:
Determine the index $t^{\bar{r}}$ of the time window allowing the earliest service at customer j:
  $t^{\bar{r}}$ the value of t yielding $\min \left\{ \tau_{tj}^{\max} \mid l_s^{end} \leq \tau_{tj}^{\max} \text{ or } \tau_{tj}^{\max} = \tau_{\bar{t}_j, j}^{\max} \right\}$.
Concatenate the current schedule to create $s^{\bar{r}}$:
if $i = 0$ and $l_s^{end} > \tau_{t^{\bar{r}},j}^{\min}$ **then**
  $a_0 \leftarrow (idle, \tau_{t^{\bar{r}},j}^{\min} - l_s^{end})$
end if
if $l_s^{end} \geq \tau_{t^{\bar{r}},j}^{\min}$ **then**
  $s \leftarrow (s, (work, w_j))$
else
  $s \leftarrow \left(s, (idle, \tau_{t^{\bar{r}},j}^{\min} - l_s^{end}), (work, w_j) \right)$
end if

2.4 Computational experiments

Because our problem is new, no benchmark instances are available for it. We have first created test instances from known VRPTW benchmark problems and we have used different objective functions to compare their impact on the solution. We have also solved

a real instance provided by Groupe Robert for a typical week. To provide some indications on the impact caused by the HOS regulations on the route structures compared to the EU legislation, we have used our tabu search algorithm to solve the benchmark instances proposed by Goel (2009) for the EU problem. We first describe the test instances and we then present our computational results.

2.4.1 Artificial instances with multiple time windows

We have first adapted the benchmark instances of Solomon (1987) for the VRPTW. These instances contain 100 customers each and are divided into six classes that differ by the geographical distribution of the customers and their time window tightness. The customers are clustered in the C1 and C2 instances, and uniformly distributed in the R1 and R2 instances. In the RC1 and RC2 instances some customers are clustered while others are uniformly distributed. The C2, R2 and RC2 instances have wider time windows and a larger load capacity per vehicle than the C1, R1 and RC1 instances, which makes them harder to solve since the number of customers per route increases considerably. For each instance, the travel time matrix and the time windows associated with each customer were modified to better suit our context. The other parameters, i.e. the geographic coordinates of customers and the depot, the distance matrices, as well as the vehicle capacities remain the same. The time intervals during which the vehicles are available in the Solomon instances were first interpreted as periods of 24 hours. The time windows of each customer have been scaled accordingly and then replicated for eight days. The available time of all vehicles was set to 192 hours ($H = 8$ days). As proposed by Goel (2009) for the EU problem, the travel time matrices have been adjusted so that the traveling speed of a vehicle is set to five distance units per hour, instead of 60 as in the original Solomon instances.

To illustrate, consider a customer i that has to be visited by a vehicle during the interval $[0, 15]$ and with $[3, 9]$ as the associated time window in the original Solomon instance. In our case, the depot time window will be $[0, 192]$ to represent the eight-day planning horizon and the set of time windows for that customer will be

$$T_i = \left\{ \left[3\left(\frac{24}{15-0}\right) + 24(t-1), 9\left(\frac{24}{15-0}\right) + 24(t-1) \right], t = 1, ..., 8 \right\}.$$

Furthermore, in order to adjust the travel time matrix of the customers visited during an eight-day horizon, each value is multiplied by 12.

2.4.2 Real-life Groupe Robert instance

We now describe the instance of Groupe Robert which concerns the distribution of goods in the US during a typical week. The geographical distribution of the 162 customers is depicted in Figure 2.6, which was created using the MapPoint software. A set of time windows are also associated with each customer depending on its delivery schedule and a service quality level guaranteed by the carrier. There are three types of goods with mutual incompatibilities. To deal with this constraint we consider two vehicle types, and a set of compatible vehicles is associated to each customer. The Groupe Robert instance is comparable to the RC1 instances since some customers are clustered while others are more scattered, and not many customers (between one and seven) can be served in the same route. Moreover, this is an open vehicle routing problem (Sariklis and Powell (2000)) since the route does not include the trip back to the depot so as to include further on-line requests. Accordingly, all distances and traveling times from any customer to the depot are set to zero (see Pisinger and Ropke, 2007).

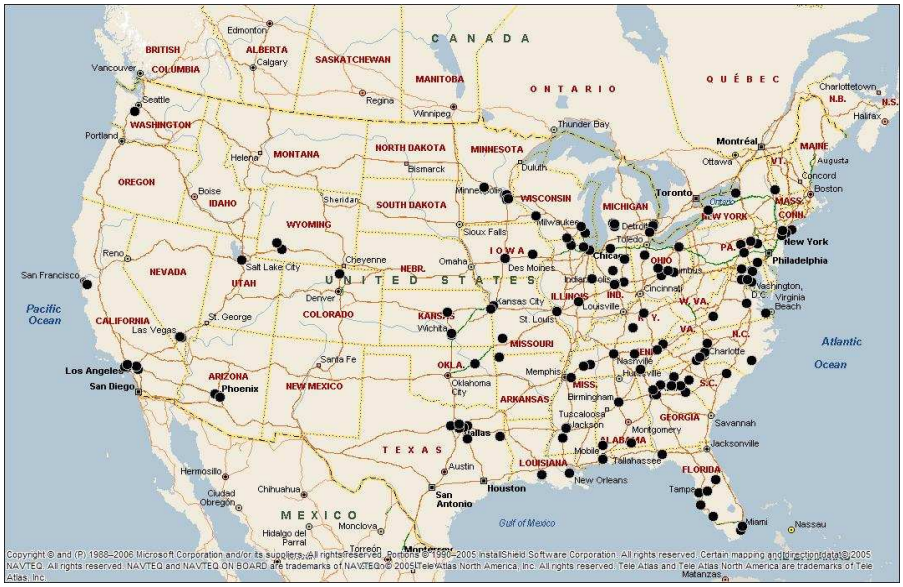

Figure 2.6: Customer locations in the Groupe Robert instance.

2.4.3 Artificial instances with single time windows

Goel (2009) has proposed benchmark instances for the EU problem also derived from the instances of Solomon (1987). These instances were generated similarly to the artificial instances for our problem. The differences are that there is only one time window per customer and that the time windows have been scaled proportionnally to a 144-hour horizon. Thus, our tabu search heuristic can solve the instances proposed by Goel (2009), but under the US regulations, since it can deal with multiple time windows. By comparing

the results of our algorithm with those obtained for the EU problem, we can provide insights on the relative impact of the EU and US rules.

2.4.4 Results and analysis

We have implemented our tabu search heuristic in C++ and have run all experiments on a Dual Core AMD Opteron 275, 2.19 GHz CPU with 8.0 GB of RAM. We have first tested the tabu search heuristic incorporating the trip scheduling algorithms on the artificial intances with mutiple time windows just described. We compare the basic trip scheduling procedure with Algorithm 2.1, and then Algorithm 2.1 with Algorithm 2.2. We also report the most relevant results obtained for Groupe Robert case and on the artificial instances with single time windows.

2.4.4.1 Comparisons of the scheduling algorithms on the artificial instances with mutiple time windows

Tables 2.IV and 2.V provide a summary of the computational experiments performed when minimizing the number of vehicles as the primary objective, and the total distance or the total duration as a secondary objective. We provide the average values of the solutions obtained after 50,000 iterations over five runs of the algorithm for each set of instances. The first colum gives the instance class, each of the next two groups of three columns compares the results obtained for each objective, and the last three colums provide the CPU time in minutes for each algorithm. The detailed results are presented in Appendix. We first compare the results obtained with the basic trip scheduling procedure (Xu et al., 2003, and Ceselli et al., 2009) and with Algorithm 2.1 embedded within the tabu search heuristic on the six sets of modified Solomon instances. Algorithms 2.1 and 2.2 are compared afterward.

Tables 2.IV and 2.V show that Algorithm 2.1 clearly outperforms the basic trip scheduling procedure. When the total distance is minimized, Algorithm 2.1 finds solutions that require an average of 4.36% fewer vehicles and whose distance is on average 5.74% shorter. When the total duration is minimized, Algorithm 2.1 finds solutions that require on average 2.27% fewer vehicles and reduce the total duration by 3.78% on average. For all sets of instances, Algorithm 2.1 finds solutions that improve on average the secondary objective.

The basic trip scheduling procedure, which allows a rest only when there is no more available driving time, is not the best procedure for trip scheduling. However, the scheduling policies applied in this procedure are often adopted in practice, Groupe Robert's drivers operate according to these policies for instance, and in some VRP studies men-

tioned in Section 2.1.1. Our results clearly demonstrate the benefits of using a sophisticated scheduling procedure that includes the possibility of scheduling rest periods before the allowable driving time is depleted.

When the total distance is minimized, Algorithm 2.2 finds solutions that require on average 3.49% fewer vehicles and 2.73% less distance. When the total duration is minimized, Algorithm 2.2 finds solutions that require on average 2.55% fewer vehicles and 2.74% less travel duration. These results illustrate the benefits of incorporating the sleeper berth provision in the driver scheduling process, especially when the instance involves a larger number of customers per route. However, the computing time increases considerabely since more schedule possibilities have to be considered during the solution process. We also note that better results are obtained when there are more customers per vehicle (instances C2, R2 and RC2). In these cases, Algorithm 2.1 and Algorithm 2.2 identify solutions with far fewer vehicles.

To better evaluate the effect of the random values on the behavior of our tabu search heuristic, we have calculated the coefficients of variation obtained after five runs of Algorithms 2.1 and 2.2 embedded within our tabu search heuristic, this for the primary objective (number of vehicles) as well as for the two secondary objectives (distance and duration). For a particular instance i and objective z, the sample coefficient of variation CV_{iz} obtained after five runs ($r = 1, ..., 5$) of our heuristic is equal to

$$CV_{iz} = \sqrt{\frac{1}{4}\sum_{r=1}^{5}\left(c_{iz}(x_r) - \bar{c}_{iz}\right)^2}/\bar{c}_{iz} \ ,$$

where $\bar{c}_{iz}$ corresponds to the average value of the objective function c_z over the five solutions of instance i. The coefficients of variation obtained for each scheduling algorithm are very small, and therefore the behaviour of the routing algorithm is not significally affected by the values that are randomly chosen during each run of the algorithm. For Algorithm 2.1 embedded within our tabu search heuristic, the largest coefficients of variation obtained on the 56 instances is 0.15 for the primary objective and 0.12 for both secondary objectives ($0.15 = \max_i \{CV_{i0}\}$ and $0.12 = \max_i \{CV_{i1}, CV_{i2}\}$, with $i = 1, ..., 56$). Similarly for Algorithm 2.2, the largest coefficients of variation observed on the 56 instances are 0.24 and 0.27 for the primary and secondary objectives, respectively. For both scheduling algorithms, the mean coefficients of variation are 0.02 for the primary objective, 0.02 for the first secondary objective, and 0.03 for the second secondary objective.

Table 2.IV: Minimizing the number of vehicles, and then the total distance

	Number of vehicles			Total distance			CPU (min)		
Instance	Basic	Algo. 1 (improv. %)	Algo. 2 (improv. %)	Basic	Algo. 1 (improv. %)	Algo. 2 (improv. %)	Basic	Algo. 1	Algo. 2
C1	10	10 (0)	10 (0)	856.76	823.61 (3.84)	823.07 (0.07)	24.38	93.44	223.75
C2	7.38	6.65 (9.2)	6.03 (9.48)	1,061.5	959.35 (9.55)	901.51 (5.18)	32.75	124.01	520.16
R1	8.02	8 (0.2)	8 (0)	914.77	865.52 (4.8)	850.3 (1.62)	32.51	134.75	394.54
R2	5.53	5 (9.21)	4.76 (4.61)	860.06	821.42 (4.35)	783.89 (4.34)	51.73	249.8	887.11
RC1	9	9 (0)	9 (0)	1,064.2	1,010.17 (4.91)	1,000.83 (0.91)	27.51	108.61	318.64
RC2	6.03	5.5 (8.31)	5.13 (6.83)	955.8	874.04 (8.22)	835.79 (4.28)	43.34	205.69	695.9
Average	7.61	7.33 (4.36)	7.15 (3.49)	942.87	885.41 (5.74)	865.9 (2.73)	35.85	155.58	506.68

Table 2.V: Minimizing the number of vehicles, and then the total duration

	Number of vehicles			Total duration (min)			CPU (min)		
Instance	Basic	Algo. 1 (improv. %)	Algo. 2 (improv. %)	Basic	Algo. 1 (improv. %)	Algo. 2 (improv. %)	Basic	Algo. 1	Algo. 2
C1	10	10 (0)	10 (0)	33,369.91	31,658.83 (5.17)	30,417.19 (3.94)	18.61	63.08	195.17
C2	6.9	6.53 (4.96)	6.15 (5.7)	40,780.78	40,132.15 (1.56)	39,793.31 (1.12)	32.43	147.51	511.95
R1	8	8 (0)	8 (0)	34,627.72	33,138.11 (4.64)	32,447.11 (1.93)	26.11	101.83	327.43
R2	5.47	5.29 (3.23)	5.07 (3.97)	31,821.72	31,295.97 (1.87)	30,353.87 (2.95)	46.45	188.41	717.46
RC1	9	9 (0)	9 (0)	38,280.4	35,968.71 (6.14)	35,439.39 (1.3)	23.94	89.83	297.61
RC2	5.98	5.63 (5.42)	5.3 (5.6)	34,832.24	33,735.31 (3.32)	31,902.3 (5.19)	40.45	165.56	617.27
Average	7.52	7.41 (2.27)	7.25 (2.55)	35,304.43	34,321.51 (3.78)	33,392.19 (2.74)	31.54	126.04	444.48

2.4.4.2 Results obtained on the Groupe Robert real-life instance

To generate a data set compatible with the format used by the algorithms proposed in this paper, we have performed some manipulations on the data provided by Groupe Robert. We have first used the MapPoint software to compute the distance and travel time matrices. Groupe Robert supplied us with the customer lists of the 40 routes executed to serve all the demand of the given instance. In practice, the drivers use scheduling schemes similar to those obtained by the basic trip scheduling procedure. Thus, we could fairly approximate the driver schedules even if they were not available in detail. Having at our disposal the list of customers visited by each vehicle, we have determined a realistic route for each of them by solving a traveling salesman problem by means of the basic trip scheduling procedure. We consider this solution to be realistic and probably even better than the one actually used by the company. We have compared the Groupe Robert solution to those generated by our heuristics. Because the routing was manually done by Groupe Robert's dispatchers, the CPU times cannot be reported.

We summarize the results of our experiments in Table 2.VI. We have first solved this instance by means of Algorithm 2.1 embedded within the tabu search heuristic and compared our solution with that of Groupe Robert. We have minimized the number of vehicles as the primary objective, and the total routing cost as the secondary objective since this is reflecting the business priority order of Groupe Robert. To speed up the solution process and to ensure reasonable computational times, we have first generated an

initial solution by applying the basic trip scheduling procedure for 50,000 iterations. We have then performed five runs of 100,000 iterations of the tabu search using Algorithm 2.1 to improve this solution. The resulting solutions require three vehicles fewer without increasing the routing cost considerably. Indeed, the primary objective is improved by 7.5% and the routing cost goes up on average by approximately 3%. Note that the costs of return trips to the depot are set to zero in this case since we consider open routes.

Since we are using a heuristic, we can only claim to approximate the Pareto front. We have identified non-dominated solutions with fewer vehicles and a larger routing cost than in the Groupe Robert solution. Since our primary objective is the minimization of the total number of vehicles used, it is unlikely that our algorithm will produce solutions that dominate those of Groupe Robert. However, an attempt to generate such solutions could be made by fixing the number of vehicles at different values. For example, by fixing the number of vehicles to 38 and 39, we have obtained solutions costs of 95,990.00 and 97,972.28, respectively. These two solutions dominate the Groupe Robert solution, but do not dominate the solutions obtained by our heuristic for 37 vehicles.

We have also tested Algorithm 2.2 by means of the same solution process. As for Algorithm 2.1, the solution of Algorithm 2.2 requires 37 vehicles. This value has been proven to be optimal since it is the smallest value for which all demands can fit in the available capacity. Allowing rest splits in the sleeper berth reduces on average the routing cost by approximately 0.35%. These results are consistent with those obtained on the RC1 instances. Indeed, experiments conducted on these instances have shown that using the sleeper berth provision yields a smaller improvement in this context. Nevertheless, we can observe benefits in using a sophisticated routing and scheduling procedure as opposed to the current dispatching process.

Table 2.VI: Summary of the results obtained on the real-life Groupe Robert instance

Algorithm	Vehicles	Routing cost	CPU (min)
Groupe Robert	40	108,139.12	–
Algorithm 2.1	37	111,496.77	77.53
Algorithm 2.2	37	111,120.54	132.07

2.4.4.3 Results obtained on the artificial instances with single time windows

This section presents computational results obtained on the instances proposed by Goel (2009) under the EU legislation. We compare the results of our tabu search heuristic, which works with the US regulations, with the results obtained by Prescott-Gagnon et al. (2010) and Kok at al. (2010) who applied the complete set of rules defined by the EU

legislation, i.e. Regulation (EC) No 561/2006 and Directive 2002/15/EC applicable to routes lasting less than one week. The results obtained by Prescott-Gagnon et al. (2010), Kok at al. (2010) and with our tabu search heuristic are presented in Table 2.VII. In the first column, we report the average on the best results of Prescott-Gagnon et al. (2010) over five runs of their heuristic and the average results of Kok at al. (2010) algorithm in the second column. In the third column, the average results of the best solutions obtained after 50,000 iterations and five runs of our tabu search heuristic embedding Algorithm 2 are presented. For each class of instances, the average number of vehicles used and the average distances are reported. The last two columns provide the percent improvement of our tabu search relative to Prescott-Gagnon et al. (2010) and Kok at al. (2010).

As mentioned in the introduction, the US regulations are less restrictive than the European ones. This implies that the results for the American problem should never be worse than those for the European problem if the solutions were obtained through exact algorithms. However, this does not necessarily follow if heuristics are used. When comparing results it is usually impossible to attribute an improvement to the fact that different problems are solved or to different heuristic performances. This being said, we always outperform the results of Kok at al. (2010). We also generate solutions having fewer vehicles than those of Prescott-Gagnon et al. (2010) but our distances are slightly worse on average.

Table 2.VII: Summary of the results obtained on instances for the European problem

Instance	EU legislation		US regulations	Improvement (%)	
	Prescott-Gagnon et al.	Kok et al.	tabu search	Prescott-Gagnon et al.	Kok et al.
C1	10	10.11	10	0	1.09
	847.61	937.08	827.29	2.4	11.72
C2	4.63	5.25	4.13	10.91	21.43
	689.95	773.8	644.75	6.55	16.68
R1	8.08	9.33	8	0.99	14.26
	971.64	1,142.62	985.33	−1.41	13.77
R2	5.45	7.36	4.82	11.6	34.54
	933.93	1,084.7	967.59	−3.6	10.8
RC1	9	10	9	0	10
	1,107.27	1,322.41	1,128.78	−1.94	14.64
RC2	6.13	8.13	5.38	12.32	33.89
	1,090.8	1,247.37	1,138.96	−4.42	8.69
Number of vehicles	7.22	8.36	6.89	5.97	19.2
Total distance	940.2	1,084.66	948.78	−0.4	12.71

2.5 Conclusions

We have developed and compared several scheduling algorithms for a VRPMTW with working hour rules. This routing and scheduling problem is encountered by several carriers providing long-haul transportation services. The presence of multiple time windows and the working hour constraints considerably complicate the standard VRP. We have proposed a tabu search heuristic that embeds various scheduling algorithms. The algo-

rithm was tested on the modified Solomon instances and on a real-life instance. The computational study performed on the six Solomon instance sets shows that better solutions are obtained when one considers the possibility of taking a rest before the allowable driving time is depleted. The quality of solutions can also be improved by allowing the algorithm to split complete rests into partial rests according to the sleeper berth provision. Our tests also reveal that sophiticated scheduling procedures tend to yield better results when the vehicle routes contain more customers. Our results on the Groupe Robert data indicate that much better solutions can be obtained in terms of the number of vehicles at the expense of a modest increase in routing cost. Gains vary with respect to the complexity of the scheduling algorithm. Since short response times are often crucial in the trucking industry, dispatchers may choose to run the tabu search heuristic with the basic trip scheduling procedure until a feasible solution is found, and then use a more sophisticated scheduling algorithm to improve the solution.

Transportation companies must consider several objectives and constraints when solving real problems. From the decision maker's point of view, the numerous objectives are obviously all interesting and should be handled within a decision-support system. For example, the number of vehicles is often known in advance, but remains an objective if not all of them should operate at the same time. In this paper, we have considered two alternative secondary objectives in conjunction with the same primary objective. To do so, we have used a weighted objective function. A potential avenue of research would be to use the full force of multi-objective optimization to generate a rich set of non-dominated solutions.

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2.6 Appendix: Detailed computational results

Table 2.VIII: Minimizing the number of vehicles, and then the total distance by using the basic trip scheduling procedure

Instance	Vehicles	Distance	Working time (min)	Rest time (min)	Total duration (min)	CPU (min)
C101	10	873.16	36314.12	19080	55394.12	24.04
C102	10	851.46	33727.5	18600	52327.5	24.71
C103	10	844.92	33267.54	15360	48627.54	23.67
C104	10	826.6	28527.06	12240	40767.06	24.77
C105	10	867.56	36179.02	19800	55979.02	23.81
C106	10	864.61	35571.21	18960	54531.21	23.86
C107	10	871.59	33661.42	18000	51661.42	25.6
C108	10	861.31	35381.78	19320	54701.78	24.36
C109	10	849.61	31245.23	16200	47445.23	24.63
C201	10	1334.42	40152.81	23520	63672.81	18.83
C202	8.4	1172.44	33911.67	19560	53471.67	25.56
C203	6.4	952.55	26209.69	14760	40969.69	36.67
C204	5	747.7	20217.5	11280	31497.5	58.62
C205	8.2	1130.17	32529.84	19320	51849.84	26.39
C206	7	1100.91	27585.83	16560	44145.83	30.71
C207	7.2	1078.38	28604.94	17040	45644.94	31.25
C208	6.8	975.45	27003.01	15960	42963.01	34.01
R101	8.2	1239.32	32703.93	19320	52023.93	26.31
R102	8	1023.92	31909.21	17280	49189.21	29.19
R103	8	880.82	31069.87	16560	47629.87	32.33
R104	8	842.86	25820.26	13440	39260.26	33.87
R105	8	963.77	30246.67	17160	47406.67	30.83
R106	8	900.19	30310.88	16680	46990.88	33.44
R107	8	856.9	27626.16	14040	41666.16	33.41
R108	8	836.44	25195.5	12960	38155.5	36.28
R109	8	886.72	29537.73	16680	46217.73	33.2
R110	8	850.66	28904.72	16200	45104.72	34.02
R111	8	859.68	29098.42	15480	44578.42	32.97
R112	8	835.9	23278	12720	35998	34.26
R201	7.2	1029.13	28945.63	16560	45505.63	31.01
R202	6.4	975.94	25875.03	14880	40755.03	38.2
R203	5.6	818.64	22677.09	12720	35397.09	47.52
R204	5	757.28	19882.31	11400	31282.31	65.14
R205	6	929.96	24138.27	13920	38058.27	40.47
R206	5.4	875.79	21456.86	12240	33696.86	51.61
R207	5	793.29	19913.5	11640	31553.5	62.13
R208	4.4	758.55	17496.19	10080	27576.19	72.3
R209	5.2	878.7	20828.74	12360	33188.74	50.77
R210	5.6	849.83	22323.39	12720	35043.39	49.37
R211	5	793.51	19775.63	11760	31535.63	60.46
RC101	9	1170.97	34259.94	19800	54059.94	25.97
RC102	9	1103.85	33309.15	18120	51429.15	26.76
RC103	9	1021.63	32422.16	17880	50302.16	27.38
RC104	9	996.64	25451.88	13920	39371.88	28.73
RC105	9	1103.83	32802.62	18120	50922.62	26.62
RC106	9	1077.35	32499.62	18480	50979.62	28.13
RC107	9	1036.99	30050.7	16440	46490.7	28.83
RC108	9	1002.32	24473.59	13920	38393.59	27.7
RC201	7.4	1121.16	29232.51	16800	46032.51	30.13
RC202	6.4	1039.81	25759.84	14520	40279.84	36.17
RC203	6	902.28	23743.81	13680	37423.81	42.63
RC204	5	806.56	19264.67	11400	30664.67	59.69
RC205	6.6	1037.71	26040.04	14760	40800.04	35.22
RC206	6.2	1004.47	24579.86	14400	38979.86	37.91
RC207	5.6	922.89	22186.59	13080	35266.59	48.58
RC208	5	811.52	19782.89	11640	31422.89	56.39

Table 2.IX: Minimizing the number of vehicles, and then the total duration by using the basic trip scheduling procedure

Instance	Vehicles	Distance	Working time (min)	Resting time (min)	Total duration (min)	CPU (min)
C101	10	1238.58	23855.18	12720	36575.18	19.08
C102	10	1209.25	22619.82	11760	34379.82	18.19
C103	10	1230.02	22374.31	11160	33534.31	17.41
C104	10	1085.04	19473.38	9840	29313.38	17.6
C105	10	1232.73	23260.43	12480	35740.43	19.39
C106	10	1225.29	22065.24	11880	33945.24	18.81
C107	10	1170.87	21174.11	11400	32574.11	20.22
C108	10	1215.85	21200.21	11400	32600.21	18.69
C109	10	1201.38	20746.52	10920	31666.52	18.11
C201	9	1833.04	33306.51	20280	53586.51	19.83
C202	7.2	1568.15	28132.55	17040	45172.55	26.21
C203	6	1270.5	22538.57	13440	35978.57	37.85
C204	5	994.82	18380.29	10680	29060.29	51.86
C205	8	1554.41	28084.48	16920	45004.48	26.23
C206	7	1481.56	25488.41	15000	40488.41	30.26
C207	7	1404.54	25543.03	15720	41263.03	31.67
C208	6	1230.51	22372.42	13320	35692.42	35.52
R101	8	1590.59	29331.54	17160	46491.54	23.74
R102	8	1470.47	26554.6	15000	41554.6	25.89
R103	8	1269.9	22507.53	12240	34747.53	26.26
R104	8	1148.95	20531.59	10200	30731.59	25.67
R105	8	1383.99	25052.8	14160	39212.8	27.12
R106	8	1352.33	23306.45	12840	36146.45	26.13
R107	8	1213.12	21214.83	11160	32374.83	27.12
R108	8	1054.39	19039.71	9360	28399.71	25.86
R109	8	1285.56	22107.67	11880	33987.67	26.51
R110	8	1186.31	20609.93	10800	31409.93	26.31
R111	8	1220.23	21124.05	11520	32644.05	26.13
R112	8	1022.74	18471.97	9360	27831.97	26.64
R201	7	1431.01	25335.14	14640	39975.14	30.16
R202	6	1291.24	22673.43	13440	36113.43	37.41
R203	5.6	1167.61	20545.61	12120	32665.61	41.39
R204	5	956.09	17759.1	9960	27719.1	56.04
R205	6	1278.23	21967	13080	35047	39.73
R206	5.6	1144.02	20205.89	11640	31845.89	42.72
R207	5	1007.23	18375.78	10800	29175.78	55.9
R208	4.4	841.28	16246.26	9480	25726.26	59.65
R209	5.4	1134.5	19958.05	11640	31598.05	42.84
R210	5.2	1100.74	19645.84	11400	31045.84	46.52
R211	5	1019.8	18326.81	10800	29126.81	58.56
RC101	9	1668.47	28459.15	16920	45379.15	23.31
RC102	9	1499.84	25394.88	14400	39794.88	23.37
RC103	9	1458.69	24489.99	13800	38289.99	23.65
RC104	9	1220.66	21093.37	11280	32373.37	25.4
RC105	9	1617.19	26903.66	15240	42143.66	24.94
RC106	9	1431.93	24493.21	14040	38533.21	23.28
RC107	9	1396.25	23331.84	13200	36531.84	23.43
RC108	9	1261.43	21437.11	11760	33197.11	24.15
RC201	6.8	1480.97	26381.78	15120	41501.78	29.18
RC202	6.4	1375.97	23773.89	13920	37693.89	32.7
RC203	6	1217.45	21530.03	12120	33650.03	40.42
RC204	5	1014.83	18362.52	10680	29042.52	57.16
RC205	6.8	1376.18	24122.78	14160	38282.78	32.06
RC206	6	1315.27	22962.28	13560	36522.28	35.34
RC207	5.8	1172.69	20617.94	11880	32497.94	43.83
RC208	5	1041.8	18666.69	10800	29466.69	52.9

Table 2.X: Minimizing the number of vehicles, and then the total distance by using Algorithm 2.1

Instance	Vehicles	Distance	Working time (min)	Resting time (min)	Total duration (min)	CPU (min)
C101	10	821.27	22225.08	19570.86	41795.93	85.02
C102	10	822.6	23129.54	19960.37	43089.92	94.75
C103	10	826.38	22702.28	20360.06	43062.34	98.11
C104	10	822.93	19363.59	19391.34	38754.92	108.01
C105	10	823.2	21457.98	17929.34	39387.32	87.54
C106	10	824.38	20983.02	20204.17	41187.19	87.8
C107	10	828.31	20675.25	24321.49	44996.74	88.8
C108	10	822.18	19959.87	26238.1	46197.96	93.96
C109	10	821.27	19206.41	23642.76	42849.18	93.38
C201	9	1214.52	23100.12	38823.62	61923.75	71.11
C202	7.2	1116.16	21345.95	31385.23	52731.18	92.24
C203	6	848.36	17609.72	29772.1	47381.83	158.2
C204	5	702.39	15332.44	19149.55	34481.99	228.36
C205	7	1049.13	19521.16	28845.1	48366.26	85.54
C206	7	896.88	18661.36	28411.75	47073.11	103.72
C207	6	954.35	18030.21	25021.04	43051.25	113.43
C208	6	893.04	17335.95	24960.15	42296.1	139.47
R101	8	1024.98	23572.94	33985.99	57558.93	104.17
R102	8	905.02	21876.4	33973.34	55849.74	127.34
R103	8	846.52	21144.68	27803.54	48948.21	140
R104	8	836.79	19439.92	17914.58	37354.5	147.1
R105	8	890.01	20610.12	35792.86	56402.98	119.82
R106	8	857.21	21466.32	29201.26	50667.57	134.21
R107	8	838.43	19373.46	23828.63	43202.1	145.19
R108	8	834.63	18001.7	17611.78	35613.48	148.9
R109	8	843.64	19010.82	31128.53	50139.35	130.65
R110	8	836.41	19690.68	24791.15	44481.83	140.25
R111	8	839.72	20099.07	24921.31	45020.39	138.85
R112	8	832.83	17358.08	14674.58	32032.66	140.51
R201	6	974.82	20069.21	29481.79	49550.99	149.99
R202	6	856.14	18683.12	29167.1	47850.22	179.93
R203	5	814.08	17111.11	21474.68	38585.8	240.47
R204	4.2	762.25	15555.7	14616.12	30171.81	307.56
R205	5	955.64	18571.07	22403.39	40974.46	205.8
R206	5	812.23	16880.45	22770.08	39650.53	243
R207	4.8	760.75	16574.45	18373.64	34948.09	300.96
R208	4	725.02	15024.06	13620.94	28644.99	367.63
R209	5	806.84	17056.34	21786.82	38843.16	228.24
R210	5	812.51	16787.02	22102.17	38889.19	230.44
R211	5	755.29	16143.68	18589.01	34732.69	293.79
RC101	9	1052.21	23290.88	34597.53	57888.41	95.1
RC102	9	1016.82	23327.06	32607.87	55934.93	108
RC103	9	1000.61	22955.08	25475.62	48430.7	112.34
RC104	9	992.96	19008.73	17878.61	36887.35	118.04
RC105	9	1028.74	23041.31	32398.67	55439.98	106.77
RC106	9	1006.82	21278.25	36824.81	58103.05	106.51
RC107	9	994.39	20248.48	28174.67	48423.14	111.14
RC108	9	988.84	19127.1	19529.17	38656.28	110.99
RC201	6.4	1018.78	21144.99	29307.1	50452.09	131.67
RC202	6	914.79	19500.45	27470.95	46971.4	167.57
RC203	5	856.26	17570	20162.4	37732.4	219.63
RC204	4.8	791.99	16182.27	13700.85	29883.12	301.43
RC205	5.8	926.06	18957.32	28250.48	47207.79	155
RC206	6	859.98	18290.34	27847.59	46137.93	180.06
RC207	5	853.8	17148.24	22335.92	39484.15	211.93
RC208	5	770.67	15882.08	17817.16	33699.24	278.26

Table 2.XI: Minimizing the number of vehicles, and then the total duration by using Algorithm 2.1

Instance	Vehicles	Distance	Working time (min)	Resting time (min)	Total duration (min)	CPU (min)
C101	10	1201.54	21820.56	12558.84	34379.4	54.77
C102	10	1169.63	20816.1	11456.51	32272.61	64.12
C103	10	1140.68	20512.3	11378.58	31890.88	66.33
C104	10	1044.81	18748.93	8806.81	27555.74	83.25
C105	10	1152.21	21143.83	13518.17	34662	54.73
C106	10	1170.93	20995.84	12005.42	33001.26	60
C107	10	1170.96	20625.47	11018.72	31644.19	56.87
C108	10	1118.21	19999.64	10662.87	30662.52	61.16
C109	10	1080.76	19221.59	9639.33	28860.92	66.52
C201	8.4	1641.13	27747.63	25055.99	52803.61	82.97
C202	7.2	1515.1	25358.46	19382.86	44741.32	106.38
C203	5.8	1222.92	21354.11	14970.03	36324.14	208.75
C204	5	981.9	18116.42	10351.52	28467.95	281
C205	7	1454.37	24220.44	19787.53	44007.96	85.93
C206	6.4	1353.22	22739.58	17087.03	39826.61	112.26
C207	6.4	1327.14	22372.61	17116.62	39489.24	122.79
C208	6	1184.35	20785.02	14611.35	35396.38	180.01
R101	8	1577.07	27194.48	19470.41	46664.88	81.74
R102	8	1477.22	25294.74	15829.79	41124.53	100.61
R103	8	1253.98	21971.71	12428.57	34400.28	104.3
R104	8	1076.08	19330.04	9538.06	28868.1	113.43
R105	8	1392.8	23790.18	14104.96	37895.14	84.09
R106	8	1241.99	21448.42	12566.88	34015.31	102.17
R107	8	1144.16	19880.88	10541.31	30422.19	107.2
R108	8	1021.15	18258.05	8223.76	26481.81	114.42
R109	8	1226.88	20964.92	11449.44	32414.37	96.31
R110	8	1121.83	19558.76	10405.41	29964.17	105.31
R111	8	1110.53	19574.04	10192.71	29766.74	104.14
R112	8	967.25	17659.68	7980.1	25639.79	108.28
R201	6.8	1394.59	24194.09	17660.81	41854.89	97.86
R202	6	1247.6	21670.09	13822.39	35492.48	147.84
R203	4.8	1048.29	18604.6	12624.09	31228.68	162.47
R204	5	944.67	17405.4	9506.69	26912.09	255.58
R205	6	1248.19	21362.77	13275.27	34638.04	149.14
R206	5.2	1139.83	19795.72	12509.78	32305.5	160.27
R207	5	988.62	17920.15	10057.05	27977.21	248.77
R208	4.4	858.62	16338.53	8646.81	24985.34	245.17
R209	5	1091.17	19172.25	11251.41	30423.66	184.5
R210	5	1061.41	18683.42	11716.46	30399.89	173.66
R211	5	995.98	18003.18	10034.69	28037.87	247.2
RC101	9	1523.09	25468.31	16956.87	42425.18	77.1
RC102	9	1493.9	24730	15462.21	40192.2	84.93
RC103	9	1372.28	22768.96	12340.2	35109.15	94.42
RC104	9	1184.42	20271.07	9802.5	30073.56	103.7
RC105	9	1514.1	24951.88	15091.98	40043.86	87.35
RC106	9	1383.23	22994.99	13185.08	36180.07	86.03
RC107	9	1280.12	21561.87	11465.22	33027.1	89.67
RC108	9	1208.79	20802.85	9895.7	30698.55	95.44
RC201	6.4	1375.73	23982.99	18001.19	41984.19	96.86
RC202	6	1284.81	22148.14	15320.47	37468.61	125.69
RC203	5.6	1150.37	20190.83	12329.18	32520	171.33
RC204	5	959.68	17552.32	9438.57	26990.89	252.12
RC205	5.6	1176.58	20245.8	15365.43	35611.23	119.36
RC206	6	1270.43	21754.45	13323.59	35078.04	152.6
RC207	5.4	1149.79	19921.73	12084.35	32006.08	177.26
RC208	5	1013.12	18157.87	10065.58	28223.45	229.28

Table 2.XII: Minimizing the number of vehicles, and then the total distance by using Algorithm 2.2

Instance	Vehicles	Distance	Working time (min)	Resting time (min)	Total duration (min)	CPU (min)
C101	10	821.06	18993.16	20408.89	39402.05	146.75
C102	10	822.18	19600.93	22652.99	42253.92	211.89
C103	10	825.23	21737.1	27568.18	49305.28	270.16
C104	10	822.77	17803.05	19424.1	37227.15	374.97
C105	10	822.3	18779.86	19364.02	38143.88	183.44
C106	10	824	20524.18	22892.29	43416.47	184.95
C107	10	826.13	21983.51	24424.72	46408.23	186.76
C108	10	822.3	21501.73	25952.37	47454.1	211.3
C109	10	821.66	19264.18	25407.27	44671.45	243.52
C201	8	1109.01	23484.62	43592.54	67077.15	232.99
C202	6.8	974.05	21320.91	35152.88	56473.79	355.72
C203	5.2	960.89	19220.78	24152.84	43373.62	768.65
C204	4.4	711.12	15802.78	16690.41	32493.2	1096.26
C205	6.8	919.76	19756.45	34044.41	53800.86	282.5
C206	6	841.68	17971.69	32810.13	50781.82	403.07
C207	6	821.56	17704.23	30937.59	48641.81	447.61
C208	5	873.99	17497.62	24212.05	41709.68	574.51
R101	8	943.75	24745.83	40330.13	65075.96	234.5
R102	8	873.01	22158.91	36834.63	58993.54	291.67
R103	8	837.04	21672.84	28335.07	50007.91	383.11
R104	8	834.08	18319.34	18477.34	36796.67	516.23
R105	8	861.9	22926.07	37320.7	60246.77	265.22
R106	8	842.5	20731.54	32006.05	52737.59	326.28
R107	8	834.64	20563.94	24037.9	44601.84	431.06
R108	8	834.09	17680.23	15902.41	33582.64	562.65
R109	8	837.17	21318.62	30894.04	52212.66	324.35
R110	8	834.86	19243.08	24221.51	43464.59	411.89
R111	8	835.55	19427.64	24665.76	44093.4	411.89
R112	8	834.98	16307.31	12886.08	29193.39	575.56
R201	6	909.16	21010.07	28507.68	49517.75	361.68
R202	5.2	872.73	18987.17	24159.16	43146.33	520.43
R203	5	763.83	17190.57	20405.72	37596.29	809.12
R204	4	747.23	15397.11	13648.35	29045.46	1418.56
R205	5	822.71	17844.85	22259.9	40104.75	551.28
R206	5	769.07	17258.2	20838.96	38097.16	765.12
R207	4	728.92	15230.91	14853.57	30084.48	1050.34
R208	4	711.03	14996.88	12289.61	27286.49	1689.51
R209	5	776.58	17217.35	20055.78	37273.12	738.46
R210	5	773.27	17320.83	21576.04	38896.87	759.23
R211	4.2	748.23	15495.29	15472.02	30967.3	1094.46
RC101	9	1030.96	25802.34	36036.11	61838.45	220.63
RC102	9	1007.24	24475.15	33222.91	57698.06	269.33
RC103	9	990.85	23267.73	28784.34	52052.07	344.96
RC104	9	989.87	19066.44	17338.94	36405.38	443.01
RC105	9	1007.74	25237.38	35710.84	60948.22	251.82
RC106	9	996.03	24184.9	31703.86	55888.76	261.8
RC107	9	992.84	21681.91	24494.7	46176.61	324.12
RC108	9	991.14	19355.9	17274.74	36630.64	433.49
RC201	6	950.84	20569.61	28456.27	49025.89	332.11
RC202	5.6	879.06	19432.46	23969.28	43401.74	475.83
RC203	5	790.53	17717.86	18925.84	36643.7	729.55
RC204	4.2	759.67	15709.75	13578.38	29288.13	1209.93
RC205	6	874.03	19858.64	28505.25	48363.88	474.25
RC206	5	888.56	18560.96	21030.58	39591.54	558
RC207	5	787.14	17168.55	20849.35	38017.9	699.2
RC208	4.2	756.46	15844.5	15357.03	31201.54	1088.32

Table 2.XIII: Minimizing the number of vehicles, and then the total duration by using Algorithm 2.2

Instance	Vehicles	Distance	Working time (min)	Resting time (min)	Total duration (min)	CPU (min)
C101	10	1133.9	20180.54	13044.48	33225.02	150.51
C102	10	1145.05	20137.81	11848.9	31986.71	177.94
C103	10	1103	19555.92	11377.18	30933.1	226.12
C104	10	1002.01	18076.09	8329.67	26405.75	329.98
C105	10	1161.92	20285.62	12048.99	32334.61	158.09
C106	10	1143.1	20062.33	11979.57	32041.9	159.56
C107	10	1103.24	19416.78	10837.71	30254.49	166.24
C108	10	1109.19	19366.1	10451.59	29817.69	173.4
C109	10	1034.12	18482.21	8273.19	26755.41	214.7
C201	7.8	1588.58	26539.57	27573.27	54112.84	218.57
C202	7	1434.78	24054.84	20419.96	44474.8	355.97
C203	5.2	1097.34	19495.89	16049.75	35545.64	813.17
C204	5	927.69	17258.32	10214.13	27472.45	1030.12
C205	6.8	1397.38	23207.4	21315.51	44522.91	286.87
C206	6	1211.76	20951.51	16818.56	37770.07	405.91
C207	6	1198.67	20741.22	18725.03	39466.25	451.83
C208	5.4	1099.07	19483.18	15498.33	34981.51	533.2
R101	8	1530.67	25897.46	19315.01	45212.47	230.35
R102	8	1388.17	23861.01	15735.62	39596.63	264.98
R103	8	1191.35	20690.04	12589.83	33279.86	330.31
R104	8	1065.6	18865.3	9194.2	28059.5	448.24
R105	8	1319.82	22198.56	14233.54	36432.1	221.61
R106	8	1267.27	21459.39	13171.83	34631.22	256.71
R107	8	1172.24	20093.71	10536.21	30629.92	348.12
R108	8	1003.21	18045.84	8582.67	26628.52	440.99
R109	8	1169.93	20112.34	10908.09	31020.44	282.35
R110	8	1078.88	18960.88	9807.97	28768.85	343.56
R111	8	1125.71	19522.36	10148.05	29670.41	329.58
R112	8	965.15	17581.85	7853.56	25435.41	432.36
R201	6.2	1360.13	22924.34	17627.97	40552.3	293.57
R202	5.8	1180.66	20487.95	14412.67	34900.62	433.58
R203	4.2	928.75	16345.72	11198.49	27544.22	484.05
R204	4.8	924.46	17118.69	9452.58	26571.27	1085.5
R205	5.6	1179.86	20307.96	13528.03	33836	434.29
R206	5	1057.6	18736.99	11887.23	30624.22	617.91
R207	5	950.29	17445.59	10021.01	27466.6	930.71
R208	4.2	828.32	15939.8	8591.6	24531.4	1595.68
R209	5	1049.98	18652.03	11306.84	29958.87	583.52
R210	5	1075.75	18981.27	11668.61	30649.88	562.46
R211	5	955.21	17464.33	9792.94	27257.26	870.8
RC101	9	1527.06	24924.84	16592.32	41517.17	211.26
RC102	9	1466.11	23897.45	15181.18	39078.63	256.1
RC103	9	1348.02	22272.23	12460.84	34733.07	300.23
RC104	9	1222.92	20690.01	10339.08	31029.08	408.42
RC105	9	1433.22	23857.39	14794.02	38651.42	251.3
RC106	9	1340.67	22382.69	13304.41	35687.1	261.21
RC107	9	1228.34	20813.79	11534.67	32348.47	313.78
RC108	9	1195.16	20399.14	10071.01	30470.15	378.56
RC201	6	1258.86	21742.65	16651.4	38394.05	376.36
RC202	6	1240.38	21234.24	14660.52	35894.76	419.07
RC203	4.8	1024.49	18187.23	11865.04	30052.27	606.9
RC204	5	963.96	17617.86	9528.97	27146.83	1052.65
RC205	5.4	1074.22	18853.72	14488.88	33342.6	332.54
RC206	5.2	1130.93	19792.46	13468.68	33261.15	664.64
RC207	5	1064.79	18889.87	11258.31	30148.18	604.3
RC208	5	955.45	17483.68	9494.87	26978.55	881.7

Chapitre 3

Multicriteria Optimization of a Long-Haul Routing and Scheduling Problem

Chapter information

An article based on this chapter is now under revision for the journal *Journal of Multi-Criteria Decision Analysis*: M.-È. Rancourt and J. Paquette. Multicriteria Optimization of a Long-Haul Routing and Scheduling Problem. Technical Report, *CIRRELT-2012-32*, Montreal, July 2012.

Abstract

Long-haul carriers are facing a shortage of drivers in North American countries. To reduce turnover rates and improve driver retention, trucking companies are making more efforts to enhance drivers' quality of life. The aim of this paper is to introduce and solve a multi-objective vehicle routing and truck driver scheduling problem under the legislative requirements on hours of service in the United States (US MOVRTDSP). We present a tabu search algorithm that solves the US MOVRTDSP and provides heuristic non-dominated solution sets from which tradeoffs between operating costs and driver inconvenience are evaluated. Results show that decreasing driver inconvenience increases carrier operating costs in a smaller proportion. The tradeoffs between the number of vehicles used and operating costs are also estimated in order to evaluate the efficacy of the rule of thumb generally applied in the industry of focusing on minimizing the number of vehicles sent on the road. We show that for most cases, operating costs increase when the number of vehicles exceeds the minimum fleet size. Overall, interpretations of the

computational results on artificial and real-life instances provide meaningful information to long-haul carriers.

Keywords: Multicriteria analysis, vehicle routing, truck driver scheduling, driver working conditions, tabu search heuristic.

3.1 Introduction

For many years, North American countries have been facing a shortage of drivers for long-haul transportation services which imply long distances traveled over several days by drivers (Johnston et al., 2009; Doss, 2012). In that context, trucking companies increasingly seek to improve driver working conditions as a way to reduce the turnover rates and enhance the retention of this labor. For example, carriers now make greater efforts to adjust schedules and routes so that drivers won't be away from their families for too many days in a row. Trucking companies are thus pursuing two different objectives simultaneously: minimizing operating costs and minimizing driver inconvenience. Moreover, to ensure road safety, different governments around the world have established working hour rules to be taken into account when planning vehicle routing and scheduling. These rules typically stipulate that truck drivers should not work for more than a certain number of hours during successive days without taking a rest. This stands in contrast to classical routing problems where vehicles leave and come back to the depot on the same day.

In the trucking industry, long-haul routes are valued by the distance and number of clients visited. The variable costs for a fixed number of customers, referred to as "operating costs" in this project, are thus proportional to the distance traveled by the trucks. Because drivers are not remunerated for resting time or waiting time, these elements account for "driver inconvenience" in this project. In fact, the larger the number of resting hours on the road, the more time a driver is away from home. We also consider waiting time to be an inconvenience given that it is idle time away from home in addition to being unpaid. According to a study by Johnston et al. (2009), time away from home is the most disagreeable aspect of being a long-distance truck driver, which is consistent with findings derived from discussions with experts from the trucking industry.

Another commonly pursued goal of trucking companies is to minimize the number of vehicles used to provide the service. Generally, dispatchers adopt the rule of thumb of using as few vehicles as possible in order to minimize operating costs while seeking to maintain the capacity to provide service in the case of last-minute demands. In this study, rather than including a fixed cost associated with the number of vehicles used in

the objective function, we will sequentially solve the problem using the minimum number of vehicles and then adding one, two and three vehicles to the minimum fleet.

The aim of this paper is to present and solve a multicriteria vehicle routing problem that has emerged in the less-than-truckload industry by taking into account the legislative requirements on the hours of service in the United States (US). This problem is referred to as the US multi-objective vehicle routing and truck driver scheduling problem (US MOVRTDSP). The contribution of this paper is threefold. First, we solve the problem by means of a scheduling algorithm and a multicriteria scheme, both embedded within a tabu search heuristic. Our study, although generally applicable for long-haul transportation in the United States, was first motivated by the case of the US Operations Division of Groupe Robert Inc., one of the largest and most widely known third-party logistics providers in Canada. In addition to the US regulations and other constraints sometimes considered in vehicle routing problems (VRPs), such as multiple time windows and a heterogeneous vehicle fleet, our study takes into account a bi-objective function representing carrier operating costs and driver inconvenience. Second, this heuristic helps to enhance the understanding of the tradeoffs between the carrier costs and the driver inconvenience through the analysis of non-dominated solution sets. Drivers are an important asset for carriers. Improving their working conditions can therefore reduce their turnover rate, thus enhancing the level of service and reducing training costs. Third, our results also improve the understanding of the tradeoffs between the number of vehicles used and the operating costs, which allows assessing the efficacy of the above-mentioned rule of thumb employed by dispatchers. Overall, interpretations of the computational results on artificial instances and on a real-life instance can provide meaningful information to carriers operating transportation services in the United States and elsewhere.

The remainder of this paper is organized as follows. Section 3.2 presents a literature review on long-haul vehicle routing and scheduling problems and on the different algorithms used to solve multicriteria combinatorial problems. Section 3.3 presents the multicriteria objective function and the constraints used to model the problem. The tabu search heuristic developed to solve this US MOVRTDSP is then described in Section 3.4. Computational results are presented and analyzed in Section 3.5, followed by the managerial implications in Section 3.6. Finally, conclusions are summarized in Section 3.7.

3.2 Literature review

In long-haul transportation worldwide, truck driver fatigue is recognized to be an important factor of accidents (see Williamson et al., 2001; European Transport Safety

Council, 2001; Federal Motor Carrier Safety Administration, 2008, as sample studies for Australia, Europe and the United States). Governments are making efforts to improve driver safety and working conditions by adopting hours of service legislation in road freight transport. These regulations typically impose restrictions on the length of driving and working times during which drivers are permitted to drive without taking a rest or a break over given periods. Trucking companies must take into account the rules that apply to their regions of operation when constructing routes and planning truck driver schedules. Even though routing problems have attracted a lot of attention in the literature, it is only until recently that working hour regulations in road freight transport are being taken into consideration in the vehicle routing and scheduling problems. Archetti and Savelsbergh (2009), Goel and Kok (2012) and Goel and Vidal (2012) proposed models and exact methods for finding a feasible schedule in compliance with US regulations for a fixed sequence of customers with time windows. Goel (2010), Goel and Rousseau (2012) and Goel et al. (2012) have studied this problem in the context of the European, Canadian and Australian regulations, respectively. The problem that combines this type of scheduling component with a routing component is called the vehicle routing and truck driver scheduling problem (VRTDSP). The scheduling component consists of the planning of the driver rest periods and the customer service times, and the routing component consists of determining the sequence of customers visited by each vehicle. Solving the VRTDSP thus involves determining a set of routes that minimize operating costs for a fleet of vehicles subject to limited capacities such that each customer is visited within given time windows and that each truck driver schedule complies with the applicable working hour regulations.

Heuristic approaches for solving the VRTDSP have been presented by Goel (2009), Kok et al. (2010) and Prescott-Gagnon et al. (2010) with regard to EU regulations and by Rancourt et al. (2012) with regard to US regulations. Other variants of the VRTDSP have been addressed by Xu et al. (2003), Zäpfel and Bögl (2008), Ceselli et al. (2009), Bartodziej et al. (2009) and Kok et al. (2011). Goel and Vidal (2012) were the first to propose an approach that is not restricted to a particular set of rules. They conducted extensive experiments to assess the impact of the different regulations in the United States, Canada, the European Union and Australia. With regard to EU regulations, their method has proven to outperform all other proposed methods for tackling the VRTDSP. They also show that the risk levels of the different countries' regulations correlate negatively with the associated operating costs, except for the Australian regulations, which rank highest in terms of risk level and operating costs. The European Union legislation provides for the highest level of safety, while the Canadian regulations are the most competitive in terms of costs.

Table 3.I summarizes the papers published on the VRTDSP. We can observe that all heuristics developed to solve the VRTDSP are single-criterion, with the primary objective being to minimize the number of vehicles used, and the secondary objective typically being to minimize operating costs, which are generally based on the total distance traveled or the total duration of routes. Rancourt et al. (2012) have considered alternative secondary objectives in conjunction with the primary objective of minimizing the number of vehicles. To do so, they have used a weighted objective function and applied a lexicographic process. However, to our knowledge, no method has been proposed to solve the VRTDSP as a multicriteria optimization problem that yields a non-dominated solution set.

Table 3.I: Summary of the references related to the VRTDSP

Article	Regulations				Objectives		
	EU	US	CAN	AUS	Distance	Duration	Cost
Xu et al. (2003)		√					√
Ceselli et al. (2009)		√[a]					√
Goel (2009)	√				√		
Kok et al. (2010)	√					√	
Prescott-Gagnon et al. (2010)	√				√		
Kok et al. (2011)	√				√		
Rancourt et al. (2012)		√			√	√	√
Goel and Vidal (2012)	√	√	√	√	√		

[a] The legislation considered in this study is not specified, but the applied rules are very similar to the US regulations

Decision-makers generally pursue more than one objective when making a decision. Subsequently, when modeling practical problems encountered in real-life applications, considering several criteria in the optimization process has become common practice. The approaches to solving these problems can be divided into three categories: (1) a priori decision-making – when the decision-maker's preferences are known before the optimization phase starts; (2) a posteriori decision-making – when the decision-maker provides his/her preferences after the optimization phase by interpreting the set of resulting solutions; (3) dynamic decision-making – when the decision-maker interacts iteratively during the optimization phase, namely by reacting to the solutions presented to him/her, to provide more information about his/her preferences.

The first category of multicriteria problem-solving is very popular. Indeed, many multicriteria studies are using weighted functions of preferences as an objective function to drive their algorithm. This enables the resolution of a single-criterion problem after scalarization, which in turn enables the use of single-criterion algorithms that already exist. A field of research on multicriteria optimization has emerged from the development of specific methods to solve multicriteria problems. The most common approaches are the ϵ-constraint method, goal programming and ranking methods. The ϵ-constraint method

consists of transforming a problem's objective functions into constraints as a way to reduce their number. Here, information on the acceptable level of the different objective functions must be known in advance. Goal programming, for its part, aims to minimize the distance to an ideal point. The ideal point values must be provided a priori by the decision-maker, as well as the weights used to put more or less emphasis on the different objectives. Finally, ranking methods, also called lexicographic methods, sequentially optimize the objective functions in the order determined by the decision-maker. Some information on the decision-maker's preferences is thus required in advance. These methods usually apply a priori known information and yield a unique optimal solution.

Other research to solve multicriteria problems has focused on extending single-criterion methods to the multicriteria context. These methods can be exact such as dynamic programming or branch-and-bound, or metaheuristics such as tabu search (Gandibleux et al., 1997) and simulated annealing (Alves and Clímaco, 2000), which provide an approximation of the set of solutions. Moreover, evolutionary algorithms (Bäck, 1996), which are global search optimization algorithms based on the mechanics of natural selection and reproduction, have proven to be very effective in solving complex multicriteria optimization problems (Cvetkovic and Parmee, 2002; Jaszkiewicz, 2003; Refanidis and Vlahavas, 2003). These methods usually provide the decision-maker with a set of non-dominated solutions. Further details on the methods for solving multicriteria combinatorial optimization problems can be found in Hansen (2000), Coello Coello et al. (2002), and Ehrgott and Gandibleux (2002).

The specific case of multicriteria routing problems has been discussed and reviewed in Boffey (1996) and Jozefowiez et al. (2008). The resolution methods mentioned earlier are similar to those used for this specific group of problems. Most research is concentrated on the bi-criteria traveling salesman problem. Some research has also been done on different vehicle routing problems (Park and Koelling, 1986; Jozefowiez et al., 2002; Murata and Itai, 2005; Ombuki et al., 2006; Tan et al., 2006; Murata and Itai, 2007; Jozefowiez et al., 2009; Parragh et al., 2009; Repoussis et al., 2009; Garcia-Najera and Bullinaria, 2011; Paquette et al., 2013). Table 3.II summarizes the problem, objectives, groups of constraints and type of algorithm presented for each article.

From this table we can see that the most common objectives in multicriteria vehicle routing problems are to (1) minimize the number of vehicles, (2) minimize the total cost (or distance, or time) and (3) equilibrate the length of routes among the vehicles. The first two objectives are also those that are most commonly used to solve the VRTDSP in a lexicographic manner. Moreover, different algorithms are used to optimize multicriteria vehicle routing problems such as evolutionary algorithms, variable neighborhood search and tabu search heuristics.

Table 3.II: Summary of the main studies on multi-objective vehicle routing problems

Article	Problem	Objectives	Algorithm
Park and Koelling (1986)	CVRP	(1) Minimize the travel distance of vehicles, (2) minimize the total deterioration of goods, and (3) maximize the total fulfillment of emergent services and compliance with conditional dependencies of stations.	Two-phase heuristic: (1) clustering heuristic and (2) goal programming (decision-maker provides a priority structure)
Jozefowiez et al. (2002)	CVRP	(1) Minimize total distance, and (2) minimize the difference between maximum route length and minimum route length.	Evolutionary algorithm with parallel and hybrid models for intensification and diversification tasks.
Murata and Itai (2005)	VRP	(1) Minimize the number of vehicles, and (2) minimize the maximum routing time among vehicles.	Evolutionary algorithm.
Ombuki et al. (2006)	VRPTW	(1) Minimize the number of vehicles, and (2) minimize total cost (distance).	Genetic algorithm.
Tan et al. (2006)	TTVRP	(1) Minimize routing distance, and (2) minimize the number of trucks.	Hybrid multi-objective evolutionary algorithm.
Murata and Itai (2007)	VRP	(1) Minimize the maximum routing time among vehicles, (2) minimize the number of vehicles, and (3) maximize the similarity of solutions.	Memetic evolutionary algorithm.
Jozefowiez et al. (2009)	VRPRB	(1) Minimize total length of routes, and (2) minimize the difference between maximum route length and minimum route length.	Evolutionary algorithm.
Parragh et al. (2009)	DARP	(1) Minimize cost, and (2) minimize mean user ride time.	Variable neighborhood search algorithma and path relinking technique.
Repoussis et al. (2009)	VRPTW	(1) Minimize the number of routes (vehicles), and (2) minimize the total travel time.	Evolutionary algorithm combined with tabu search heuristic and lexicographic evaluation in a first phase; with a guided local search in a second phase.
Garcia-Najera and Bullinaria (2011)	VRPTW	(1) Minimize the number of routes (vehicles), (2) minimize total travel distance, and (3) minimize total travel time.	Evolutionary algorithm.
Paquette et al. (2013)	DARP	(1) Minimize cost, (2) minimize waiting time within the destination time window for an outbound trip, (3) minimize waiting time within the origin time window for an inbound trip, and (4) minimize ratio of actual ride time over direct ride time.	Tabu search heuristic and reference point method.

This paper is the first study that proposes a methodology that exploits the strengths of multicriteria optimization to generate a set of non-dominated solutions for a variant of the VRTDSP. Our results will allow to measure the tradeoffs between the operating costs and the driver inconvenience and to assess the impact of using more vehicles than the minimum fleet size.

3.3 Problem description

The problem considered in this paper is a bi-objective VRTDSP in compliance with the current Hours of Service (HOS) regulations for commercial vehicle drivers (Part 395 of the US Department of Transportation) as well as other VRP constraints. In this section, we first present the HOS regulations, followed by a description of the ensuing VRTDSP and its constraints and objectives.

3.3.1 Hours of service regulations

In the United States, the Federal Motor Carrier Safety Agency is responsible of publishing the HOS regulations. These regulations mainly restrict the amount of cumulated driving and working time between rest periods. The regulation distinguishes between on-duty time and off-duty time. On-duty time consists of the time when a driver is performing work or is required to be available for work. On-duty time includes driving activities as well as any other type of work such as loading and unloading. In this project, we adopt a conservative definition of idle time in that we consider waiting time to be on-duty time, mainly because we assume that drivers may have to remain in the vehicle during these waiting periods. Off-duty time refers to time during which drivers have no obligation to perform work, in other words, time during which they are free to pursue any activity and leave the vehicles where they are parked. For example, resting time is considered to be off-duty time.

The HOS regulations essentially impose limits on the duration of times during which drivers of commercial motor vehicles can drive or be on-duty without taking off-duty periods of prescribed durations. Table 3.III describes the three fundamental rules: the 60/70-hour on-duty limit, the 11-hour driving limit and the 14-hour limit. The first rule prescribes a limit on on-duty time during a defined number of consecutive days. In our study, we use the 70-hour on-duty limit to be consistent with Groupe Robert's practice. The second rule limits to 11 hours the driving time after an off-duty period of at least 10 hours, which means that a driver must take an off-duty period of at least 10 hours to regain the right to drive after cumulating 11 hours of driving. The third rule forbids driving after an on-duty period of 14 hours that begins right after an off-duty period of

10 hours. However, a driver may perform work other than driving beyond this 14-hour limit. We point out that an off-duty period of at least 10 consecutive hours but less than 34 hours will be considered a rest period in the remainder of this paper. A driver can also use the sleeper berth provision to get the equivalent of 10 consecutive off-duty hours with two separate split rest periods of at least eight and two hours. However, neither this special provision, nor a new provision to come into effect starting July 2013, will be taken into consideration in this paper. The interested reader can obtain more information on HOS regulations from the U.S. Department of Transportation (2012) website.

Table 3.III: Hours of service regulations

60/70-hour on-duty limit	A driver may not drive after 60/70 hours on-duty in 7/8 consecutive days. He/she may again start a 7/8 consecutive day period after 34 or more consecutive off-duty hours.
11-hour driving limit	A driver may only drive a maximum of 11 hours after 10 consecutive off-duty hours.
14-hour limit	A driver may not drive beyond the 14^{th} consecutive hour after coming on-duty following a period of 10 consecutive hours off-duty. Off-duty time does not delay the 14-hour period.

In summary, a driver may drive at most h^{drive} hours and may be on-duty at most h^{on_duty} hours before taking a rest of at least h^{rest} hours to regain the right to drive. In other words, a rest period must be taken at the latest when the driving limit or the on-duty limit is reached. Duty time consists primarily of driving, waiting and service time (loading and unloading activities). Moreover, a driver may be on-duty for at most h^{total_duty} during a horizon of H consecutive days. We can thus set the following parameters:

H = eight days, the number of consecutive days during a planning horizon;

$h^{total_duty} = 70$ hours, the maximum cumulated on-duty time during the planning horizon H;

$h^{drive} = 11$ hours, the maximum cumulated driving hours between two prescribed off-duty periods;

$h^{on_duty} = 14$ hours, the maximum cumulated on-duty hours after which it is prohibited to drive without resting;

$h^{rest} = 10$ hours, the minimum duration of a rest period in order to be granted the right to drive again after the 11-hour or the 14-hour limits are reached.

3.3.2 Vehicle routing and scheduling constraints

We now describe the constraints considered in the VRTDSP we are studying in this paper. Given a fleet of m vehicles based at a depot, the problem consists of determining a

set of feasible routes to serve a set V of customers in order to minimize a given objective (in the standard version of the problem) or two objectives (in this multicriteria version of the problem described hereafter). The depot is denoted by 0 and we define V_0 as being $V \cup \{0\}$. Let c_{ij} be the travel distance between i and j, where $i, j \in V_0$, and let d_{ij} be the driving time to reach j from i. The problem is solved over a planning horizon of length H. A unique time window $[\tau_{1,0}^{\min}, \tau_{1,0}^{\max}]$ of length H is associated with the depot, where $\tau_{1,0}^{\min}$ and $\tau_{1,0}^{\max}$ represent the earliest possible departure time from the depot and the latest admissible arrival time at the depot, respectively.

An ordered set of time windows $T_i = \{[\tau_{ti}^{\min}, \tau_{ti}^{\max}], t = 1, \ldots, \bar{t}_i\}$, with $\tau_{t-1,i}^{\max} \leq \tau_{ti}^{\max}$ $(t = 2, \ldots, \bar{t}_i)$, is also associated with each customer i. These sets of time windows restrict the time intervals within which delivery is allowed. Each customer $i \in V_0$ must be visited once by a vehicle during l_i time units, without service interruption. Consequently, a single time window must be chosen for each customer delivery. If a vehicle arrives before the opening of this time window, it has to wait. It must also arrive before the closing of the selected time window, otherwise the driver will have to wait until the opening of the next available time window. Groupe Robert seeks to meet customer requirements by using a heterogeneous fleet of vehicles suited to various functions (dry and heated vehicles in this case). Consequently, every customer $i \in V_0$ has a non-negative demand q_i and can be served only by a subset of the vehicle fleet. Every vehicle type has a given load capacity that cannot be exceeded by the total demand it carries.

The routing and scheduling constraints just described consist of a vehicle routing problem with multiple time windows and a heterogeneous fleet. By including the HOS regulations in the scheduling component of this problem, we obtain the resulting decision problem that can be denoted the US VRTDSP.

3.3.3 Vehicle routing and scheduling objectives

Carriers try to arrange schedules and routes to accommodate their drivers' preferences, in particular with regard to reducing the number of consecutive days they are away from their families. However, while pursuing the objective of minimizing driver inconvenience, the trucking companies also seek to minimize operating costs. Given the aim to optimize both of these objectives simultaneously, the problem in question is referred to as the multi-objective vehicle routing and truck driver scheduling problem (US MOVRTDSP). One objective aims to minimize the operating costs, which are proportional to the total distance traveled by vehicles. The other objective aims to minimize the driver inconvenience, considered to be the sum of the resting time and waiting time of all drivers. Waiting time is measured by the difference, if it is positive, between the beginning of the time window and the arrival time of the vehicle at the customer.

3.4 Multicriteria solution approach

In this section, we present the multicriteria tabu search algorithm we have developed to solve the US MOVRTDSP. The method we are proposing is a generalization of the algorithm proposed by Rancourt et al. (2012) for the single-criterion US VRTDSP and aims to determine a set of heuristic non-dominated solutions. To do so, we implemented a search mechanism that consists of a single thread in which the weighting attributed to the two objectives, namely operating costs and driver inconvenience, are dynamically modified and in which dominated solutions are discarded along the search. The principle used to adapt the objective function and changes in the weighting have been proven to be efficient by Paquette et al. (2013). In the following, we first explain the outlines of the tabu search. We then describe the scheduling algorithm embedded within the tabu search that enables handling the HOS regulations. Finally, we present how the tabu search has been adapted to manage the bi-objective function and yield a non-dominated solution set.

3.4.1 Tabu search principles

The tabu search heuristic is first initialized with a solution x_0. This solution is constructed by selecting the customer located the farthest away from the depot and by adding the customer that is closest to the current route until the thresholds with regard to capacity or duration have been met. This process is sequentially repeated until all the customers are assigned to a route. The obtained solution then forms the initial solution x_0, which is not necessarily feasible. The algorithm then moves at each iteration from a solution x to another solution x' in the neighborhood $N(x)$ of x for a fixed number of iterations. The neighborhood $N(x)$ is composed of all the solutions that can be obtained by applying a given type of transformation to x. A solution x is identified with an attribute $B(x) = \{(i,k) : i \in V, k = 1, ..., m\}$ that indicates on which route k each customer i is visited. A neighbor solution is thus obtained by replacing a pair $(i,k) \in B(x)$ with another non-tabu pair $(i,k') \notin B(x)$. The move that best minimizes the increase of the objective function is performed at each iteration and the attribute (i,k) is declared tabu for a fixed number of iterations. However, an aspiration criterion allows the search process to accept a solution x containing a tabu attribute (i,k) if this solution is the best known solution for this attribute.

The search is broadened by accepting intermediate infeasible solutions. This is achieved through the use of a penalized objective function with self-adjusting penalties applied to the constraint violations. Relaxing the constraints allows the algorithm to explore infeasible solutions in order to reach better solutions that may not be possible to obtain

otherwise. For a given solution x, let $q(x)$ be the violation of capacity constraints, $w(x)$ the violation of on-duty constraints emerging from the 70-hour limit, and $v(x)$ the violation of time window constraints. The objectives of the carrier are represented by a function $f(x)$ and the total duration of the solution x is represented by $d(x)$. The global objective function $F(x)$ corresponds to:

$$F(x) = f(x) + \alpha q(x) + \beta w(x) + \gamma v(x) + \lambda d(x),$$

where the parameters α, β, and γ are dynamically updated throughout the search. After each iteration, the values of these parameters are modified by a factor of $1+\delta$, where δ is chosen randomly in the interval $[0, 1]$ at each iteration. If the current solution is feasible with respect to a constraint, the value of the parameter associated to this constraint is divided by $1 + \delta$; if not feasible with respect to a constraint, it is multiplied by $1 + \delta$. A perturbation mechanism has also been implemented by modifying parameter λ during the tabu search. If no solution improving $F(x)$ or one of the carrier objectives in $f(x)$ has been found for 1,000 iterations, the parameter λ will be set equal to 10 for a fixed number of iterations. Otherwise, this parameter is equal to zero. This mechanism helps to diversify the search by increasing the weight on the value of the total duration in the global cost function. The classic diversification and intensification schemes proposed by Cordeau et al. (2001) are also used to improve the search. The goal of the diversification is to penalize solutions containing frequently encountered attributes, whereas intensification is a process aimed at deepening the search around good solutions.

To evaluate the costs and the time constraint violations of a solution, a schedule complying with the HOS regulations has to be determined. To do so, a rest scheduling algorithm that tackles the HOS regulations and the multiple time windows is embedded within the tabu search heuristic.

3.4.2 Scheduling heuristic

The routes constructed during the course of the search are evaluated using an algorithm proposed by Rancourt et al. (2012), referred to as Algorithm 1 in their paper. This procedure allows determining a schedule complying with the HOS regulations for a given sequence of customers so that the attributes of a route, such as customer service time, driver waiting and resting time can be computed. For a route $r = (i_0 = 0, i_1, ..., i_p, i_{p+1}, ..., i_{n_r} = 0)$ of n_r customers, the forward labeling procedure iteratively generate a set S_p of schedules for each partial route $r_p = (i_0, i_1, ..., i_p)$, with $p \in \{0, ..., n_r\}$.

The algorithm starts with a partial route containing nothing other than the depot. The only schedule in S_0 is the one departing from the depot at the beginning of its time window. In the subsequent iterations $p = (1, ..., n_r)$, each schedule of S_p is extended into a new schedule for the partial route r_p by successively appending driving, waiting, working and rest periods to the end of the schedule that is currently expanded. Once the subsequent customer of the current route is reached, the algorithm generates two possible schedules, namely the direct execution of the service without a rest and the insertion of an anticipated rest before the execution of the service. To minimize the waiting time and to ensure that the driver is as flexible as possible for subsequent activities, unnecessary waiting time is prohibited and the duration of the previously scheduled rest periods is extended (or the departure from the depot is delayed) by computing the forward time slack since the last rest.

By applying this process sequentially, beginning with the depot and continuing with each succeeding node in a route, multiple schedules are generated to reach each customer. To reduce the number of possibilities and to speed up the process, some schedules are pruned during the enumeration by using a heuristic principle of dominance. The retained schedule is the one that allows to complete the trip within the shortest amount of time. For more details on how the schedules are extended and on how the alternative schedules are managed within the labeling process, see Rancourt et al. (2012).

3.4.3 Adaptation of the tabu search to the bi-objective problem

In this section, we explain how the tabu search heuristic was adapted to handle the bi-objective problem and find a non-dominated solution set. Each solution is represented by a vector, the elements of which correspond to the values of each objective. The reference point method of Clímaco et al. (2006), which was first designed for generic multicriteria problems, is now adapted to our case. According to this method, potential solutions identified during the search process are evaluated by their distance from an ideal point. This point, which is generally infeasible, is defined by a vector featuring the minimum value of each objective optimized separately. The distance between a potential solution and the ideal point is computed with the Manhattan metric for its ease of implementation in the tabu search heuristic. The objective function we are using is defined as:

$$f(x) = \omega_1|c(x) - c^*| + \omega_2|i(x) - i^*|,$$

where $c(x)$ are the operating costs, $i(x)$ the driver inconvenience, ω_z the weight put on criterion z ($z = 1$ and 2), and (c^*, i^*) the ideal point. Because we are seeking a set of solutions and not only one optimal solution, the weights are changed dynamically and

every feasible solution x' found during the search is compared to the solutions kept in a pool X of non-dominated solutions, even if $F(x') > F(x^*)$, with x^* the value of x yielding $\min\{F(x) \mid x \in X\}$. Indeed, having $F(x') > F(x^*)$ does not necessarily mean that solution x' is dominated when considering the two objectives $c(x)$ and $i(x)$.

The weights ω_1 and ω_2 play two distinct roles. First, since the first objective is measured in units of distance and the second objective in units of time, the weights are used to put the two objectives on a comparable scale. As recommended by Clímaco et al. (2006), we use the scaling factors $\sigma_z = 1/(UB_z - LB_z)$, where UB_z and LB_z are the upper and lower bounds on the value of criterion z. The bounds have to be computed empirically given the absence of a priori information in this case. Second, the weights also help exploring different parts of the solution space, which could be seen as a form of diversification procedure. To this end, three strategies that differ in the way the weights are changed dynamically have been tested.

Strategy 1 is the one developed by Paquette et al. (2013), which updates the weights whenever κ iterations have elapsed since the last feasible solution was encountered, or whenever the algorithm has not identified any feasible solution for more than ι consecutive iterations. The procedure to update the weights is as follows:

$$\omega_1 = \sigma_1\omega_1|c(x) - c^*|;$$

$$\omega_2 = \sigma_2\omega_2|i(x) - i^*|;$$

$$\omega_z = \omega_z/(\omega_1 + \omega_2), \text{ with } z = 1 \text{ and } 2.$$

This procedure puts more emphasis on the term of the objective function for which the worst value was obtained compared to the ideal point at the last iteration. At the same time, the the weights are normalized by setting their sum equal to one. Whenever the weights are updated, the tabu list is emptied.

Strategy 2 has four distinct phases. In the first phase, λ is set equal to 1, and ω_1 as well as ω_2 are fixed equal to zero for the first 10,000 iterations. Thus, the objective function is oriented toward finding solutions with the best duration, which speeds up the process of finding feasible solutions at the beginning of the search. In the second phase, which lasts 20,000 iterations, the procedure described in Strategy 1 is applied. In the third and fourth phases, which last 10,000 iterations each, ω_1 and then ω_2 are respectively set equal to 1. These phases are intensification procedures applied to help finding the two tails of the Pareto front.

Strategy 3 implemented to change the weights is similar to the first one. The only difference is that λ is set equal to 1, and ω_1 as well as ω_2 are fixed to zero for the first 1,000 iterations. Thus, the objective at the beginning of the search is to find solutions

with the best duration. Afterwards, the same procedure described for Strategy 1 is applied. Calibrations of the algorithm will first enable us to establish the best values of the parameters ι and κ, and to then determine which strategy of the three is the best.

In the literature, studies on the VRTDSP have solved the problem by minimizing the number of vehicles as the primary objective by adding a large fixed cost on the number of vehicles used. In order to evaluate the impact of increasing the number of vehicles on the operating costs and the driver inconvenience, the tabu search heuristic is sequentially applied for $k = 0, 1, 2$, and 3, where k corresponds to an increment of vehicles made to the minimum number of vehicles in the fleet. In other words, k=0 means that only the minimum fleet is used and k=3 means that three vehicles are added to the minimum fleet. By applying this process, a set of non-dominated solutions can be determined for the four different fleet sizes. Note that the minimum fleet size m_{min} of each instance was extracted from preliminary experiments and it might not correspond to the optimal value because it was obtained using a heuristic approach.

3.5 Computational results

The algorithm was first calibrated using 12 of the 56 instances developed by Rancourt et al. (2012) for the US VRTDSP. Using a representative sub-group of the artificial instances enables us to determine the best values for parameters ι and κ as well as the best weight-changing strategy. The calibrated multicriteria algorithm was then applied to solve all 56 artificial instances to provide results before solving the real-life instance of Groupe Robert. In this section, we first describe the different groups of instances. We then explain the indicators used to compare the different parameterizations of the algorithm, followed by a presentation of the results of the different calibrations. Finally, the tradeoffs between the number of vehicles, operating costs and driver inconvenience are evaluated for the artificial instances and the real-life instance.

3.5.1 Artificial instances

The artificial instances were borrowed from Rancourt et al. (2012), who had generated them based on the benchmark instances of Solomon (1987) by adding multiple time windows for visiting the customers and changing the travel time matrices. They contain 100 customers each and are divided in six classes that differ with regard to the geographical distribution of the customers and their time window tightness. In the C1 and C2 classes, the customers are clustered, unlike in the classes R1 and R2, where the customers are uniformly distributed. Some customers are clustered while others are uniformly distributed in classes RC1 and RC2. The C1, R1 and RC1 classes have narrow time windows and

smaller load capacity per vehicle than the C2, R2 and RC2 classes. These latter classes are more difficult to solve since the number of customers per route increases, which considerably increases the number of possibilities evaluated in the scheduling process.

All customers have eight time windows during which they can be visited. The available time of all vehicles is set to 192 hours (or 8 days). The traveling speed of a vehicle is set to five distance units per hour as suggested by Goel (2009). Furthermore, in order to adjust the travel matrix of the customers visited during an eight-day horizon, each value is multiplied by 12. The geographic coordinates of the customer and the depot, the distance matrices and the vehicle capacities remain the same as in the Solomon instances.

3.5.2 Real-life Groupe Robert instance

The instance of Groupe Robert corresponds to a typical week of distribution of goods to 162 customers in the United States as depicted in Figure 3.1. Up to eight time windows are associated with each customer depending on the service quality level guaranteed to the customer and the delivery schedule. In order to handle three types of goods with mutual incompatibilities, two vehicles types are considered and a set of compatible vehicles is associated to each customer. Because the routes do not include the trips back to the depot, this real-life instance corresponds to an open vehicle routing problem. Indeed, planning does not consider backhaul loads, as these are only known a posteriori. On-line requests for backhaul opportunities are thus be handled after the deliveries have been completed. As a result, the distances and traveling times from any customer back to the depot are set to zero, as suggested by Pisinger and Ropke (2007).

Figure 3.1: Customer locations and depot location (GR) in the Groupe Robert instance.

3.5.3 Calibration of the algorithm

To assess the quality of the solutions, we have used five performance measures, two of which are indicators frequently used in the literature on evolutionary algorithms (Zitzler et al., 2003, 2010). The first measure is the *hypervolume indicator*, which computes the volume in the objective space formed between the nadir point and all points in the set of non-dominated solutions. The hypervolume indicator thus measures the diversity of the solutions found, which is of great value to decision-makers. Indeed, solutions must be diverse in order to obtain meaningful estimates of the tradeoffs between operating costs and driver inconvenience in different parts of the objective space. The algorithm developed by Fonseca et al. (2006) was used to compute the hypervolume indicators.

The second measure is the *multiplicative unary epsilon indicator*. It represents the smallest value of epsilon by which each point in a reference set has to be multiplied in order to obtain a set that is dominated by the set of non-dominated solutions. Ideally, the reference set should be the Pareto front. However, since our instances cannot be solved exactly, we will use the combination of all the solutions found for the same instance across all the different runs performed on this instance to form a heuristic reference set. For this indicator, a small value is preferable because it means that the evaluated set of non-dominated solutions is close to the reference set.

The other three measures considered to assess the quality of the solutions are the *number of non-dominated solutions found*, the *best encountered value of the operating costs* and the *best encountered value of the driver inconvenience*.

The calibration of the algorithm was realized with 12 of the 56 artificial instances. Two instances were randomly chosen in each class (C101, C108, R103, R110, RC104, RC105, C207, C208, R205, R209, RC202 and RC206). The parameterization has two goals. First, it aims to identify the best values of the number of iterations ι and κ after which the weights are dynamically changed. Second, the calibration will enable determining the best strategy to adopt for changing the weights.

Each of the twelve artificial instances were solved for 50,000 iterations taking the minimum number of vehicles necessary for finding a feasible solution (k=0). Then, each instance was solved by using a fleet that exceeds the minimum fleet size by three vehicles (k=3). The algorithm was first tested using the following values of ι and κ: (1,000; 100), (1,000; 200), (1,000; 500), (2,000; 100), (2,000; 200), (2,000; 500). Tables 3.IV and 3.V show the five solution quality measures obtained with the different parameterizations of ι and κ with an increment of k trucks to the minimum fleet size ($k = 0$ and 3).

The best values of ι and κ were then selected according with the measures employed to evaluate the quality of the resulting solution sets. Each measure yields a different best

Table 3.IV: Average solution quality measures with different ι and κ values and minimum fleet size (k=0)

ι	κ	Epsilon indicator	Hypervolume indicator	Number of solutions	Best cost	Best inconvenience	Average ranking
1,000	100	1.0984	139,979,621.8	29.17	856.05	12,904.94	3.2
1,000	200	1.0899*	139,981,765.8	27.75	858.97	12,530.51	3.2
1,000	**500**	**1.0973**	**140,191,091.0**	**30.00***	**857.16**	**12,769.48**	**2.4***
2,000	100	1.1184	139,756,096.3	25.83	855.17*	13,135.00	5.0
2,000	**200**	**1.1008**	**140,342,369.9***	**28.33**	**856.26**	**12,499.13***	**2.4***
2,000	500	1.1152	139,891,209.3	27.17	858.00	12,785.81	4.8

Table 3.V: Average solution quality measures with different ι and κ values and minimum fleet size incremented by three vehicles (k=3)

ι	κ	Epsilon indicator	Hypervolume indicator	Number of solutions	Best cost	Best inconvenience	Average ranking
1,000	100	1.1796	137,189,434.4	18.33	860.35	14,934.65	4.0
1,000	200	1.1559*	136,891,235.7	20.25	864.70	14,689.70	3.0
1,000	500	1.2155	137,454,893.0	22.58*	858.05*	14,890.22	2.6
2,000	**100**	**1.1848**	**137,478,455.5***	**20.25**	**860.25**	**14,828.98**	**2.4***
2,000	200	1.1582	137,112,368.6	20.08	865.15	14,632.73*	3.4
2,000	500	1.2158	136,645,404.0	19.58	863.03	15,151.33	5.4

parameterization depending on whether we consider the results with the minimum fleet or with a fleet containing three additional vehicles. To analyze these tables, the different parameterizations were ranked for each of the five measures, followed by a calculation of the average ranking for all measures. If we use this ranking method for k=0, the best values of ι and κ are (1,000; 500) and (2,000; 200). For k=3, the best values are (2,000; 100).

However, if we aggregate the results as shown in Table 3.VI, we observe that three of the measures identify (1,000; 500) as the best values. Moreover, if we rank the assessed parameterizations according to the different measures, we obtain once again (1,000; 500) as the best calibration, followed closely by (2,000; 200). The parameterization (2,000; 100), which was best for the fleet with three additional vehicles, is high in this ranking because it performs very poorly in tests using the minimum fleet size. For these reasons, we chose to further compare the parameterizations (1,000; 500) and (2,000; 200) in the evaluation of the three weight-changing strategies.

Table 3.VI: Average on the two fleet sizes of the measures representing the quality of solutions obtained with the different parameterizations of ι and κ

ι	κ	Epsilon indicator	Hypervolume indicator	Number of solutions	Best cost	Best inconvenience	Average ranking
1,000	100	1.1390	138,584,528.10	23.75	858.20	13,919.80	3.6
1,000	200	1.1229*	138,436,500.76	24.00	861.84	13,610.10	3.4
1,000	**500**	**1.1564**	**138,822,991.99***	**26.29***	**857.61***	**13,829.85**	**2.2***
2,000	100	1.1516	138,617,275.88	23.04	857.71	13,981.99	4.2
2,000	**200**	**1.1295**	**138,727,369.21**	**24.21**	**860.70**	**13,565.93***	**2.4**
2,000	500	1.1655	138,268,306.67	23.38	860.51	13,968.57	5.2

The calibration also aimed to identify which of the three strategies can best execute the weight changes. To evaluate the three weight-changing strategies, we used the same five quality measures to compare the results obtained on the twelve instances for 50,000

iterations of our tabu search. Table 3.VII presents the results obtained with the three tested strategies using the parameterizations (1,000; 500) and (2,000; 200). The results are listed for two different fleet sizes ($k = 0$ and $k = 3$), and for the average of these. The bold numbers represent the best values obtained for each measure across the three strategies. From this table, we observe that, for the average on the two fleet sizes, Strategy 3 using parameters (2,000; 200) is the best strategy according to all solution quality measures except for *best encountered value of the operating costs*. This parameterization was thus selected for the tests described in the next subsection.

Table 3.VII: Average solution quality measures with the different weight-changing strategies implemented during the search with parameterizations (1,000; 500) and (2,000; 200)

Strategy	Number of vehicles	ι	κ	Epsilon indicator	Hypervolume indicator	Number of solutions	Best cost	Best inconvenience
1	0	1,000	500	1.17	139,841,144.8	28.17	**851.56**	13,602.28
	3	1,000	500	1.21	**137,445,744.6**	17.25	**857.56**	15,105.05
	Average	1,000	500	1.19	138,643,444.7	22.71	**854.56**	14,353.67
	0	2,000	200	1.17	138,811,734.3	26.75	858.76	13,502.37
	3	2,000	200	1.41	135,357,701.2	**20.08**	865.30	15,954.80
	Average	2,000	200	1.29	137,084,717.8	23.42	862.03	14,728.59
2	0	1,000	500	1.19	138,136,620.5	21.75	861.20	13,992.54
	3	1,000	500	1.23	136,478,627.5	18.00	864.92	15,081.12
	Average	1,000	500	1.21	137,307,624.0	19.88	863.06	14,536.83
	0	2,000	200	**1.11**	138,972,083.6	27.00	872.05	12,161.50
	3	2,000	200	1.28	136,122,565.9	19.00	867.26	15,063.57
	Average	2,000	200	1.19	137,547,324.8	23.00	869.66	13,612.54
3	0	1,000	500	1.11	140,170,100.5	**29.25**	860.77	**12,068.57**
	3	1,000	500	1.23	135,524,870.4	19.17	876.11	15,334.09
	Average	1,000	500	1.17	137,847,485.4	**24.21**	868.44	13,701.33
	0	2,000	200	1.13	**140,342,369.9**	28.33	856.26	12,499.13
	3	2,000	200	**1.16**	137,112,368.6	20.08	865.15	**14,632.73**
	Average	2,000	200	**1.14**	**138,727,369.2**	**24.21**	860.70	**13,565.93**

3.5.4 Results for artificial instances

In this sub-section, we analyze the results of the tests run on the 56 modified Solomon instances using the best calibration, which is Strategy 3 with ι equal to 2,000 and κ equal to 200. Our analysis has two goals. First, we want to find out if the dispatchers' rule of thumb of using as few vehicles as possible is effective for minimizing the operating costs. To do so, we will identify the best solutions obtained in terms of costs using different fleet sizes, which allows us to better understand the tradeoffs between the number of vehicles used and the operating costs. Second, we want to better understand the tradeoffs between the carrier's operating costs and the driver inconvenience for a given fleet size. This information is useful for carriers who are looking for ways to improve the working conditions for their drivers while keeping increases of operating costs within reasonable limits. Indeed, increasing the costs of transportation means increasing the price charged to customers, who may well be price sensitive. To estimate the impacts that a reduction of driver inconvenience has on operating costs, we will analyze the results using an approximation of the operating cost increases generated by decreasing driver inconvenience by 1%, 5%, 10%, 25% and 50%.

To accomplish our first goal, we ran tests sequentially on all 56 instances using four different sizes of available vehicle fleets. Solution sets X_k were thus found using k vehicles in addition to the minimum fleet size, where $k = 0, 1, 2$ and 3. As an example, Figure 3.2 shows X_k, with $k = 0, 1, 2$ and 3, for instance RC106. Because the four runs of the heuristic were performed sequentially using different fleet sizes, some solutions found with a certain k could be dominated by another solution found with a different fleet size. To eliminate dominated solutions for each instance, the four solution sets X_k were first combined to form the solution set X, subsequent to which the dominance principles were applied. The number of vehicles represents a third objective for eliminating the dominated solutions in X. Thus, the vector representing a solution x becomes $(c(x), i(x), m_{min} + k)$. The solutions were compared, and the dominated solutions in X were discarded to form the global set of non-dominated solutions X'. One set of non-dominated solutions X'_k was also determined for each fleet size $m_{min} + k$, with $k = 0, 1, 2$ and 3, by extracting the solutions using $m_{min} + k$ vehicles in X'. Figure 3.3 shows the non-dominated solution sets X'_k, which consists of the global set of non-dominated solutions X' for instance RC106. This procedure was applied to all instances. The detailed results are presented in the Appendix and the aggregated results in Table 3.VIII.

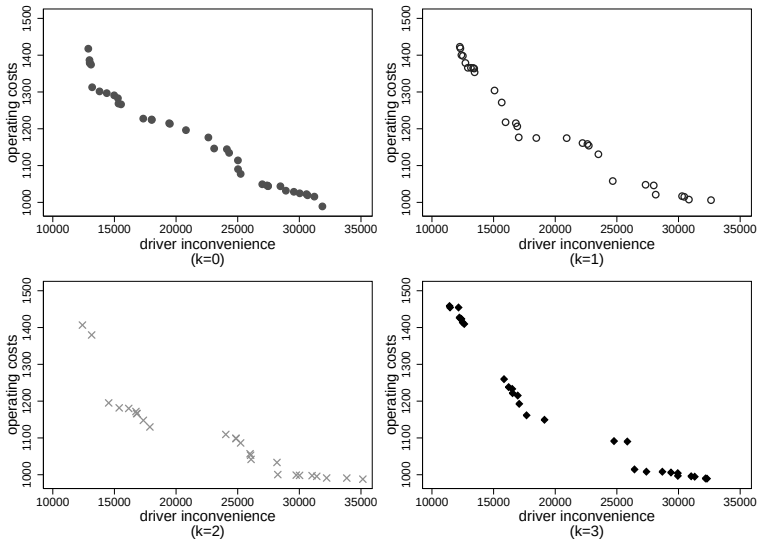


Figure 3.2: Solution sets X_k for instance RC106, with $k = 0, 1, 2$ and 3.

The first rows of Table 3.VIII contain the results aggregated by classes of instances (C1, R1, RC1, C2, R2 and RC2) for the tests run sequentially using the different fleet sizes. The last eight rows represent the results aggregated a level further and show the averages for Class 1 (C1, R1 and RC1) and Class 2 (C2, R2 and RC2). The first column indicates the class of instances; the second column shows the number of k vehicles added to the minimum fleet size; the third column indicates the numbers of solutions in X'_k after the dominance rules were verified on the global solution set X; and the fourth column

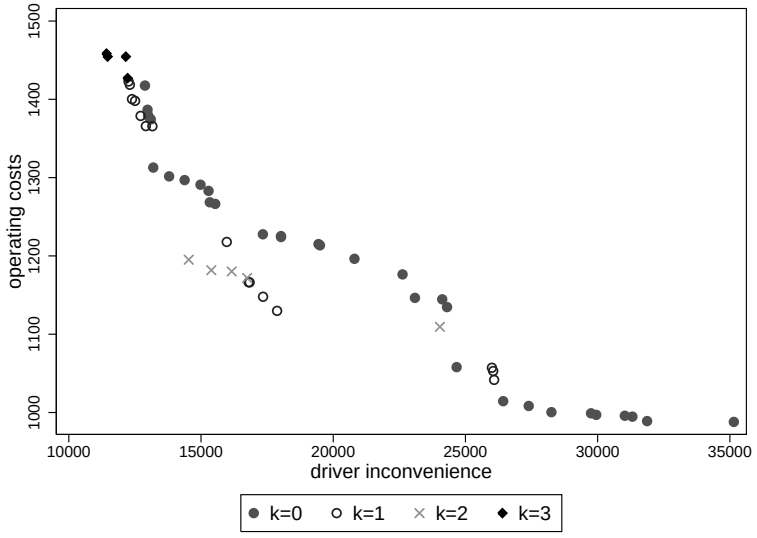


Figure 3.3: Non-dominated solution sets X'_k for instance RC106, with $k = 0, 1, 2$ and 3.

represents the best encountered value of operating costs $c(x^*_k)$ in solution set X'_k, with x^*_k the value of x yielding $\min\{c(x) \mid x \in X'_k\}$. If a non-dominated solution exists with the corresponding augmented fleet sizes, we calculate the variations of operating costs between the best encountered value obtained with the minimum fleet size and the best encountered objective value obtained with the augmented fleet sizes. These variations are expressed as the percentages of the cost increases or decreases that resulted from augmenting the fleet size to serve customers ($100(c(x^*_k) - c(x^*_0))/c(x^*_0)$, with $k = 1, 2$ and 3) and are shown in the fifth column of Table 3.VIII. The last column provides the CPU times in minutes.

From the results in Table 3.VIII, we observe that for instances in Class 1 and RC2, the number of vehicles used should not exceed the minimum fleet size, even if vehicles are available, as this would lead to a considerable increase in operating costs. For class R2, it can be beneficial to use one additional vehicle depending on the instance. However, for this class of instances, operating costs increase when using two or three additional vehicles. For class C2, adding one or more vehicles can reduce operating costs, but it can also have the opposite effect. Which effect takes place probably depends on the location of the customer clusters relative to the depot. In general, however, for artificial instances, using more vehicles than the minimum fleet size increases the operating costs. From the analysis of the computational results on artificial instances, we can conclude that the rule of thumb applied by most dispatchers of using as few vehicles as possible is appropriate to minimize operating costs.

To accomplish the second goal, we performed the following analyses in order to enhance our understanding of the tradeoffs between operating costs and driver inconve-

Table 3.VIII: Average results of the impact of fleet sizes on operating costs

Instances	k	$\lvert X'_k \rvert$	Best cost ($c(x^*_k)$)	Increase in cost (%)	CPU (min)
C1	0	20.3	819.56	–	96.98
	1	2.1	944.21	15.21	92.09
	2	1.2	960.42	17.19	89.43
	3	0.6	1,043.66	27.34	83.79
C2	0	23.0	960.35	–	209.98
	1	23.6	930.62	–3.61	177.34
	2	7.7	1,035.60	4.20	178.64
	3	1.1	1,147.78	–6.41	166.22
R1	0	35.2	863.32	–	144.85
	1	8.7	1,020.14	17.75	135.53
	2	2.2	1,093.76	27.93	121.17
	3	1.8	1,133.82	30.95	122.53
R2	0	25.3	738.05	–	288.81
	1	17.0	720.86	–1.54	253.22
	2	8.3	880.98	17.95	225.98
	3	2.7	925.24	25.84	208.12
RC1	0	23.5	995.54	–	115.19
	1	8.9	1,089.77	9.43	104.44
	2	7.8	1,161.24	16.43	95.84
	3	1.9	1,309.50	31.55	93.53
RC2	0	26.6	841.60	–	219.10
	1	17.1	882.51	1.65	195.10
	2	3.0	1,061.72	22.13	182.06
	3	1.6	1,133.80	40.71	175.65
Class 1	0	26.3	892.80	–	115.19
	1	6.6	1,018.04	14.13	110.69
	2	3.7	1,071.81	20.52	102.14
	3	1.4	1,162.33	29.95	99.95
Class 2	0	25.0	846.67		239.30
	1	19.3	844.66	–1.17	208.55
	2	6.3	992.77	14.76	195.56
	3	1.8	1,068.94	20.05	183.33

nience. To do so, all the solutions contained in the set of non-dominated solutions were first proportionally transformed according to a scale ranging from zero to one for each instance. We then estimated the Pareto front using a piecewise linear function where two consecutive points are linked with a straight segment. This allowed to extrapolate the percentage increases in operating costs obtained by improving driver inconvenience for each instance. Figure 3.4 shows, on the left side, an example of the set of non-dominated solutions obtained for instance RC106, while on the right side, it shows its corresponding scaled set in which each solution $(c(x), i(x)) \in X'_1$, has been transformed according to the following rule:

$$(c'(x), i'(x)) = ((c(x) - 1,042)/(1,423 - 1,042), (i(x) - 12,261)/(26,085 - 12,261)),$$

where 1,042 and 12,261 are the minimum cost and inconvenience values observed, and where 1,423 and 26,085 are the maximum cost and inconvenience values observed. The according piecewise linear function is shown on Figure 3.4. The corresponding estimated increase in operating costs obtained by improving the driver inconvenience by 25% is also highlighted with the straight grey lines. These estimates were calculated for all instances. The detailed results are presented in the Appendix and the aggregated results of each class in Table 3.IX.

The first rows of Table 3.IX contain the results aggregated by classes of instances (C1, R1, RC1, C2, R2 and RC2) for the tests run sequentially using the different fleet sizes. The last eight rows represent the average results for Class 1 and Class 2. The

first column indicates the instance class and the second column shows the number of k vehicles added to the minimum fleet size. The other columns indicate the operating cost increases in percentages for decreases in driver inconvenience of 1%, 5%, 10%, 25% and 50%. Similarly, Figure 3.4 shows the average variations in operating costs for decreases in driver inconvenience of 1%, 5%, 10%, 25% and 50% for the instances of Class 1 and Class 2.

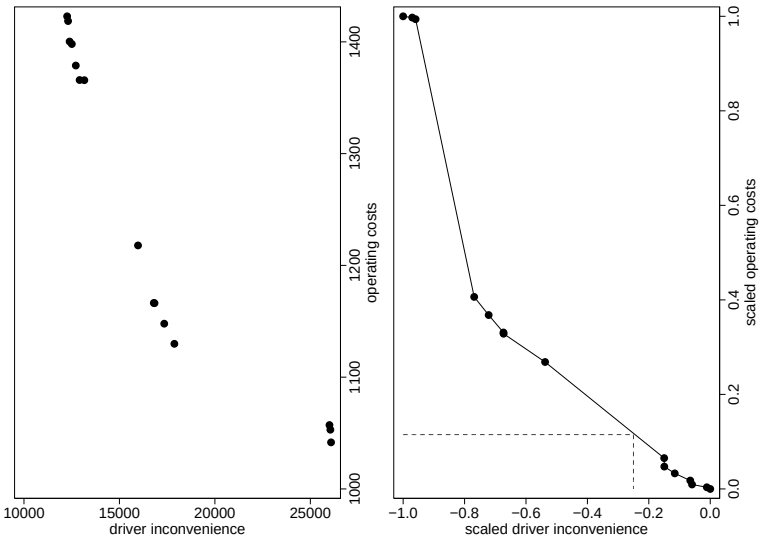


Figure 3.4: Evaluations of the tradeoffs between operating costs and driver inconvenience for instance RC106.

We observe from Figure 3.5 and Table 3.IX that for the calculated average value of the instances in Class 1, a 0.38% cost increase corresponds to a 1% reduction of driver inconvenience when using the minimum fleet size. Improving driver inconvenience by 5% and 10% will result in 0.87% and 1.26% cost increases, respectively. Thus, we can decrease driver inconvenience up to 10% by increasing costs by less than 1.5%. However, a decrease of 50% in driver inconvenience would cause a 16.8% increase in operating costs, which is not acceptable. Similarly, we observe that for the calculated average value of the instances in Class 2 using the minimum fleet size, a 0.66% cost increase corresponds to a 1% reduction of driver inconvenience. Improving driver inconvenience by 5% and 10% will result in 2.38% and 4.28% cost increases, respectively. Thus, we can decrease driver inconvenience up to 10% by increasing costs by less than 5%. Finally, a decrease of 50% in driver inconvenience would cause a 22.34% increase of operating costs, which is also not acceptable.

The results presented by Figure 3.5 clearly show a negative correlation between operating costs and driver inconvenience. The more the driver inconvenience decreases, the more costly it is. The relationship between these two variables seems to be linear in general. Moreover, we can observe that it is more costly to improve driver inconvenience

with a larger fleet size then it is with the minimum fleet size, this without taking into account a fixed cost related to vehicles. This figure also depicts the minimum and maximum variations observed on all instances and vehicle fleet sizes, values which represent the best and worst case scenarios that were observed.

Table 3.IX: Tradeoffs between operating costs and driver inconvenience (average over all instances in the same class)

Instances	k	Increase in operating costs (%) for decreases in driver inconvenience of				
		1%	5%	10%	25%	50%
C1	0	0.48	1.16	1.53	4.42	12.03
	1	5.87	8.66	12.15	22.61	39.78
	2	0.93	4.63	9.26	23.16	46.32
	3	1.00	5.00	10.00	25.00	50.00
C2	0	0.47	1.93	2.80	6.30	20.65
	1	0.64	2.71	5.94	16.00	29.81
	2	0.15	0.69	1.84	9.51	22.56
	3	8.33	41.64	52.79	54.03	54.85
R1	0	0.40	0.95	1.57	4.28	17.15
	1	0.68	3.32	7.03	17.11	34.39
	2	1.34	5.79	9.90	26.62	49.48
	3	30.80	44.25	45.44	48.04	64.42
R2	0	0.57	1.61	3.00	7.19	19.12
	1	0.51	1.23	2.36	8.62	19.67
	2	0.74	2.69	4.22	13.30	35.41
	3	1.24	5.13	8.65	18.92	40.97
RC1	0	0.26	0.51	0.67	2.93	21.10
	1	2.59	8.64	13.75	23.30	41.00
	2	2.18	4.61	7.45	22.31	46.61
	3	3.24	16.21	28.75	39.05	56.22
RC2	0	0.92	3.60	7.04	11.47	27.25
	1	0.34	0.85	1.91	5.60	19.21
	2	1.44	7.21	14.42	26.97	46.19
	3	2.45	9.53	11.47	17.31	32.95
Class 1	0	0.38	0.87	1.26	3.88	16.76
	1	3.05	6.87	10.97	21.01	38.39
	2	1.48	5.01	8.87	24.03	47.47
	3	11.68	21.82	28.06	37.36	56.88
Class 2	0	0.66	2.38	4.28	8.32	22.34
	1	0.50	1.60	3.40	10.08	22.90
	2	0.78	3.53	6.82	16.59	34.72
	3	4.01	18.77	24.30	30.08	42.92

3.5.5 Results for the real-life instance

Tests for five different fleet sizes have also been sequentially run on the instance provided by Groupe Robert. Here, the same parameterization and weight-change strategy as used in the artificial instances were implemented in the tabu search heuristic. The algorithm finds non-dominated solutions in terms of operating costs and driver inconvenience for $k = 0, 1, 2, 3$ and 4 as shown in Figure 3.6. The solution established by the dispatchers of Groupe Robert is provided in the last graph on this figure. When dominated solutions are eliminated considering the number of vehicles as a third objective, we obtain non-dominated solution sets X'_k only for k=0, 1 and 4. Figure 3.7 shows these three sets of non-dominated solutions and the solution applied by Groupe Robert. When compared to the solution that Groupe Robert used for this instance, our solutions reduce operating costs and driver inconvenience simultaneously. The solution from Groupe Robert is dominated by solutions that have been identified by the multicriteria tabu search heuristic. The results presented in Table 3.X show the best value encountered in terms of operating costs for different fleet sizes. We observe from this table and Figure 3.7 that costs decrease

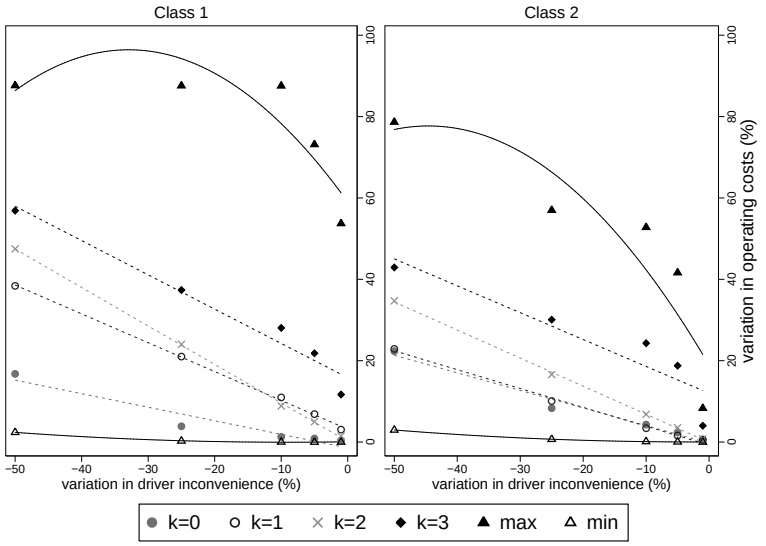


Figure 3.5: Average over all instances of Class 1 (left side) and Class 2 (right side) of variations in operating costs for different decreases in driver inconvenience.

when fleet size increases. Thus, the rule of thumb does not seem to apply to the real-life instance.

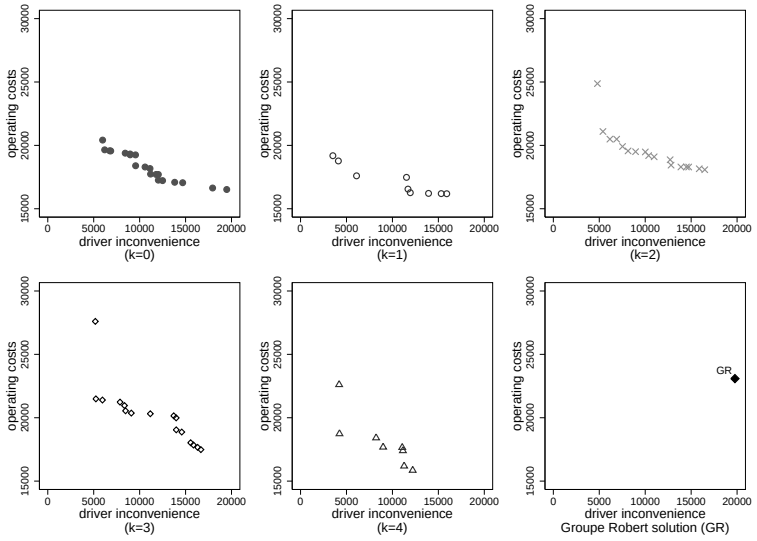


Figure 3.6: Solution sets X_k for Groupe Robert instance, with $k = 0, 1, 2, 3$ and 4, and Groupe Robert solution.

Figure 3.8 and Table 3.XI present the variations in operating costs for decreases in driver inconvenience of 1%, 5%, 10%, 25% and 50% for fleets of 37, 38 and 41 vehicles. We observe that to decrease driver inconvenience by 1%, operating costs will increase by 0.26% when using the minimum fleet size. Decreasing driver inconvenience by 5% and 10% will lead to 1.31% and 2.62% cost increases, respectively. Thus, we can decrease driver inconvenience by up to 10% by increasing costs by less than 3%. Finally, a 50%

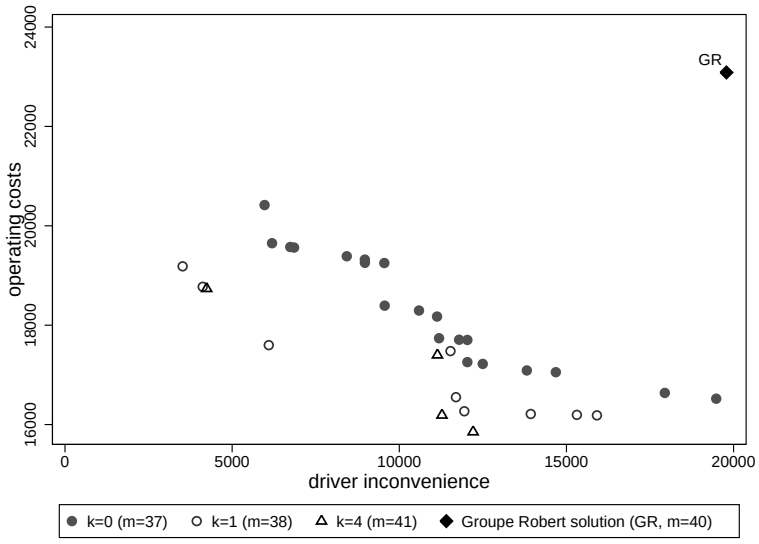


Figure 3.7: Non-dominated solution sets X'_k for Groupe Robert instance, with $k = 0, 1$ and 4, and Groupe Robert solution.

Table 3.X: Results for the real-life instance provided by Groupe Robert

m	Number of solutions	Best cost	Increase in cost (%)	CPU (min)
37	20	16,520.50		74.38
38	9	16,185.30	–2.03	45.83
39	0	–	–	90.34
40	0	–	–	89.39
41	4	15,853.10	–4.04	44.81

decrease in driver inconvenience would result in a 17.38% increase of operating costs, which is not acceptable. We also observe that when 41 vehicles are used, the cost of decreasing driver inconvenience increases significantly. Moreover, a decrease of driver inconvenience between 1% and 30% appears to be less costly with a fleet of 38 vehicles than with the minimum fleet size, while decreasing driver inconvenience by more than 30% becomes more costly with a fleet of 38 vehicles than with the minimum fleet size.

Table 3.XI: Tradeoffs between driver inconvenience and operating costs for the real-life instance with different fleet sizes

m	Increase in operating costs (%) for decreases in driver inconvenience of				
	1%	5%	10%	25%	50%
37	0.26	1.31	2.62	9.03	17.38
38	0.07	0.34	0.61	1.95	44.45
39	–	–	–	–	–
40	–	–	–	–	–
41	1.00	5.00	9.99	59.86	73.24

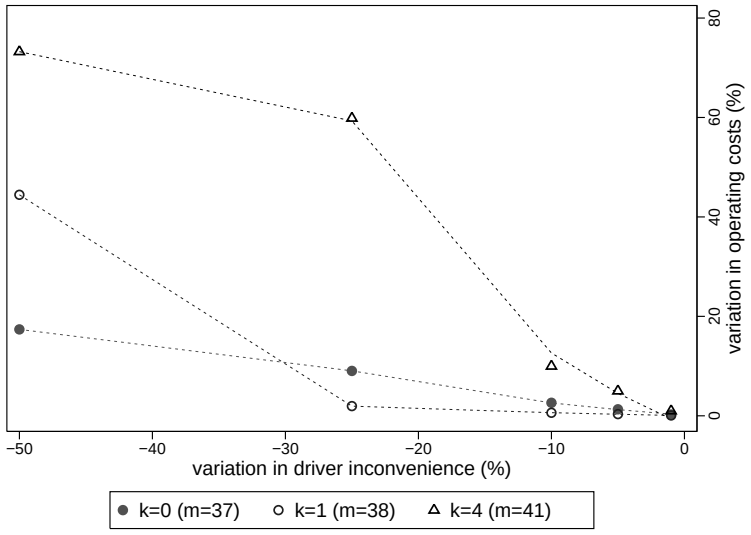


Figure 3.8: Tradeoffs between operating costs and driver inconvenience for the real-life instance with different fleet sizes.

3.6 Discussion

Carriers in North American countries are facing a driver shortage. To tackle this issue, we propose a decision tool that can provide trucking companies with information for better understanding the tradeoffs between the number of vehicles used and the operating costs. The tradeoffs between operating costs and driver inconvenience on the global non-dominated solution sets have also been analyzed.

3.6.1 Tradeoffs between fleet sizes and operating costs

Results presented in Section 3.5 show that for the C1, R1 and RC1 instance classes, which are characterized by tight time windows and lower vehicle capacities, operating costs always increase when more vehicles are used to serve the same pool of customers. This could be explained by the fact that customers are located far from the depot, this being a context of long-haul vehicle routing, and that these instances are highly constrained. Thus, the range of different feasible solutions is rather small, with little possibility for re-optimization even when using a supplement vehicle. In this circumstance, using one more vehicle can add a long-distance stretch to reach a customer that was already served by another vehicle without necessarily significantly reducing the distance traveled between two customers. This phenomenon is illustrated with the example of Figure 3.9. Carriers that usually have to manage with tight time windows to serve their customers should continue to make use of the rule of thumb that aims to use as few vehicles as possible to minimize their operating costs and to enhance the capability of the carrier to provide

service in the case of last-minute demands by keeping vehicles available at the depot if possible.

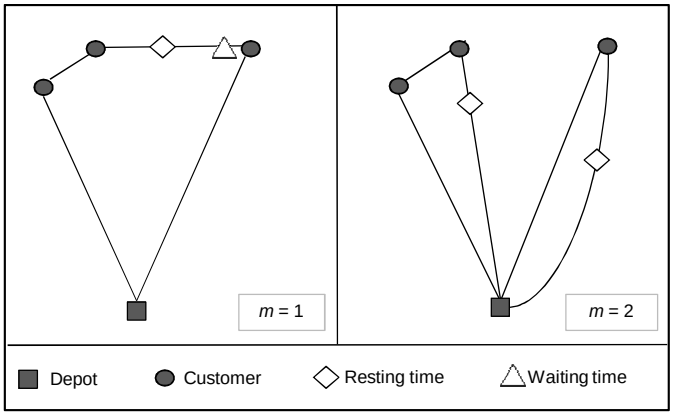


Figure 3.9: Example where using one more vehicle adds a long-distance stretch.

The results for classes C2, R2 and RC2 will be analyzed separately. Results for instances in class RC2 are similar to those from Class 1. Increasing the number of vehicles available increases the operating costs of the carrier. For instances in Class C2, which are characterized by wide time windows and geographically clustered customers, using one or more vehicles decreases operating costs for some instances and increases them for other instances. This could be explained by the fact that some instances have customer clusters located close to the depot whereas for other instances all clusters are farther away. In the first case, adding a vehicle does not significantly increase long distance stretches, but in the second case it does, which would explain the irregular impacts on operating costs. As an exception to the rule, carriers having a cluster of customers close to their depots should consider adding one or more vehicles to the minimum fleet in order to better serve these customers, and determine whether this decreases their operating costs. For instances of class R2, operating costs generally increase when two or more vehicles are added to the minimum fleet, which confirms the rule of thumb. However, sometimes operating costs decrease only when one vehicle is added to the minimum fleet. Even if operating costs sometimes decrease for some instances, the rule of thumb still holds, by and large, for the artificial instances.

The results from the real-life instance stand in contrast to the ones obtained with the artificial instances. Adding vehicles to the minimum fleet of 37 vehicles reduces operating costs. This could be explained by the fact that there is no cost for returning to the depot in this case. Indeed, Groupe Robert's problem is considered as an open routing problem in that returns are not planned or scheduled until after all deliveries are completed. Thus, we do not consider the long distance to be traveled from the last visited customer to the depot when adding a vehicle, a factor that would most likely offset the impact which an additional vehicle has on operating costs. However, sending another vehicle on the road

would increase the risk for the carrier because backhaul opportunities are not guaranteed. The 2% decrease in operating costs may not be large enough to compensate for the added risks for the carrier.

3.6.2 Tradeoffs between operating costs and driver inconvenience

According to the results found in Figures 3.5 and 3.8, there exists a negative correlation between operating costs and driver inconvenience for all instances. The more driver inconvenience decreases, the more costly it is. This could be explained by the fact that in order to reduce waiting time or resting time, routes have to be adjusted, which increases the total distance traveled. Thus, to improve driver working conditions, trucking companies have to increase their fuel and maintenance costs. Moreover, we could conclude that it is less costly to improve driver inconvenience with the minimum fleet size than it is with an augmented fleet. This could be explained with the relationship between fleet size and operating costs obtained from previous results on tradeoffs. Because the variations of operating costs increase more than the variation of driver inconvenience when vehicles are added to the fleet, the proportion to improve driver inconvenience becomes higher when more vehicles are used.

Carriers who want to improve the working conditions for drivers will have to (1) increase their prices, which could be difficult in this highly competitive market, (2) reduce their profit margin, which are already low or (3) offer a better service to their customers for an increased price, thereby differentiating themselves with value-added services. Of these three strategies, the last one appears to be the most profitable and sustainable one for these carriers. Overall, drivers are in direct contact with customers more so than any other employees of the carrier. Thus, motivated and dedicated drivers are a good means to improve the service provided to customers. We argue that it is feasible for carriers to offer a better service to their customers for the same price, or for a slightly higher price, by reducing turnover rates, decreasing expenditures for training new drivers and maintaining stability in their workforce.

3.7 Conclusions

This paper was motivated by the existing shortage of truck drivers in North America, which is partly due to their difficult working conditions. This can be remedied by constructing routes and schedules that not only minimize costs, but also take drivers' welfare into account. We have described a multicriteria tabu search algorithm that can simultaneously account for both these goals.

The multicriteria tabu search heuristic developed for this problem was capable of identifying a set of non-dominated solutions for each artificial instance and for the real-life instance of Groupe Robert within reasonable computational times. Our algorithm provides better solutions in terms of the number of vehicles, operating costs and driver inconvenience, compared to the solution implemented by Groupe Robert. Moreover, our heuristic yields a decision support tool which provides meaningful information to long-haul carriers.

Our results help gain a better understanding of the tradeoffs between the number of vehicles and the operating costs of a solution. Extensive analyses enabled us to verify the efficacy of a rule of thumb which is commonly used in the transportation industry and which is, by and large, also applicable to artificial instances. We show that for most cases, operating costs increase when the number of vehicles exceeds the minimum fleet size. However, in the case of the real-life instance which is an open routing problem, the rule of thumb appears to be less appropriate.

Our results also improve our understanding of the potential tradeoffs between operating costs and driver inconvenience. Drivers are an important asset for carriers. Improving their working conditions can thus reduce their turnover rates, thereby improving the level of service and reducing training costs. Results show that decreasing driver inconvenience increases carriers' operating costs in a smaller proportion. For example, for Groupe Robert, we could decrease driver inconvenience by up to 10% when increasing costs by less than 2.6%.

Acknowledgements

This work was partly funded by HEC Montréal. This support is gratefully acknowledged. We also thank Groupe Robert for their kind cooperation.

3.8 Appendix: Detailed computational results

Table 3.XII: Detailed results for instance class C1

Instance	k	m	$\lvert X'_k \rvert$	Best objective values		Increase in operating costs (%) for decreases in driver inconvenience of					CPU (min)
				cost	inconvenience	1%	5%	10%	25%	50%	
C101	0	10	18	819.56	8947.87	0.13	0.67	1.34	4.91	10.37	83.73
C101	1	11	1	875.1	9617.47	–	–	–	–	–	82.62
C101	2	12	0	–	–	–	–	–	–	–	44.94
C101	3	13	0	–	–	–	–	–	–	–	66.63
C102	0	10	21	819.56	8181.93	0.41	1.27	1.45	6.41	8.51	99.45
C102	1	11	0	–	–	–	–	–	–	–	69.51
C102	2	12	0	–	–	–	–	–	–	–	119.36
C102	3	13	0	–	–	–	–	–	–	–	58.03
C103	0	10	35	819.56	9598.7	0.2	0.56	0.7	2.86	6.06	102.14
C103	1	11	13	946.92	8922.29	15.62	15.99	16.45	17.82	19.35	145.36
C103	2	12	0	–	–	–	–	–	–	–	123.79
C103	3	13	0	–	–	–	–	–	–	–	94.53
C104	0	10	20	819.56	7880.76	0.04	0.19	0.39	1.51	7.43	115.71
C104	1	11	2	926.39	7800	1	5	10	25	50	101.61
C104	2	12	1	949.19	7922.75	–	–	–	–	–	81.31
C104	3	13	2	1001.45	6683.7	1	5	10	25	50	111.37
C105	0	10	23	819.56	8819.79	1.11	2.66	2.91	5.76	15.92	90.33
C105	1	11	0	–	–	–	–	–	–	–	66.16
C105	2	12	0	–	–	–	–	–	–	–	81.70
C105	3	13	1	1008.41	8799.45	–	–	–	–	–	70.43
C106	0	10	15	819.56	8306.58	1.18	2.94	3.7	10.21	12.41	87.71
C106	1	11	0	–	–	–	–	–	–	–	83.68
C106	2	12	0	–	–	–	–	–	–	–	65.12
C106	3	13	0	–	–	–	–	–	–	–	81.89
C107	0	10	21	819.56	9433.24	0.2	0.69	1.3	3.1	9.64	98.64
C107	1	11	0	–	–	–	–	–	–	–	95.70
C107	2	12	8	972.34	8518.26	0.85	4.26	8.53	21.32	42.64	95.71
C107	3	13	0	–	–	–	–	–	–	–	87.29
C108	0	10	7	819.56	10124.4	0.09	0.43	0.85	2.46	3.45	95.63
C108	1	11	1	961.87	11102.7	–	–	–	–	–	75.32
C108	2	12	2	959.73	9697.56	1	5	10	25	50	78.94
C108	3	13	2	1121.13	9076.13	1	5	10	25	50	103.16
C109	0	10	23	819.56	8402.76	1.01	1.04	1.13	2.51	34.51	99.51
C109	1	11	2	1010.76	8803.1	1	5	10	25	50	108.90
C109	2	12	0	–	–	–	–	–	–	–	113.98
C109	3	13	0	–	–	–	–	–	–	–	80.77

Table 3.XIII: Detailed results for instance class C2

Instance	k	m	$\lvert X'_k \rvert$	Best objective values		Increase in operating costs (%) for decreases in driver inconvenience of					CPU
				cost	inconvenience	1%	5%	10%	25%	50%	(min)
C201	0	8	28	1566.94	25485.8	0.97	2.19	3.96	6.7	20.48	120.08
C201	1	9	42	1278.24	24675.1	0.99	3.17	4.52	5.83	19.57	123.67
C201	2	10	11	1254.38	24594.2	0	0.05	0.79	2.99	26.68	111.42
C201	3	11	7	1205.65	42132.3	8.33	41.64	52.79	54.03	54.85	126.69
C202	0	7	18	1197.21	23222.2	0.09	0.68	1.49	4.38	40.77	231.02
C202	1	8	44	965.25	22678.6	0.06	0.29	0.5	2.97	13.1	179.11
C202	2	9	27	963.05	18959.8	0.14	0.35	1.83	7.83	28.11	204.91
C202	3	10	0	–	–	–	–	–	–	–	180.67
C203	0	6	28	813.08	15989.6	0.29	1.45	2.31	10.63	37.16	215.98
C203	1	7	6	1011.94	18365.3	1.01	5.05	15.21	56.99	69.38	201.77
C203	2	8	10	1017.91	15306.9	0.17	0.85	1.7	4.24	8.48	273.43
C203	3	9	0	–	–	–	–	–	–	–	206.31
C204	0	5	35	676.08	9480.66	0.17	0.89	1.8	4.51	9.05	295.91
C204	1	6	3	760.46	10978	1.08	5.38	10.77	26.92	53.08	234.36
C204	2	7	1	830.23	11191.3	–	–	–	–	–	236.24
C204	3	8	0	–	–	–	–	–	–	–	181.43
C205	0	6	1	870.56	24230.3	–	–	–	–	–	183.46
C205	1	7	44	814.76	16362	0.01	0.05	1.86	3.97	19.09	145.35
C205	2	8	0	–	–	–	–	–	–	–	143.13
C205	3	9	0	–	–	–	–	–	–	–	146.89
C206	0	6	25	988.74	17724.3	0.16	4.72	6.12	12.98	29.98	225.72
C206	1	7	35	879.64	16283.6	0.13	0.65	2.59	5.01	20.95	176.97
C206	2	8	5	1112.43	16211.9	0.3	1.52	3.05	22.97	26.96	145.69
C206	3	9	1	1089.9	20199.5						100.77
C207	0	6	25	705.7	15127.3	0.38	0.5	0.69	1.34	2.97	178.51
C207	1	7	0	–	–	–	–	–	–	–	171.34
C207	2	8	0	–	–	–	–	–	–	–	120.41
C207	3	9	0	–	–	–	–	–	–	–	165.20
C208	0	6	24	864.51	14223.9	1.24	3.08	3.2	3.54	4.11	229.15
C208	1	7	15	804.02	22118.8	1.18	4.42	6.14	10.33	13.53	186.16
C208	2	8	0	–	–	–	–	–	–	–	193.86
C208	3	9	0	–	–	–	–	–	–	–	221.80

Table 3.XIV: Detailed results for instance class R1

Instance	k	m	$\lvert X'_k \rvert$	Best objective values		Increase in operating costs (%) for decreases in driver inconvenience of					CPU
				cost	inconvenience	1%	5%	10%	25%	50%	(min)
R101	0	8	27	1012.34	22496.5	0.68	2.79	3.76	8.89	34.83	120.89
R101	1	9	46	934.72	18463.7	0	0	5.36	11.51	28.84	121.98
R101	2	10	0	–	–	–	–	–	–	–	113.00
R101	3	11	0	–	–	–	–	–	–	–	122.78
R102	0	8	38	901.17	20106	0.52	0.99	1.25	1.26	8.67	130.25
R102	1	9	21	1129.61	18637.9	0.78	2.97	4.14	10.06	17.51	127.86
R102	2	10	13	1431.74	17690.1	2.29	12.05	19.93	40.86	59.5	123.35
R102	3	11	1	1063.1	26790.5	–	–	–	–	–	–
R103	0	8	37	853.33	14072.6	0.04	0.71	1	1.04	10.94	132.86
R103	1	9	1	1087.59	15627.6	–	–	–	–	–	–
R103	2	10	0	–	–	–	–	–	–	–	136.16
R103	3	11	4	1240.49	12900.7	53.73	73.16	73.67	75.2	77.75	143.02
R104	0	8	29	837.73	9840.88	0.12	1.25	2.24	3.62	14.15	156.26
R104	1	9	2	1024.83	9876.54	1	5	10	25	50	196.47
R104	2	10	1	1126.99	9731.92	–	–	–	–	–	–
R104	3	11	1	1025.07	9600.61	–	–	–	–	–	–
R105	0	8	33	873.81	13961.4	1.62	2.45	5.62	15.1	43.33	137.71
R105	1	9	9	964.32	13442.7	0.92	4.58	9.16	22.89	45.79	129.20
R105	2	10	5	1065.83	14079.4	0.96	1.41	1.98	17.33	43.84	132.12
R105	3	11	15	1206.62	11823.2	7.88	15.35	17.22	20.88	51.09	122.44
R106	0	8	45	861.63	11725.8	0.2	0.2	0.3	4.39	38.12	156.92
R106	1	9	3	1060.74	19317.7	0.89	4.45	8.91	22.27	44.55	125.47
R106	2	10	1	1013.75	21996.1	–	–	–	–	–	–
R106	3	11	0	–	–	–	–	–	–	–	167.16
R107	0	8	43	841.45	12247.8	0.2	0.95	1.53	3.48	6.4	171.27
R107	1	9	4	992.06	9937.25	0.83	4.14	8.27	20.68	41.35	139.26
R107	2	10	4	1006.96	9083.63	0.78	3.9	7.8	21.66	45.11	108.12
R107	3	11	0	–	–	–	–	–	–	–	132.79
R108	0	8	28	829.16	8634.42	1.13	1.47	1.9	3.94	17.42	141.23
R108	1	9	2	943.25	8160.69	1	5	10	25	50	115.47
R108	2	10	1	983.27	8150.21	–	–	–	–	–	–
R108	3	11	0	–	–	–	–	–	–	–	96.16
R109	0	8	47	840.95	11159.7	0.13	0.22	0.41	2.3	12.32	146.42
R109	1	9	7	1039.05	13226.2	0.65	3.27	6.54	14.38	27.04	141.46
R109	2	10	0	–	–	–	–	–	–	–	148.00
R109	3	11	0	–	–	–	–	–	–	–	120.24
R110	0	8	32	835.75	9816.85	0.01	0.06	0.11	0.28	2.39	151.71
R110	1	9	0	–	–	–	–	–	–	–	126.91
R110	2	10	0	–	–	–	–	–	–	–	122.83
R110	3	11	0	–	–	–	–	–	–	–	92.33
R111	0	8	45	845.08	10378.1	0.07	0.1	0.32	2.46	9.58	156.63
R111	1	9	9	1025.27	9962.95	0.09	0.44	0.88	2.2	4.4	166.01
R111	2	10	0	–	–	–	–	–	–	–	151.66
R111	3	11	0	–	–	–	–	–	–	–	147.47
R112	0	8	18	827.39	7800	0.04	0.2	0.41	4.6	7.64	136.06
R112	1	9	0	–	–	–	–	–	–	–	116.75
R112	2	10	1	1027.8	7242.39	–	–	–	–	–	–
R112	3	11	0	–	–	–	–	–	–	–	91.18

Table 3.XV: Detailed results for instance class R2

Instance	k	m	$\lvert X'_k \rvert$	Best objective values		Increase in operating costs (%) for decreases in driver inconvenience of					CPU
				cost	inconvenience	1%	5%	10%	25%	50%	(min)
R201	0	6	17	1024.72	21533.2	0.04	0.22	0.43	6.97	18.32	225.25
R201	1	7	40	877.06	17060.7	2.21	3.58	4.71	25.9	41.29	202.78
R201	2	8	29	1115.87	14682.8	3.41	4.28	4.68	5.87	34.55	165.06
R201	3	9	2	1410.5	14954.5	1	5	10	25	50	169.35
R202	0	6	46	833.66	18234.6	2.31	3.01	3.19	7.46	12.09	243.65
R202	1	7	18	846.77	16259.8	0.07	0.66	1.91	4.65	23.69	220.80
R202	2	8	16	1061.67	14722.5	0.02	0.1	0.2	27.49	50.32	213.39
R202	3	9	17	1224.84	13703.8	0.64	4.05	7.42	15.61	51.96	198.15
R203	0	5	25	790.31	14266.6	2.89	8.47	9.28	11.72	31.9	192.43
R203	1	6	22	762.4	13522.9	1.11	1.16	1.84	5.46	26.11	136.34
R203	2	7	5	1035.16	11484.9	0.07	0.36	0.73	1.82	3.64	112.94
R203	3	8	0	–	–	–	–	–	–	–	89.02
R204	0	5	30	742.08	10010.7	0.01	0.07	0.13	4.8	7.54	301.19
R204	1	6	12	779.33	9537.6	0.77	1.4	1.58	13.92	17.26	278.51
R204	2	7	3	995.84	9155.24	0.53	2.65	5.31	13.27	26.54	267.67
R204	3	8	2	939.26	9138.81	1	5	10	25	50	241.14
R205	0	6	41	821.26	13916.5	0.18	0.39	0.79	7.06	16.17	228.59
R205	1	7	29	809.15	13734.4	0.11	0.58	1.74	3.07	13.45	217.51
R205	2	8	15	1003.38	12383.7	1.6	9.47	10.33	22.09	44.9	193.52
R205	3	9	0	–	–	–	–	–	–	–	195.03
R206	0	5	18	806.57	15975	0.08	0.42	6.02	9.74	17.86	318.74
R206	1	6	38	781.51	11674.2	0.06	0.43	1.38	4.51	11.84	286.92
R206	2	7	11	787.96	12861.9	0.08	0.42	0.59	14.4	40.96	220.75
R206	3	8	7	992.97	11873.3	4.03	11.88	13.11	16.81	34.81	209.63
R207	0	5	33	735.18	8572.78	0.29	1.45	5.5	13.8	28.81	325.88
R207	1	6	5	793.08	11655.3	0.8	4	8	20.01	40.01	267.36
R207	2	7	0	–	–	–	–	–	–	–	246.34
R207	3	8	0	–	–	–	–	–	–	–	223.24
R208	0	4	15	727.43	8420.46	0.76	3.8	7.6	11.62	20.54	393.52
R208	1	5	15	722.53	8400	0.31	0.59	0.64	3.49	7.93	336.68
R208	2	6	2	791.51	8776.27	1	5	10	25	50	314.24
R208	3	7	2	814.27	8017.43	1	5	10	25	50	257.19
R209	0	5	31	812.71	10944.5	0.03	0.14	0.27	0.68	22.28	312.26
R209	1	6	17	773.4	12507.6	0.17	0.86	3.58	7.92	23.55	272.83
R209	2	7	9	795.79	10894.8	0.34	1.6	3.17	7.88	35.35	225.41
R209	3	8	2	1094.86	10765.2	1	5	10	25	50	175.03
R210	0	5	16	811.39	12583.8	0.26	1.28	2.56	11.26	50.2	313.11
R210	1	6	8	784.28	12363	0.05	0.27	0.53	5.92	11.26	273.63
R210	2	7	8	1071.37	11598.1	0.14	0.69	1.37	3.44	53.27	252.61
R210	3	8	0	–	–	–	–	–	–	–	260.30
R211	0	5	32	751.26	9600	0.04	0.1	0.21	1.14	3.71	322.31
R211	1	6	0	–	–	–	–	–	–	–	292.06
R211	2	7	2	1032.26	9000	1	5	10	25	50	273.78
R211	3	8	0	–	–	–	–	–	–	–	271.29

Table 3.XVI: Detailed results for instance class RC1

Instance	k	m	$\lvert X'_k \rvert$	Best objective values		Increase in operating costs (%) for decreases in driver inconvenience of					CPU
				cost	inconvenience	1%	5%	10%	25%	50%	(min)
RC101	0	9	25	1023.25	15897.2	0.4	1.6	1.7	6.79	48.34	118.80
RC101	1	10	16	1077.53	15504.9	4.67	14.84	18.21	28.34	53.24	110.26
RC101	2	11	21	1200.03	14364.2	0.19	0.94	4.49	40.82	58.03	106.35
RC101	3	12	3	1300.94	21237.7	0.07	0.33	0.67	1.67	3.34	111.14
RC102	0	9	25	1010.04	14079.8	0	0.05	0.14	0.28	11.6	126.36
RC102	1	10	10	1251.8	15032.5	3.45	12.78	14.95	23.34	26.43	130.00
RC102	2	11	5	1184.69	17110.8	11.58	14.3	17.39	33.7	60.9	109.66
RC102	3	12	0	–	–	–	–	–	–	–	133.54
RC103	0	9	22	987.36	11230	1.4	1.64	2.15	8.61	33.24	124.18
RC103	1	10	9	1032.11	11147.9	0.52	2.43	3.7	4.82	33.36	123.06
RC103	2	11	14	1072.5	11011.2	0.87	4.2	7.3	15.5	29.06	128.86
RC103	3	12	3	1355.23	10821.7	1.68	8.39	16.78	41.95	83.91	159.46
RC104	0	9	23	985.67	9533.4	0	0.01	0.03	1.99	10.21	112.60
RC104	1	10	6	1068.65	9054.48	0.25	1.24	20.51	33.04	43.19	113.45
RC104	2	11	0	–	–	–	–	–	–	–	110.50
RC104	3	12	1	1283.25	8478.05	–	–	–	–	–	–
RC105	0	9	23	997.91	14576.8	0.02	0.08	0.16	0.41	12.59	110.37
RC105	1	10	2	1207.09	17093.8	1	5	10	25	50	106.20
RC105	2	11	9	1263	12279.3	0.3	1.51	3.03	18.14	58.4	116.88
RC105	3	12	0	–	–	–	–	–	–	–	107.60
RC106	0	9	32	988.01	12880.8	0.02	0.08	0.16	2.6	36.48	115.86
RC106	1	10	15	1041.68	12260.5	4.19	5.49	7.11	11.98	20.09	90.06
RC106	2	11	5	1109.47	14536.6	0.95	4.75	9.49	23.73	47.46	58.61
RC106	3	12	4	1427.03	11425.2	10.22	51.11	87.56	87.59	87.65	64.79
RC107	0	9	20	994.62	11523.2	0.1	0.52	0.84	1.41	12.16	109.33
RC107	1	10	7	1007.14	13481.1	1.58	7.53	13.89	32.96	64.74	89.14
RC107	2	11	5	1251.58	9399.42	0.66	3.13	3.62	7.2	35.64	74.79
RC107	3	12	2	1181.07	12155.8	1	5	10	25	50	43.26
RC108	0	9	18	977.45	9190.71	0.11	0.13	0.17	1.37	4.15	104.05
RC108	1	10	6	1032.19	8123.68	5.07	19.82	21.59	26.92	36.93	73.38
RC108	2	11	3	1047.44	9570.54	0.68	3.42	6.84	17.11	36.75	61.06
RC108	3	12	0	–	–	–	–	–	–	–	55.59

Table 3.XVII: Detailed results for instance class RC2

Instance	k	m	$\lvert X'_k \rvert$	Best objective values		Increase in operating costs (%) for decreases in driver inconvenience of					CPU
				cost	inconvenience	1%	5%	10%	25%	50%	(min)
RC201	0	6	33	1033.55	19581.7	0.47	2.2	8.57	14.42	47.69	230.87
RC201	1	7	45	937.46	18504.7	0.58	2	4.89	9.85	17.64	189.81
RC201	2	8	0	–	–	–	–	–	–	–	179.21
RC201	3	9	0	–	–	–	–	–	–	–	156.26
RC202	0	6	27	885.48	15494.4	0.22	0.89	1.33	2	5.4	235.11
RC202	1	7	23	878.27	14888.5	0.02	0.1	0.27	3.04	19.82	219.12
RC202	2	8	4	1282.87	13838.7	0.18	0.9	1.8	4.51	9.02	202.24
RC202	3	9	0	–	–	–	–	–	–	–	202.31
RC203	0	5	22	834.2	13891.9	0.62	0.93	1.09	1.56	6.95	294.22
RC203	1	6	34	805.62	12205.6	1.07	1.08	1.48	2.55	13.33	244.32
RC203	2	7	2	984.91	12858	1	5	10	25	50	208.59
RC203	3	8	6	1123.48	11382.9	5.18	18.75	19.56	21.99	43.82	219.31
RC204	0	5	24	755.7	9006.52	1.07	1.1	1.35	2.54	26.3	295.57
RC204	1	6	0	–	–	–	–	–	–	–	274.02
RC204	2	7	0	–	–	–	–	–	–	–	252.42
RC204	3	8	0	–	–	–	–	–	–	–	272.35
RC205	0	5	28	707.41	11374.5	0.54	1.87	3.08	12.2	36.3	90.26
RC205	1	6	0	–	–	–	–	–	–	–	103.52
RC205	2	7	0	–	–	–	–	–	–	–	95.45
RC205	3	8	0	–	–	–	–	–	–	–	90.07
RC206	0	6	34	828.85	13211.1	0.32	0.79	1.15	6.48	22.14	230.68
RC206	1	7	8	850.21	16405.7	0.27	1.33	2.67	6.18	11.76	212.03
RC206	2	8	8	1014.11	15258.8	4	19.98	39.96	57	78.66	213.72
RC206	3	9	5	1245.33	11908.8	1.17	4.84	4.86	4.93	5.04	201.40
RC207	0	5	23	934.98	12755.2	3.73	19.01	36.91	47.65	58.07	180.42
RC207	1	6	24	827.01	12400.7	0.01	0.06	1.01	6.19	15.49	140.64
RC207	2	7	10	964.97	11262	0.59	2.95	5.89	21.37	47.08	135.17
RC207	3	8	0								111.77
RC208	0	5	22	752.64	9757.76	0.41	2.04	2.82	4.94	15.16	195.68
RC208	1	6	3	996.49	9008.09	0.11	0.55	1.11	5.8	37.2	177.34
RC208	2	7	0	–	–	–	–	–	–	–	169.66
RC208	3	8	2	1032.6	8411.13	1	5	10	25	50	151.77

Deuxième partie

Planification du transport de longue distance dans des pays en voie de développement. Le cas de l'Afrique de l'Est

Chapitre 4

Market Analysis and Transportation Procurement for Food Aid in Ethiopia

Chapter information

M.-È. Rancourt, F. Bellavance et J. Goentzel. Market Analysis and Transportation Procurement for Food Aid in Ethiopia. Technical Report, *Cahier du CIRRELT–2013–30*, Montreal, May 2013.

Abstract

To transport food aid, the World Food Programme (WFP) primarily contracts with third-party transport carriers in markets that are not well understood. We analyze historical contracts between the WFP in Ethiopia and private carriers using multiple linear regression to gain insights in these markets. Analyses of bids and contracts in Ethiopia show that distance alone explains less than 20% of the variability in effective transportation tariffs. By incorporating additional variables for linehaul costs, market structure measures and socio-economics factors, we obtain a model that explains more than 84% of the variability for the international corridors and 78% for the domestic lanes. Analyses of the various factors provide insights for shippers to improve procurement processes, for carriers to devise competitive business models, and for government authorities to define effective investments and policies. Econometric research to characterize transportation markets in developing countries is scarce, and our study provides an initial basis for further work in other countries.

Keywords: Transportation procurement, linehaul cost, market structure, regional economic analysis, food aid.

4.1 Introduction

In Africa, freight transportation can be a costly and time-consuming component of the supply chain due to issues such as poor infrastructure, security risks, complex regulations, and lack of available information. For basic goods and commodities, transportation can represent a significant portion of the overall cost to the consumer. In humanitarian supply chains, high transportation costs reduce the number of beneficiaries that aid organizations can reach with the funding they receive. In the private sector, uncertain transportation markets are seen as a challenge for multinational companies looking to Africa as a key region for growth. Increasing the competitiveness and transparency of transportation markets should enable many African countries to better meet the needs of their citizens and be positioned for economic investment.

The markets for freight transportation in African countries are not well understood. Few studies have been conducted, in part due to the lack of available data. Previous studies are based on surveys which may be unreliable, especially when carriers are asked about their cost structures. In this study, we analyze shipper data that include bids from numerous carriers and the subsequent contracted tariffs that were effective in the market. Data were provided by the World Food Programme (WFP) in Ethiopia, one of the largest shippers in the country. We have collected over 10,000 data points from over 75 carriers that span numerous origin-destination lanes within Ethiopia as well as international corridors from nearby seaports. To our knowledge, this study is the first to analyze carrier bids and effective transportation tariffs for the understanding of the transportation market in an African country.

We use multiple linear regression to determine which factors influence the linehaul truck transportation tariffs, our dependent variable. The tariffs are specified in cost per tonne for transportation service by lane, which is the route between the origin and destination points for the cargo. Our model considers a number of independent variables grouped into three broad sets: cost driven factors, market structure measures, and socio-economic variables. The cost driven factors are composed of linehaul cost drivers, such as distance, road conditions and risk, as well as variables related to economies of scale and scope in the transportation sector. The market structure measures incorporate the full set of carrier bids, and not only the effective transportation tariff. Socio-economics factors are based on regional statistics, such as population and economic activity.

Our results show that market structure, particularly competition intensity, is a good predictor of the tariffs paid by the WFP in Ethiopia. The market structure measures are also correlated with other variables such as road quality and socio-economic factors, which indicate that the carrier's bidding is influenced by these factors. Taking out the market structure measures, we gain a truer sense of the underlying cost structure and carrier economies. Contrary to similar studies of transportation markets in developed countries, which generally find very little variations in prices per kilometer across lanes, our results show that road conditions and competition levels explain significant levels of the variability observed in transportation tariffs for Ethiopia. At a macro-level, we are able to quantify the causes for the generally poor development of transportation in East Africa. Simple reduced form counterfactual exercises show that better road conditions should reduce shipping costs by 18% and increase competition by up to 44% on the international corridors. Similarly for the domestics routes, better road conditions would reduce shipping costs by 12% and increase competition should reduce them by 39%.

Insights from the econometric models can serve several purposes. First, shippers, like the WFP, can improve procurement processes. By understanding the cost drivers and estimating fair pricing for transportation services, shippers can identify opportunities for costs savings and facilitate better contracting processes. For example, the lanes for which there is an objective need for negotiations can easily be indentified based on the difference between predicted and actual tariffs. Second, accurate cost estimates improve broad supply chain decisions for shippers, such as selecting the best corridors and stocking locations, and evaluating expansion into new markets. For carriers, better information about the cost drivers and competitive landscape help them identify market opportunities and refine their business model. Finally, government authorities can use model insights to guide investment strategies in infrastructure and policy decisions. As such, the study aims to provide general insights and introduce useful information for developing competitive logistics capacity in Ethiopia.

The paper is organized as follows. Section 4.2 reviews the literature on transportation market analysis, focusing on truckload and less-than-truckload sectors in both Africa and more mature markets. Section 4.3 describes the WFP operations in Ethiopia and outlines its transportation procurement process. Section 4.4 describes the data collected for this study and the variables used in the regression models. Section 4.5 discusses the model building process and presents the results as well as their interpretations. This is followed by conclusions in Section 4.6.

4.2 Literature Review

Very few empirical studies have attempted to understand transportation costs or prices in Africa. One reason is likely due to the absence of computerized archived data and to the difficulty of accessing them. Empirical studies based on surveys of the trucking industry carried out in the last 20 years show that transportation prices were higher in Africa than in developed countries and most developing countries. Rizet and Hine (1993) have found freight tariffs to be four to six times higher in three African countries (Cameroon, Ivory Coast and Mali) than in Pakistan during the late 1980s. These authors also present an analysis of the main factors behind these differences in tariffs, such as transportation costs, taxes, profitability and vehicle productivity. Teravaninthorn and Raballand (2010) have extensively studied four main international corridors in four African sub-regions (West, Central, East and Southern Africa). In order to analyze the differences in transportation cost and price structures, the potential explaining factors were disaggregated into three categories: the vehicle operating costs, the overall commercial providers' costs and the transportation prices paid by end users. The authors observe that market organization and strict regulations lead to low transportation service quality and high profit margins in West and Central Africa, while the trucking market is more mature and competitive in East Africa. Southern African corridors are found to be the most efficient in terms of price competiveness and service quality.

Lall et al. (2009) aim to explain high transportation prices in Malawi, based on trucking surveys designed according to the methodology developed by Teravaninthorn and Raballand (2010). They perform two sets of empirical analyses: farmers' costs for transporting tobacco to markets, and carriers' prices for transporting commodities on routes both within the country and on specific international corridors. Their analyses reveal that both the infrastructure quality and the market structure of the trucking industry are important contributors to transport prices. The quality of the trunk road network is not a major constraint, but differences in the quality of the feeder roads that connect villages to the main roads have a significant bearing on transport prices. These findings are consistent with those of Pedersen (2001) who shows that transportation costs depend on the availability of infrastructure and on the density of demand on specific links, which implies that Africa is especially disadvantaged with low and dispersed demand and many landlocked countries which are difficult to serve. On a macroeconomic level, some studies have shown that the cost of transporting goods and getting them across borders is a major obstacle to African trade performance. Limão and Venables (2001) found that the relatively low level of African trade flows is largely due to poor infrastructures which also affect transportation costs. Portugal-Perez and Wilson (2008) provide estimates suggest-

ing that improvements in logistics are more important in terms of trade expansion than are reductions of barrier tariffs.

In contrast to most African markets, the United States (US) transportation market is mature and well-studied, especially since the deregulation of the trucking industry in 1980 which contributed to open up competition. Caplice (2007) and Nandiraju and Regan (2008) describe the American truckload (TL) transportation market in detail and explain how the procurement of transportation services is managed in the context of electronic marketplace formats. Combinatorial auction mechanisms, by which carriers can bid on bundles of items for more economically efficient allocations, are commonly used for TL transportation procurement in practice (see Caplice and Sheffi, 2003; Elmaghraby and Keskinocak, 2003). In transportation procurement, the savings that can be generated by the use of combinatorial auctions are based on the principle of economies of scope, which strongly influence transportation costs. Shippers commonly use sophisticated transportation management systems to manage their TL operations, but determining the auction's winners is an NP-hard problem for which optimization algorithms must be implemented (see Sandholm et al., 2005, and Ma et al., 2010, for examples). Powell et al. (1988) and Ergun et al. (2007) have studied TL operations and pricing strategies from the carrier's perspective considering uncertainty. For food aid procurement and ocean transportation services, Trestrail et al. (2009) have proposed a mixed-integer programming decision tool that reproduces the United States Department of Agriculture bidding process in order to improve the bidder pricing strategies. Bagchi et al. (2011) have shown that the current bid process for American food aid does not enable the capture of potential synergies between suppliers and carriers. They have thus presented recommendations for optimal award allocation.

The American TL market is probably best suited for using combinatorial auctions since the North American TL network is well developed and state-of-the-art technologies are accessible. However, this is not the case in developing countries like Ethiopia where backhaul opportunities are almost inexistent and where TL operations are not managed through the use of electronic catalogs but mostly manually. As mentioned by Kunaka (2011), one fundamental factor preventing good quality of logistics infrastructure and services in lagging regions is the low demand spread both spatially and temporally in large areas, which prevents economies of scale. Long distances and dispersed economic activity inhibit access to information on market conditions and lead to erratic freight flows. In such a context, tools similar to the ones that have been developed for less-than-truckload (LTL) services in the US are more appropriate to better understand the transportation market in Ethiopia than those based on combinatorial auctions.

Smith et al. (2007) and Ozkaya et al. (2010) have presented a regression-based methodology to estimate the LTL market tariffs in the US. These studies aim to identify the significant drivers of LTL pricing and produce tariff estimates that can be useful for negotiation and contracting practices. Smith et al. (2007) have relied on data from a single US motor carrier to construct statistical models which focus on quantitative factors such as distances, weight and number of shipments. To produce better tariff predictions, Ozkaya et al. (2010) have improved this methodology by quantifying intangible qualitative factors through a scorecard process. They also used an extensive dataset in terms of lane coverage and transaction diversity for freight classes as well as carrier-shipper combinations.

To our knowledge, our study is the first to use observed market tariffs as opposed to survey data for a developing country. It is also the first contribution to provide empirical results on the Ethiopian transportation market. The methodology used to support our findings is similar to that used by Smith et al. (2007) and Ozkaya et al. (2010) for the LTL US markets, but it is applied in the context of an emerging country as was done by Lall et al. (2009) in Malawi.

4.3 The WFP transportation management in Ethiopia

The WFP is the United Nations' core agency for food security. The organization aims to "improve the lives of the poorest people who, either permanently or during crisis periods, are unable to produce enough food or do not have the resources to otherwise obtain the food that they and their households require for active and healthy lives" (see WFP, 2012b). Ranked 174th out of 187 in the 2011 Human Development Index of the United Nations Development Programme, Ethiopia is one of the least developed countries in the world. The 2005 Demographic Health Survey (2005) highlights the underlying vulnerability of Ethiopians to nutrition crises. A case study on Ethiopia (2004) notes that an estimated 50% of the population is food-insecure and approximately 22% of the total population receives food aid, although not on a regular basis. The WFP has maintained a continuous presence in Ethiopia since 1974. In 2011, it assisted over 3.8 million people in this country of about 80 million people, distributing over 425,000 tonnes of food aid (WFP, 2011). For 2013, the WFP estimates it will assist about 7.2 million people and will distribute 846,000 tonnes of food (WFP, 2013).

Ethiopia is a landlocked country located between Djibouti, Kenya, Somalia, Sudan and Eritrea in East Africa (see Figure 4.1). There are four classes of administrative divisions in the country: kebele, woreda, zone and region (ethnically-based regions and governing administrative cities). The kebeles are the smallest administrative divisions

while the regional divisions are the largest. As in other emerging nations, the infrastructure in Ethiopia is underdeveloped. Railways are inoperable and less than 20% of roadways are paved. Because of the landlocked geographical location, limited railway capacity and costly air transportation of this country, shippers largely depend on ground transportation to move commodities in Ethiopia. The Ethiopian Government and the WFP share responsibility for food aid transportation within the country. Ground transportation is shared between two phases: international and domestic transportation. The WFP Ethiopia's logistics division is completely in charge of the international transportation movements, which are primarily controlled by commercial providers. The Ethiopian government manages most of the domestic transportation movements as well as the food aid distribution (hand-out to beneficiaries), except in the Somali region where it has handed responsibility to the WFP due to challenges in meeting food demand amidst security concerns.

4.3.1 Transportation procurement

In Ethiopia, the WFP contracts third-party carriers instead of relying on a private fleet. The organization procures transportation services in a similar way as is done in the commercial sector of developed economies, using a request for quotation (RFQ) mechanism which allows carriers to gain business through competitive bidding. The WFP first sends out questionnaires asking about transportation companies' profiles and launches tenders only to those carriers whose profiles match their standards (core set of carriers). Every six months, the WFP invites its core set of carriers to submit rate proposals (bids) on lanes that may require transportation services. It is through this RFQ mechanism that tariffs are established and carriers awarded transportation services are specified for each network segment. Carriers receive loading orders when the WFP needs to move cargo, and waybills are used to track shipments. Carriers are monitored according to the contract and may be blacklisted if they do not perform up to the stipulated standards. The WFP actively utilizes its contracts established for international transportation. While only providing backup capacity for most domestic transportation, it still conducts RFQs and establishes contracts for an extensive domestic transportation network to supplement government capacity when necessary.

4.3.2 International versus domestic transportation operations

The first phase of transportation, movements on international corridors, consists in transporting food aid from ports to main warehouses, which are known as Extended Delivery Points (EDPs). Because Ethiopia is landlocked, transportation from seaports necessarily involves international movements. Port of Djibouti is the main port of oper-

Figure 4.1: Map of Ethiopia (Logistics Cluster, 2012).

ation for Ethiopia, and 90% of WFP's food aid is routed through it. Because of delays at Djibouti, food aid is also received at Berbera and Sudan since 2009. In this study, we concentrate our analysis on the ports of Djibouti and Berbera for international transportation. The EDPs are located in strategic regions in the country where primary storage infrastructure is available, and act as transshipment hubs for the second transportation phase. This phase is the movement of food aid on domestic roads from the EDPs to the Final Delivery Points (FDPs), where the food is stored and directly distributed to the beneficiaries. The FDPs are temporary deposits such as shelters, schools and community centers which can be located in remote regions depending on the needs of the beneficiaries.

The international and domestic transportation markets differ in several ways. Trucks operating on international corridors, typically having a 40-tonne capacity, are uncommon on domestic lanes which tend to use smaller trucks that can handle poor road conditions. Larger quantities of food are moved within a short period of time over international corridors, especially when a ship is docked. The loading and offloading operations are usually faster and easier at ports and at EDPs, which are located in major cities with better infrastructure as opposed to FDPs. International transportation also requires carriers to have special permits to operate in multiple countries. They can be subject to delays at ports and borders, which are not common on domestic lanes.

4.4 Data sources and variable description

Data from two different sources were gathered to conduct our analysis. We have compiled data from a specific RFQ executed by the WFP in Ethiopia as well as from different reports of the Central Statistical Agency of Ethiopia (CSAE). In this section, we present and discuss these two sources of data. We also present the variables derived from these data sets and used later in the statistical analyses. We first describe the effective transportation tariffs, which will account for the dependent variable of our statistical models. We then describe the independent variables grouped in three categories: cost driven factors (linehaul cost and carrier economies), market structure measures and socio-economic variables.

4.4.1 Variables extracted from the data provided by the WFP

Data were gathered from an RFQ executed by the WFP in Ethiopia. An RFQ is an efficient competitive mechanism (reverse auction) used to aggregate and reveal scattered information about the market participant valuations of a service in order to dynamically set a price. The contracts derived from this specific RFQ were valid for the planning period from September 2010 to March 2011. The data describe carriers who participated in the RFQ, the lanes of the WFP network and the set of bids offered on each lane. Table 4.I illustrates the compiled information of the RFQ for a given origin ($orig_1$).

This data set provides a unique description of the Ethiopian transportation market. The access to accurate and up-to-date information in Africa is often limited. As mentioned by Teravaninthorn and Raballand (2010), trucking data collection is largely inadequate in most countries of Sub-Saharan Africa. The data provided by the WFP are sourced from only one shipper which conducts business with several carriers, and we are thus essentially only looking at the supply side of the transportation market. However, the WFP is one of the most important purchasers of transport services in the country (alongside the Ethiopian Government) and we therefore consider the data to adequately represent the overall transportation market and the costs of transport. We make the assumption that the WFP faces similar costs as other buyers and does not profit from monopsony power. In the following, we describe the variables based on the WFP RFQ data. We first describe the determination of the effective transportation tariffs for the international and domestic transportation markets, which will define the dependent variable of our statistical models. We then describe the independent variables grouped in two categories: cost driven factors (linehaul cost and carrier economies) and market structure measures.

Table 4.I: Illustrative RFQ data table for one specific origin ($orig_1$)

Lane		Tariff	Lane characteristics					Carrier rate offers (bids)			
			Distances			Tonnage		Carrier			
Origin (port or EDP)	Destination (EDP or woreda)	Tariff (Birr/tonne)	Total (km)	Paved (km)	Unpaved (km)	estimate (tonne)	Risk (scale)	1	2	...	m
								(Birr/tonne)			
$orig_1$	$dest_1$	$tariff_1$	$dist_1$	$paved_1$	$unpaved_1$	ton_1	$risk_1$	bid_{11}	bid_{12}	...	bid_{1m}
$orig_1$	$dest_2$	$tariff_2$	$dist_2$	$paved_2$	$unpaved_2$	–	$risk_2$	bid_{21}	–	...	bid_{2m}
$orig_1$	$dest_3$	$tariff_3$	$dist_3$	$paved_3$	$unpaved_3$	ton_3	$risk_3$	–	bid_{32}	...	bid_{3m}
$orig_1$	$dest_4$	$tariff_4$	$dist_4$	–	–	ton_4	–	bid_{41}	bid_{42}	...	–
$orig_1$	$dest_5$	$tariff_5$	–	–	–	–	–	bid_{51}	–	...	bid_{5m}
...	...	...	...	...	...	...	...	...	...	...	
$orig_1$	$dest_{n_1}$	$tariff_{n_1}$	$dist_{n_1}$	$paved_{n_1}$	$unpaved_{n_1}$	ton_{n_1}	$risk_{n_1}$	$bid_{n_1 1}$	$bid_{n_1 2}$	...	$bid_{n_1 m}$

4.4.1.1 Effective transportation tariffs

The dependent variable in our regression models represents the tariffs in Birr per tonne (Birr/tonne) paid by the WFP from September 2010 to March 2011 for transportation services on a specific lane. These effective transportation tariffs (*tariff*) are determined by the WFP through the bidding process (RFQ). For domestic transport, the tariff determined by the WFP for a lane corresponds to the lowest bid made on that lane in the RFQ. The carrier who made this lowest offer is awarded the transportation contract on that lane although there is no commitment to execute shipments when they will occur. For international transportation, since no carrier has the capacity to handle alone all the transportation services required on a corridor, a tariff is determined by the WFP in order to capture enough capacity. There is no formal procedure for fixing the effective transportation tariffs on the international corridors. The WFP determines international tariffs in order to capture enough transportation capacity based on their judgement, the received offers in the RFQ and market prices for transporting commodities such as sugar, fertilizers or cement. This tariff is sent as a counter offer to the carriers who participated in the RFQ and will correspond to the effective transportation tariff during the planning period of the RFQ. The carriers that accept the WFP counter offer and conditions are awarded transportation services proportionally to their total dedicated fleet capacity. The dependent variable in our regression models corresponds to the natural logarithm of these tariffs ($\ln(tariff)$). As explained in Section 4.5.1, regressing *tariff* yielded heteroscedasticity which was eliminated when regressing $\ln(tariff)$.

4.4.1.2 Cost driven factors

The transportation tariffs should partially reflect the carrier operating costs. We define as cost driven factors the variables recognized to directly affect carrier operating costs. We separate these variables in two classes: linehaul cost drivers and carrier economies. Using cost driven factors to estimate the transportation tariff will thus enable us to determine the significant variables of the cost-based pricing structure in Ethiopia.

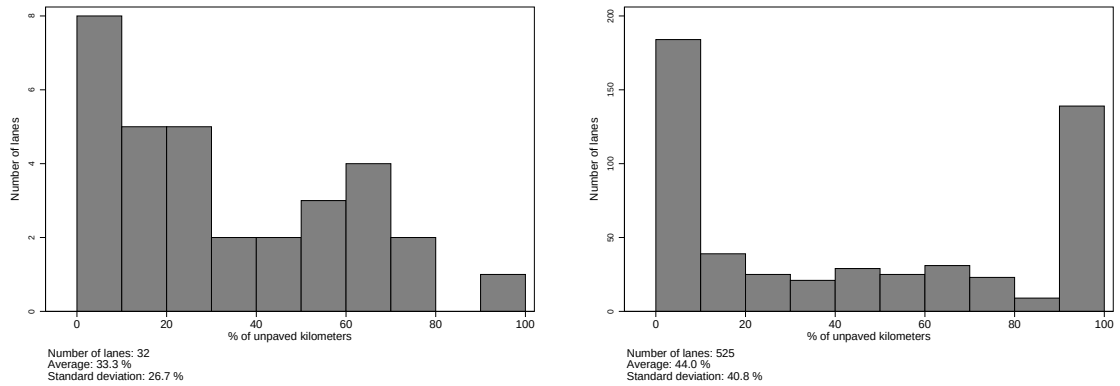
Linehaul cost drivers

The linehaul costs are the costs related to freight movements including fuel, maintenance, depreciation, driver wages and others (Liu, 2006). In particular, we include lane-specific cost drivers that are unique to the context of developing countries: measures of road infrastructure quality and perception of operational risks.

Distance and road conditions

Distance is the primary cost factor in linehaul movements since the main trucking operating costs (fuel, tires, maintenance, and driver wage) vary directly according to it (see Caplice, 1996; Daganzo, 2005). However, in developing countries road quality also matters. At the macro-level, an analysis of bilateral trade data by Limão and Venables (2001) shows the influence of road infrastructure on transportation costs. To account for road quality, the total length of the lanes was decomposed into their paved (*paved*) and unpaved (*unpaved*) distances in kilometers, using Geographical Information System (GIS) data.

The disaggregation into paved and unpaved distances is available for all the lanes of the international corridors, but for only 72% of the domestic transportation lanes. In order to discard as few observations as possible on the domestic transportation market, we have created a road condition indicator based on the percentage of unpaved kilometers per lane with the four following categories: good (less than 10% unpaved), intermediate (between 10% and 70% unpaved), poor (70% or more unpaved) and unknown. These bounds were chosen in order to ensure that the number of observations in each category was fairly distributed (see Figure 4.2). To capture the effect of the total length of the lanes, we also consider a continuous variable for the total distance (*distance*) in addition to the road condition indicator.



(a) International corridors.

(b) Domestic lanes.

Figure 4.2: Bar charts of the corridor and lane unpaved kilometer percentages.

Risk perception

Chander and Shear (2009) suggested that carrier rates are likely to reflect the risks involved in providing transportation services in conflict areas of Ethiopia. A risk level was associated to some lanes within the Somali region by the WFP, while the other lanes were

not graded in terms of risk. Note that the Somali region is recognized as the most underdeveloped and conflict-impacted region of Ethiopia. In order to account for the security issues occurring in this particular region, a risk level has been integrated according to the following four WFP categories: no security issue, low risk, high risk and unspecified risk for the lanes within the Somali region. The fifth category of this risk scale is unknown risk for regions other than Somali. The international corridors with a non-zero specified risk by the WFP were all put in the high level category, which is not the case for the domestic lanes. It is important to mention that when no risk level has been specified by the WFP, this does not imply that the risk is zero but only that the information is unknown.

Carrier economies

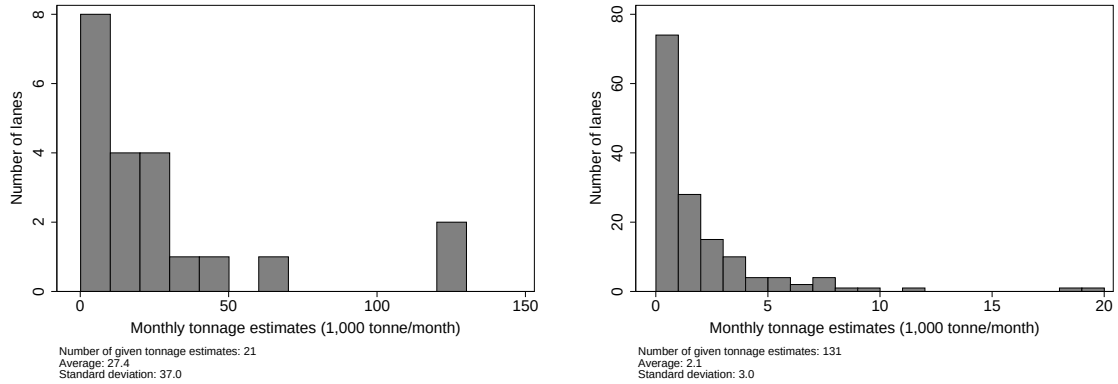
Economies of *scale* occur when the average cost per unit decreases as the scale of output increases. In truckload services, fixed costs could be allocated over a larger base unit (tonnes shipped) with more quantities transported on the linehaul or the backhaul. For the linehaul, this means that larger loads per shipment result in economies of scale by reducing the cost per tonne. The cost of serving a lane is also affected by the probability of finding a backhaul load at the destination, which translates into economies of scope for the carriers (Sheffi, 2004). Data that indicate, but do not guarantee, shipping volumes are available for a limited number of lanes. Data that systematically measure the backhaul opportunities are unavailable; however, we can test for the potential effects of economies of *scope* using different indicator variables, as described below.

Economies of scale

A higher estimated tonnage to be transported per month can lead to lower unit costs through economies of scale. In the RFQ, the WFP provides estimates of the monthly tonnage to be transported for 66% of the international corridors and 17.9% of the domestic lanes. These estimates are based on historical data, projected demands and requirements. However, the lack of an estimate does not imply that no transportation service will be required on the lane, nor does a given estimate guarantee business on the lane. Carriers are invited to bid on all lanes considering the information provided. We have included estimated tonnage indicators in order to test for potential economies of scale reflected in transportation tariffs.

Because of missing data, we have generated an indicator for the estimated tonnage to be transported monthly. The indicator variable designate low or high tonnage estimates depending on a threshold $\bar{t}$, with $\bar{t} = 20,000$ tonnes/month for the international corridors

and $\bar{t} = 1,000$ tonnes/month for the domestic lanes. The thresholds were determined to ensure that the number of observations in each category was fairly distributed (see Figure 4.3). The third category of this indicator represents missing data on tonnage estimates.



(a) International corridors.

(b) Domestic lanes.

Figure 4.3: Bar charts of monthly tonnage estimates by transportation network segment.

Economies of scope

Backhaul opportunities can also reduce costs and affect transportation tariffs. However, we do not have the data required to observe backhaul opportunities directly. One way of identifying their potential impact is to investigate variations at the regional level, i.e. unobserved factors either at the region of origin or at the region of destination which may indicate backhaul opportunities. In order to remain agnostic about which factors determine backhaul opportunities, we include region-specific indicator variables for both the origin and the destination to account for all residual cross-regional variability not captured by our other explanatory variables. Note that regional indicators were successfully used to identify economies of scope in truckload transportation markets in the US. For all the domestic lanes, we have defined a regional indicator for the origin and the destination regions, as well as an indicator for the destination region of the international corridors. These correspond to the 11 regions of Ethiopia: Addis Ababa, Affar, Amhara, Benishangul-Gumuz, Dire Dawa, Gambella, Harari, Oromia, SNNP, Somali and Tigray.

When no significant differences between regions are found, we can rule out the possibility for backhaul opportunities to explain variability in tariffs, at least at the regional level. However, we cannot claim that economies of scope alone explain any cross-regional variability observed; other unobserved factors could also explain them. One of these is related to the market structure. Indeed, we will see that the characteristics of the marketplace are an essential factor in establishing transportation tariffs. Moreover, this dimension might encompass the effect of economies of scope described above.

4.4.1.3 Market structure measures

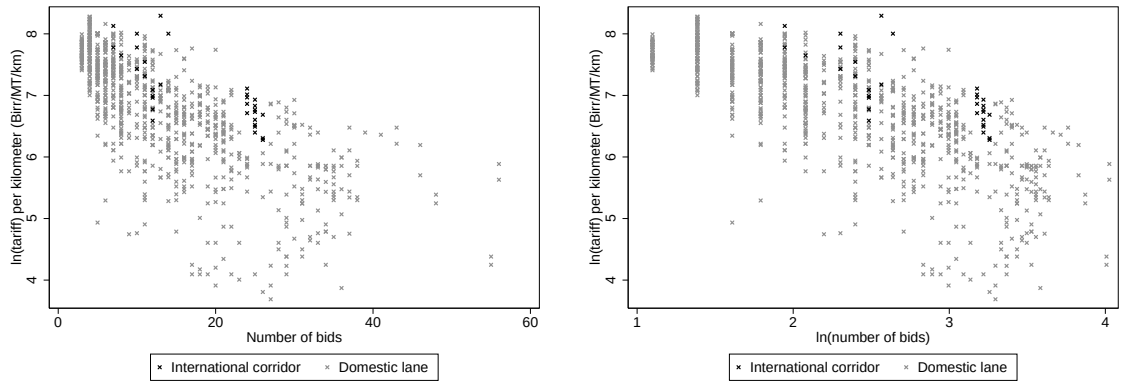
The second group of explanatory variables concerns the structure of the trucking market. Truckload transportation markets in developing countries such as Ethiopia are unlikely to resemble the competitive markets found in developed countries. If competition is low, monopoly power will allow carriers to include a higher markup over marginal cost in their pricing structure. Exploiting the unique nature of our data, we use information from the bid distribution as a proxy to measure the impact of market structure on transportation tariffs. To this end, proxies associated with competition intensity, market dispersion and market concentration were included in the regression models. These variables were computed from information extracted from the internal supply chain of the WFP derived from the RFQ.

Competition intensity

We hypothesize that the competition intensity on a network segment is related to the number of bids made on the corresponding international corridor or domestic lane. Figure 4.4a depicts the tendency for the natural logarithm of tariffs per kilometer per tonne to decline as the number of carriers bidding on a lane increases. It also shows this relationship to be non-linear: each additional bidder reduces the tariffs, but this effect decreases with the number of bidders. Thus, competition appears to considerably affect transportation tariffs, but adding players in the bidding process becomes less influential when the competition intensity has reached a certain level. This non-linear relationship is estimated in the regression models by including the natural logarithm of the number of bids per lane, $\ln(\#bids)$, as a proxy for competition intensity. Figure 4.4b shows the relationship between the transportation tariffs and the logarithm of the number of bids to be linear.

Market dispersion

In a mature and efficient market, information about prices should be known by all participating actors, and the dispersion in bids for each transportation network segment should be small. We hypothesize that a large dispersion in bids reveals a disorganized market in which information does not circulate well between the carriers. Therefore, the difference between the third and the first quartiles of the bids on each lane have been computed to measure the variation in bids without considering the extreme bids. To standardize this measure, the difference between the third and the first quartiles has been divided by the median. The ensuing variable is called *bid dispersion*.



(a) Effect of the number of bids on tariff rates per kilometer.

(b) Effect of ln(number of bids) on tariff rates per kilometer.

Figure 4.4: Tariffs per kilometer as function of the competition intensity.

Market concentration

To reflect the market concentration at the shipping origins and destinations, we have created two types of predictors: the number of active carriers and bid-related Herfindahl-Hirschmann indices (Herfindahl, 1950; Hirschman, 1945). The number of active carriers (*carrier*) is the number of carriers that are willing to provide services from an origin or to a destination, i.e. the number of distinct carriers who have bid on a lane originating from a specific origin or ending at at a specific destination in the RFQ.

The Herfindahl index is equal to the sum of the squared market share s_t of carrier t $(t = 1, ..., m)$: $hhi = \sum_{t=1}^{m} s_t^2$. Lacking information on carriers' market shares, we have used the number of bids by carriers as a proxy. Let b_t be the number of bids made by carrier t, and let B be the total number of bids that have been made at the origin or at the destination. Market shares s_t are estimated by b_t/B. The Herfindahl index measures the amount of market power from which firms profit from. An industry with few large competitors will have a high level of concentration (hhi close to one), while a fragmented market with many small competitors results in low concentration (hhi close to zero). We have evaluated the transportation market concentration hhi both at the origin and at the destination of each network segment.

4.4.2 Variables extracted from data published by the Central Statistical Agency of Ethiopia

The last group of explanatory variables consists of regional demographic and economic factors. These data are external to the WFP supply chain, so they can be used in conjunction with the cost driven factors to predict transportation tariffs when extensive

RFQ data are not available or not representative of the global market. This situation could also occur for the prediction of the transportation tariff of a new lane without information on the competition environment. Thus, the geographic concentration of population and economic activities at the origins and at the destinations could be used as a substitute for market predictors.

Data on economic activities were compiled from the latest reports published by the Central Statistical Agency of Ethiopia (CSAE). The CSAE is a government agency designated to supervise and provide all survey and census reports in Ethiopia in order to monitor economic and social indicators. For the 11 regional states of Ethiopia, we have extracted data on the following three categories: the number of manufactures of the major industrial groups (CSAE (2010)), the agricultural production (CSAE (2009)), and major livestock types (CSAE (2008)). We have also extracted data on the population from the latest Population and Housing Census of Ethiopia conducted by the Ethiopian Population Census Commision (Population Census Commission (2008)). We use the socio-economic data at the regional administrative level because this information is not available for the smallest administrative levels such as woreda or kebele. Note that there are no regional socio-economic indicators associated with the origins of the international corridors since these correspond to foreign ports.

The compiled socio-economic statistics for Ethiopia are presented in Table 4.V of Appendix 1. Brief descriptions of the considered elements are given in the first column of this table, while their values together with their relative percentages are presented in the last two columns. Note that we only provide the statistics applicable to the whole country, and not for each region. Such information can be found in the CSAE public reports.

The variable *population* represents the total population, and the variable $manufacture$ corresponds to the total number of manufactures (the sum of all types of manufactures) in the region of origin or destination. The variables *grain*, *vegetable* and *coffee* are the total quintals of crop grains, vegetable and coffee produced in all regions. The variable *agriculture* is the total output of agriculture production, which corresponds to the sum of the three previous variables. The variables *cattle*, *sheep*, *goat* are the number of registered animals of each type. The variable *livestock* is the total number of animals (the sum of the number of cattle, sheep and goats). Note that for the agricultural production and the livestock, we have only considered the three more important and significant elements regarding the Ethiopian actual economic situation.

Table 4.VI of Appendix 1 shows the correlation coefficients between socio-economic variables. We note that all the agricultural production variables (*grain*, *vegetable*, *coffee* and *agriculture*) and all the livestock variables (*cattle*, *sheep* and *goat*) are strongly

correlated to each other. This implies that the different agricultural activities are concentrated in the same regions. Moreover, when comparing the correlation coefficients of *agriculture*, *livestock* and *population*, we observe that these three variables are positively correlated. This indicates that the more populated regions are also more active in terms of agricultural production, which is not necessarily the case for the manufacturing activities having no strong significant correlation with *population* nor *agriculture*. Indeed, more than 85% of the Ethiopian population lives in rural areas where agriculture is the main economic activity.

4.4.3 Descriptive statistics

Table 4.II contains descriptive statistics for the main variables of interest for the two markets. This table clearly shows that the international transportation network is denser than the domestic network, with fewer lanes to cover but more tonnage to transport per lane. The average distance of the international corridors is greater than that of the domestic lanes, but both domestic and international markets are considered to be long-haul transportation. The last row of Table 4.II shows that the tariffs per kilometer are lower on average for the international corridors than for the domestic lanes. Moreover, the standard deviation of the tariffs per kilometer is smaller for the international corridors than for the domestic lanes. The international market seems more competitive since it generates on average more bids per lane than the domestic market. Note that in the remainder of this paper the information on the carriers is not used to explain the effective transportation tariffs, but only to analyze the bids.

Table 4.II: Network description

Market	International market			Domestic market		
Network	2 origins (ports) 24 destinations (EDPs) 32 lanes 46 carriers			33 origins (EDPs) 98 destinations (FDPs) 926 lanes 59 carriers		
Descriptive statistics	n	mean	standard deviation	n	mean	standard deviation
Distance (km)	32	756.1	289.7	731	589.8	356.3
Estimated tonnage per lane (tonne/month)	21	27,426.9	36,969.3	131	2,055.4	3,028.2
Number of bids per lane	32	17.9	7.3	731	14.9	10.3
Number of bids per carrier	46	14.4	5.5	59	212.3	190.5
Valid bids (Birr/tonne)	572	1,317.6	1,016.1	12,231	1,322.1	1,286.7
Tariff (Birr/tonne)	32	1,405.3	902.5	731	1,138.8	844.6
Tariff per km (Birr/tonne·km)	32	2.0	1.2	731	2.4	2.1

More detailed descriptive statistics about the WFP data for all variables in both the international and domestic markets are reported in Tables 4.VII and 4.VIII of Appendix 1. These tables contain information describing the distribution of each variable including the mean, median, standard deviation, as well as the minimum and maximum values.

4.5 Results

We have used multiple linear regression models to determine which of the factors have a significant impact on transportation tariffs in Ethiopia. Separate analyses are conducted for the international and domestic Ethiopian transportation markets since, as discussed above, these are two distinct markets. We now explain the process implemented to determine our best regression models before presenting and describing them. Note that all statistical analyses were executed using Stata 11.

4.5.1 Methodology

For each transportation market, we have constructed two distinct type of models which both include the cost driven factors (C): one with the market structure measures (M) and the other with regional socio-economic variables (E). There are different reasons for this choice. The socio-economic variables are derived from public information independent of the WFP operations. Because the socio-economic variables partly explain the market structure, they can thus be considered as proxies for it when specific data, such as the WFP data in this case, are not available. These two models can be compared to better understand the effects of the market structure on transportation tariffs, measured from the WFP information or from socio-economic statistics.

For the international and the domestic transportation markets we aim to define multiple linear regression models explaining $\ln(\textit{tariff})$, i.e. $\ln(\textit{tariff}) = f_1(C, M) + \epsilon_1$ and $\ln(\textit{tariff}) = f_2(C, S) + \epsilon_2$, where ϵ_1 and ϵ_2 are random errors due to unobservable factors. Heteroscedasticity has been identified with Breusch-Pagan/Cook-Weisberg and White tests (Baum, 2006) when using *tariff* as dependent variable. Indeed, we note from Figures 4.10a and 4.12a of Appendix 3, which show the standardized residuals plotted against the fitted values obtained through a backward regression, a tendency for the residuals to increase with the fitted values. This problem is removed by using $\ln(\textit{tariff})$ as shown in Figures 4.10b and 4.12b of Appendix 2. Moreover, the standardized residuals obtained from the models using $\ln(\textit{tariff})$ are close to being normally distributed, as depicted in Figures 4.11 and 4.13 of Appendix 2.

We have constructed various model specifications by using different sets of independent variables. For each market, we have first regressed $\ln(\textit{tariff})$ on the variables related to the road attributes and we have then added the competition intensity to this specification. We now explain how the variables were selected to build our final regression models. For the models with the market structure measures, the HHI indices (hhi) were omitted because they were highly correlated with other market structure measures (see Tables 4.IX and 4.X of Appendix 1) and were not effective predictors. For the models with

the regional socio-economic variables, the variables associated with agricultural activities (*agriculture* and *livestock*) at the origin and destination were discarded because of their correlation with the population (*population*). Only the remaining suitable variables were used into the statistical models $\ln(\textit{tariff}) = f_1(C, M) + \epsilon_1$ and $\ln(\textit{tariff}) = f_2(C, S) + \epsilon_2$. Lastly, backward regressions allowed us to determine our final statistical models for the (1) international and (2) domestic transportation markets, i.e. the models including the markets structure variables (Models 1.4 and 2.4) and the models including the socio-economic variables (Models 1.6 and 2.6).

4.5.2 Multiple regression models

Tables 4.III and 4.IV display the results obtained for six different specifications for the international corridors and for the domestic lanes. In each table, the first specification corresponds to a regression of the natural logarithm of transportation tariffs ($\ln(\textit{tariff})$) on variables associated with the distance and road conditions measures only. The second specification adds variables describing competition intensity. The third specification considers all the explanatory variables, except for the regional socio-economic factors, and the fourth specification results from a backward regression which initially considered the same independent variables. The last two specifications include the regional population and the manufacturing activity variables instead of the market structure measures. The fifth specification includes all the explaining variables, and the sixth model was obtained by applying a backward regression.

The number of observation considered (n), the R-squared, the adjusted R-squared and the maximum variance inflation factor (VIF) values are given for each specification presented in Tables 4.III and 4.IV. VIF statistics were estimated for the different models to detect multi-collinearity issues. There is no theoretical threshold value for recognizing multi-collinearity, but a common rule of thumb suggests that variables with a VIF value greater than five or ten should be discarded, five being more restrictive than ten (see O'Brien, 2007, and Haan, 2002). The highest VIF values obtained are 3.36 and 3.07 for our final international and domestic models, respectively. In Tables 4.III and 4.IV, we provide the robust standard errors associated with the regression coefficients, as suggested by Berry and Feldman (1985). For each model, in order to validate the coefficients, we ensured that their signs and their magnitudes were the same as those obtained when regressing the transportation tariff on each individual variable separately. We thus consider that there are no multi-collinearity problems.

From the results presented in Tables 4.III and 4.IV, we note that including the market structure measures as explanatory factors leads to statistical models that explain more variability in transportation tariffs than those including the socio-economic factors, this

being true for both international and domestic markets: the adjusted R-squared associated with Models 1.4 and 2.4 are indeed 21.7% and 8.9% higher than those of Models 1.6 and 2.6. In the remainder of this paper, we will therefore consider Models 1.4 and 2.4 presented in Tables 4.III and 4.IV as our best models to explain the international and domestic transportation markets, respectively.

Table 4.III: Regression models for ln(*tariff*) (Birr/tonne) for the international transportation market

	Models					
Variables	(1.1)	(1.2)	(1.3)	(1.4)[a]	(1.5)	(1.6)[b]
Cost driven						
Road conditions						
paved (km)	0.000137	0.000580***	0.000392**	0.000497**	0.000874**	0.000859**
	(0.000335)	(0.000180)	(0.000184)	(0.000194)	(0.000352)	(0.000338)
unpaved (km)	0.00160***	0.00103**	0.00109***	0.00116***	0.000940***	0.000927***
	(0.000408)	(0.000389)	(0.000302)	(0.000318)	(0.000310)	(0.000299)
Risk perception[c]						
high			0.552***	0.607***	0.549**	0.590**
			(0.170)	(0.161)	(0.262)	(0.251)
not specified			0.0131	0.0604	0.290	0.325*
			(0.108)	(0.119)	(0.190)	(0.175)
Tonnage estimates[d]						
low			–0.102		–0.0816	–0.0954
			(0.128)		(0.168)	(0.162)
high			–0.227		–0.378*	–0.379*
			(0.152)		(0.191)	(0.187)
Market structure						
Competition intensity						
ln(*#bids*)		–0.823***	–0.881***	–0.888***		
		(0.0863)	(0.0809)	(0.105)		
Market dispersion						
bid dispersion			–1.662***	–1.510***		
			(0.406)	(0.282)		
Market concentration						
carrier destination			–0.00335	–0.00525*		
			(0.00307)	(0.00272)		
Socio-economic						
population destination					–4.46e-05	
					(7.71e-05)	
manufacture destination					–0.000847**	–0.000868**
					(0.000345)	(0.000416)
Constant	6.618***	8.829***	9.661***	9.561***	6.550***	6.508***
	(0.250)	(0.328)	(0.398)	(0.453)	(0.341)	(0.330)
n	32	32	32	32	32	32
R-squared	0.442	0.738	0.890	0.878	0.713	0.710
Adj. R-squared	0.404	0.710	0.845	0.842	0.612	0.625
Max. VIF value	1.19	1.53	3.71	3.31	3.52	3.36

Robust standard errors in parentheses, *** p<0.01, ** p<0.05 and * p<0.1

[a] This model corresponds to Model 1.3 after backward elimination of non-significant variables.
[b] This model corresponds to Model 1.5 after backward elimination of non-significant variables.
[c] The category of reference is “not specified" for regions other than Somali.
[d] The category of reference is “not specified".

Table 4.IV: Regression models for ln(*tariff*) (Birr/tonne) for the domestic transportation market

	Models					
Variables	(2.1)	(2.2)	(2.3)	(2.4)[e]	(2.5)	(2.6)[f]
Cost driven						
distance (km)	0.00164***	0.00123***	0.00109***	0.00112***	0.00138***	0.00138***
	(7.32e-05)	(6.42e-05)	(6.73e-05)	(6.14e-05)	(7.61e-05)	(7.54e-05)
Road conditions[g]						
poor	1.102***	0.258***	0.219***	0.204***	0.441***	0.441***
	(0.0685)	(0.0687)	(0.0616)	(0.0604)	(0.0783)	(0.0781)
intermediate	0.310***	–0.0573	–0.0761	–0.0838	–0.0867	–0.0867
	(0.0701)	(0.0583)	(0.0539)	(0.0535)	(0.0658)	(0.0658)
good	–0.325***	–0.256***	–0.137**	–0.149***	–0.376***	–0.378***
	(0.0634)	(0.0517)	(0.0545)	(0.0495)	(0.0632)	(0.0631)
Risk perception[h]						
none			–0.112	–0.145	–0.0507	–0.0478
			(0.109)	(0.0999)	(0.139)	(0.136)
low			0.468***	0.431***	0.575***	0.577***
			(0.0799)	(0.0771)	(0.0969)	(0.0943)
high			0.647***	0.644***	0.611***	0.613***
			(0.0725)	(0.0701)	(0.0977)	(0.0957)
not specified			0.216***	0.232***	0.349***	0.351***
			(0.0574)	(0.0527)	(0.0647)	(0.0626)
Tonnage estimates[i]						
low			–0.0213		–0.0967	–0.0961
			(0.0622)		(0.0799)	(0.0800)
high			–0.111		–0.310***	–0.310***
			(0.0717)		(0.0773)	(0.0774)
Market structure						
Competition intensity						
ln(#bids)		–0.717***	–0.605***	–0.564***		
		(0.0359)	(0.0610)	(0.0402)		
Market dispersion						
bid dispersion			–0.724***	–0.718***		
			(0.0924)	(0.0891)		
Origin						
Market concentration						
carrier origin			0.00269			
			(0.00248)			
carrier destination			–0.00530***	–0.00557***		
			(0.00110)	(0.00107)		
Socio-economic						
population origin					–6.08e-05**	–6.10e-05**
					(2.39e-05)	(2.39e-05)
population destination					–7.72e-06	
					(3.32e-05)	
manufacture origin					–0.000616***	–0.000617***
					(0.000118)	(0.000118)
manufacture destination					–0.000831***	–0.000848***
					(0.000138)	(0.000144)
Constant	5.471***	7.737***	7.855***	7.806***	5.977***	5.971***
	(0.0716)	(0.120)	(0.158)	(0.140)	(0.116)	(0.107)
n	731	731	731	731	731	731
R-squared	0.564	0.727	0.780	0.778	0.689	0.689
Adj. *R*-squared	0.561	0.725	0.775	0.775	0.683	0.683
Max. VIF value	1.38	2.23	6.11	3.07	2.82	2.77

Robust standard errors in parentheses, *** p<0.01, ** p<0.05 and * p<0.1

[e]This model corresponds to Model 2.3 after backward elimination of non-significant variables.

[f]This model corresponds to Model 2.5 after backward elimination of non-significant variables.

[g]The category of reference is “unknown"

[h]The category of reference is “not specified" for regions other than Somali.

[i]The category of reference is “not specified".

4.5.3 Insights

In this section, we highlight the significant determinants of transportation tariffs and quantify their impact. We aim to discuss the ability of the different variables to predict Ethiopian transportation tariffs by putting a particular emphasis on factors which are specific to emerging markets. We first look at the cost driven factors and then at the measures associated with market structure before discussing the results of the models considering the socio-economic variables. Note that Kennedy (1981) suggested the following estimator for the percentage impact of a dummy variable on the variable being explained in semi-logarithmic equations:

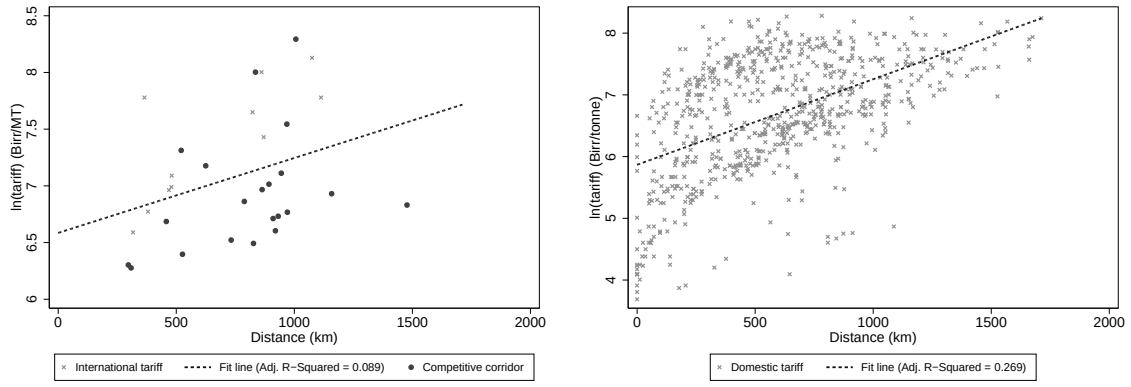
$$100\left[\exp\left(\hat{\beta}-\frac{1}{2}\widehat{V}(\widehat{\beta})\right)-1\right],$$

with $\widehat{\beta}$ being the dummy variable coefficient and $\widehat{V}(\widehat{\beta})$ being an estimate of the variance for $\widehat{\beta}$. We will thus use this estimator with $\widehat{V}(\widehat{\beta})$ equal to the squared robust error of a coefficient β, in order to analyze the impact of our indicator variables on *tariff*.

4.5.3.1 Analysis of the linehaul cost drivers

In linehaul movements, distance is recognized to be an important contributor to the cost of doing business for freight carriers (Kirkeby, 2012, and Rodrigue et al. 2009). Figure 4.5 illustrates the relationship between the natural logarithm of transportation tariffs and distance. This figure reveals that, despite a certain linear tendency, a large amount of variability in tariffs remains. The transaction prices are not tightly concentrated along the fitted line and distance alone only explains 9% and 27% of the variability in tariffs for international and domestic transportation. This is a striking fact, especially considering that transport prices are known to increase almost directly proportionally to distance in mature transportation markets. In the US for instance, a fixed price and a constant variable price per kilometer alone explain about 80% of the variability in tariffs. Thus, the need to take into account factors other than distance to explain the Ethiopian transportation market is obvious. In Figure 4.5, the international corridors and the domestic lanes where the number of bids is larger than the average (16.3 for corridors and 11.6 for lanes) are distinguished with dark grey dots. We note that the transportation tariffs tend to be lower on these more competitive network segments.

The first specifications presented in Tables 4.III and 4.IV emphasize the importance of incorporating road conditions to better explain transportation tariffs. When comparing the adjusted R-squared of Models 1.1 with the simple univariate model displayed in Figure 4.5, we note that 31.5% more variability in tariffs can be explained only by decomposing the total distance of the lanes into their paved and unpaved distances for the international



(a) International corridors

(b) Domestic lanes

Figure 4.5: Natural logarithm of transportation tariffs as a function of distance.

corridors. We can also observe in Model 1.4 that the coefficient of unpaved kilometer is highly significant while the coefficient of paved kilometer is less significant. This indicates that carriers tend to set their tariffs proportionally to the unpaved distance. A small change in unpaved and paved distance increases tariffs by 0.116% and 0.0497% on average when controlling for significant factors including the market structure, as in Model 1.4. For the domestic market, we note that adding road condition to distance in the regression model increases its predicting power by 34.1% (comparing the adjusted R-squared of Models 2.1 and the one of the basic regression shown in Figure 4.5). We can also observe from the statistical models of Table 4.IV that the transportation cost on the lanes with poor road conditions is much more expensive than on the lanes with intermediate or good conditions. Indeed, based on the coefficients of Model 2.4, and compared with lanes without available information on road conditions, poor road conditions increase the tariffs by 22.4%, while good conditions decrease the tariff by 13.9%.

Carriers operating in the Somali region are vulnerable to various risks such as hijacking or delays caused by escorting processes or expected disruptions. It is likely that they will take these factors into account in their tariff structures. The coefficients of risk perception in Models 1.4 and 2.4 confirm that the lanes with a higher or unknown risk have significantly greater tariffs. For the international market, the transportation tariffs are 81.1% higher on corridors in which risk is specified. For the domestic lanes, the transportation tariffs are not significantly lower when it is specified that the lanes are not risky. For low and high specified risk, the transportation tariffs are 53.4% and 89.9% higher, compared to lanes with non-specified risk for regions other than Somali. Transportation in the Somali region also tends to increase the transportation tariff significantly. Even if the risk is not specified, it is 25.0% more expensive to transport food aid within the Somali region than on the other domestic lanes.

4.5.3.2 Analysis of the carrier economies

The indicator variables associated with the estimated quantity of aid food to be transported monthly (*low* and *high* tonnage) are not significant at the 90% level in Models 1.3 and 2.3 and do not appear in Models 1.4 and 2.4. Even by regressing on a smaller sample, where only the lanes with a specified tonnage value are taken into account, the estimated tonnage does not significantly explain transportation tariffs, and the regression coefficients remain similar to those of Models 1.3 and 2.3. This implies that, with respect to estimated tonnage data we have, there is no clear evidence of economies of scale for transportation services in Ethiopia when controlling for the market structure. This is surprising since decreasing unit transport costs for grains can generally be expected (Rodrigue et al., 2009) and larger regional volumes of trade usually correspond to lower freight tariffs (Skiba, 2007).

To further test for economies of scale at the level of carriers, we also consider the bid as a dependent variable. We add indicator dummies per carrier uniquely to identify the carriers across lanes, allowing control for any carrier-specific characteristics that might influence their bids. The international and domestic specifications obtained from this regression are presented in Table 4.XI of the Appendix. Results show that the tonnage indicators have a statistically significant impact in lowering the bids, regardless of whether the estimate is low or high. Carriers perhaps bid more competitively when tonnage estimates are provided, regardless of the volume level, since even a low estimate indicates some degree of certainty about volumes, although it is not a tonnage guarantee by the WFP. The decrease in bids when the estimated tonnage moves from low to high for both markets indicates that this aspect of bidding behavior could be related to economies of scale. There is therefore some evidence regarding the influence of economies of scale at the level of carriers among these sets of bids. Since Jara-Díaz and Basso (2003) indicate that economies of scale and scope are the main determinants of the transportation industry structure, we must look further into economies of scope.

To investigate potential for economies of scope to determine the variability in tariffs on the Ethiopian transportation network, we have tested the relevance of including the regional indicators in the regression models 1.4 and 2.4. For the international market, we have conducted an F-test of joint significance for the inclusion of the regional destination indicator cluster into Model 1.4. The F statistic shows that the destination regions do not add significant explanatory power to the model (the p-value is 0.696). This result implies that there is no significant variability in tariffs between the destination regions, which is not already accounted for in the model, and we conclude that there is no clear evidence of backhaul opportunities or economies of scope to explain variability in tariffs at the regional level. This finding is consistent with the observed practice of carriers.

The time required to find and manage a backhaul load is usually rather long in Ethiopia. Carriers cannot afford to waste time and hold back their resources in the hope of obtaining backhaul loads when large quantities of food should be cleaned out at the ports as quickly as possible. As a result, returning to port locations for the next load is usually done with empty trucks.

As for the domestic market, we have conducted an F-test on the significance of the destination indicators and the origin indicators in Model 2.4. The F statistics show that the regional indicators for the destination regions add some explanatory power to the model, but that the increase in R-squared is less than 1.35% when the origin and destination regions are added in separate clusters and only 1.64% when they are added in one cluster. The inclusion of the regional destination indicator cluster do not add significant explanatory power to the model (the p-value is 0.226 and the change in R-squared is less than 0.3%). Some of the coefficients on the regional indicators are significant at the 5% significance level. These results imply that there are differences between the origin and destination regions, and we cannot rule out the impact of backhaul opportunities on transportation tariffs. We cannot assume that backhaul opportunities are the only factor explaining the differences between regions, but we can state that they can explain at most 1.64% of the variability in tariffs in a model that controls for competition intensity. We conclude that the economies of scope are not major determinants of the transportation tariffs, which makes sense since there are only few backhaul opportunities in Ethiopia.

4.5.3.3 Analysis of the market structure

Beyond carrier cost structures and economies, transportation tariffs may also be affected by the level of competition. Simple univariate regressions reveal that the number of carriers submitting rate offers in the RFQ for a specific lane has an impact on the effective market tariff. A regression of the transportation tariffs on $\ln(\#bids)$ and a constant explains about 55% of the variability in tariffs for both the international corridors and the domestic lanes, which suggests that competition intensity has a considerable influence on transportation tariffs.

Models 1.4 and 2.4 further indicate that the intensity of competition, measured by $\ln(\#bids)$, has a significant impact on transportation tariffs for both international and domestic transportation markets. Indeed, a one percent increase in $\#bids$, all other variables being held constant, generates a 0.888% and 0.564% decreases (elasticities) in the transportation tariff for the international corridors and domestic lanes. The importance and consequences of the competition intensity in the transportation market will be further analyzed in the following sub-section.

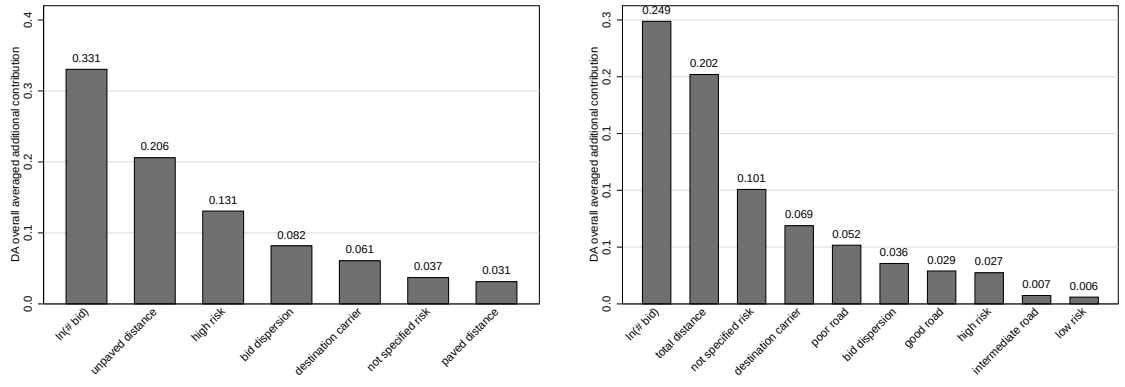
An alternate way to test the importance of competition is to regress not only the effective transportation tariffs but also the complete distribution of bids. Since we are able to uniquely identify the carriers across lanes, we can add indicator dummies per carrier to control for systematic differences in the average bid submitted by each carrier. Results from this regression show that the number of bids per lane also has a statistically significant and negative impact on the bids. The intensity of competition not only has an impact on the effective transportation tariffs but also on the carrier bids in general (see Table 4.XI in the Appendix).

From Models 1.4 and 2.4, we also note that transportation tariffs tend to decrease when there are more active carriers at the network segment's destination (variable *carrier destination* for the corridor's and lane's destinations), for both international and domestic markets. The number of active carriers at a location is an indicator of business attractiveness, and transportation tariffs tend to be lower for a lane's ending at an attractive destination. Although the international data do not have an indicator variable for the number of carriers at the origin, the coefficient of the number of carriers at the lane's origin (*carrier*) is not significant for the domestic market. (Behrens and Picard, 2011) show that the opportunity costs of returning empty increase freight rates, and that transport costs should be higher from destinations that are net exporters than from regions that are net importers. Our findings can be reconciled with this theory by making the hypothesis that carriers tend to locate in net exporting regions rather than in net importing regions. However, given the limited data, this hypothesis cannot be tested. If true, a relatively higher number of carriers at origin indicates a net exporting location, for which there will exist relatively fewer backhaul opportunities, in addition, a destination location with more carriers is a net exporter, with more business activities and lower tariffs, which is what we observe.

We also observe in Models 1.4 and 2.4 that the coefficients of the standardized dispersion in bids (*bid dispersion*) are negative and significant, which implies that the disparity between bids leads to lower transportation tariffs and that prices are not necessarily higher in disorganized markets. Having a wide dispersion between bids on a lane increases the chance of having a lower bid, resulting in a lower effective transportation tariff. This may mean that some carriers are bidding below the cost drivers to be competitive or that they do not understand their cost structure well. Informal discussions with shippers in Ethiopia indicated that they feel that some carriers are bidding at levels that do not support their operations, which may provide short term cost savings but not sustainable capacity. Another explanation is that this could constitute an evidence for collusion. If carriers collude to set prices on certain lanes as in a cartel, there will be less variability in bids on those lanes, and the effective transportation tariff will be higher. However,

further analyses would need to be conducted in order to identify cartels and analyze their impact.

In order to compare the relative importance of the cost driven and the market structure predictors of Model 1.4 and Model 2.4, we have implemented the dominance analysis (DA) proposed by Azen and Budescu (2003). These authors have introduced several quantitative measures of dominance for predictors in multiple regression, based on an examination of the R-squared values for all possible subset models of independent variables. Figure 4.6 illustrates the overall averaged additional contribution to the proportion of variance in $\ln(tariff)$ accounted for by each predictor in the subset models. When the DA overall averaged additional contribution of a predictor is greater than another, this predictor is said to generally dominate it and, therefore, we can state that this predictor is relatively more important than the other. These values thus provide an idea on the magnitude of importance of the different explaining factors considered in our models. For the international corridors (Figure 4.6a), the competition intensity and the unpaved distance appear to be the major determinants of transportation tariffs, followed by the high risk perception to go in Somali. For the domestic lanes (Figure 4.6b), competition intensity appears to be the dominant determinant of tariffs, followed by distance. Providing transportation services in the region of Somali and the number of active carriers at destination also have an impact on the tariffs, but their importance drops significantly compared with distance. The results of Models 1.4 and 2.4, as well as the bar charts of Figure 4.6, show the importance of the competition intensity on the transportation tariffs in Ethiopia. Note that for the international corridors, the competition intensity completely dominates all the other predictors (Azen and Budescu, 2003).



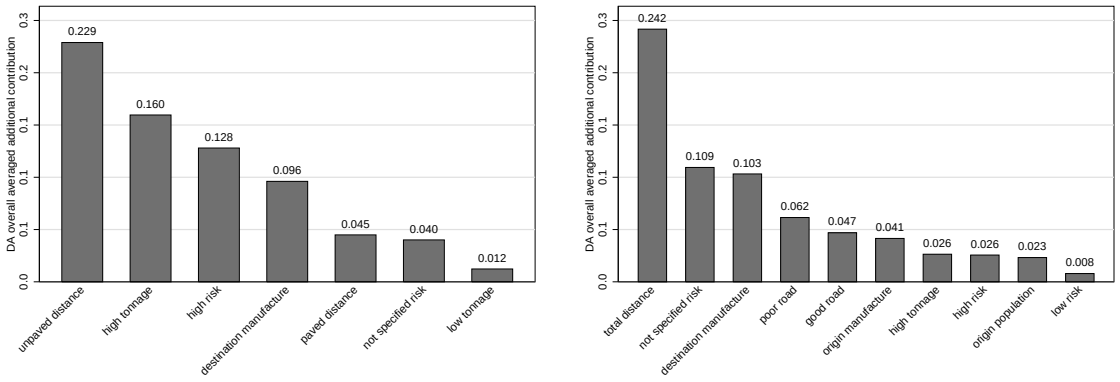
(a) International market, Model 1.4.

(b) Domestic market, Model 2.4.

Figure 4.6: Dominance analysis overall additional contributions for the models considering the market factors.

4.5.3.4 Analysis of the socio-economic factors

Comparing the adjusted R-squared values of Models 1.4 and 2.4 with the ones of Models 1.6 and 2.6, we observe that the socio-economic factors do not explain the variability in tariffs as well as the market structure measures. However, they make use of variables derived from public information, independent of the WFP operations, which are generally available to shippers. As above, in order to assess the relative importance of the combined cost and socio-economic factors in Models 1.6 and 2.6, we have considered the DA overall averaged additional contribution of each predictor shown in Figure 4.7. Unpaved distance is the most important explaining factor for the transportation tariffs, followed by high tonnage and risk for the international corridors (Figure 4.7a). When using the socio-economic factors instead of the market structure variables, the high estimated tonnage indicator becomes a significant variable. This indicates that the market structures variables may encompass the effect of this variable in the other model. However, the paved distance remains one of the least important predictor of transportation tariffs on the international corridors. For the domestic lanes (Figure 4.7b), distance has a major impact on the transportation tariffs, followed by non-specified risk in the region of Somali and the number of manufactures at destination. For both markets, international and domestic, regions with more manufacturing activities appear to be attractive for the carriers, which is reflected by a negative impact on transportation tariffs, indicating that the manufacturing activities could lead to more competitive transportation markets. As when controlling for the market structure, transporting food aid within the Somali region of Ethiopia also has an important impact on the tariffs when controlling for the socio-economic factors.



(a) International market, Model 1.6.

(b) Domestic market, Model 2.6.

Figure 4.7: Dominance analysis overall additional contributions for the models considering the socio-economic factors.

4.5.4 Discussions and implications

We now show how our models can be used to compute counterfactual costs and determine potential outliers. Assessing counterfactual costs will enable us to evaluate "what if" scenarios such as the consequences on transportation tariffs of improving road conditions or increasing competition in Ethiopia. These counterfactuals are done using the simple reduced-form estimates and do not consider the interaction of independent variables with each other. They are therefore not predictors for long-term development, but can assist short-term scenario analyses. We also identify potential outliers to support the WFP by pointing to transportation network segments where tariffs might need to be reviewed.

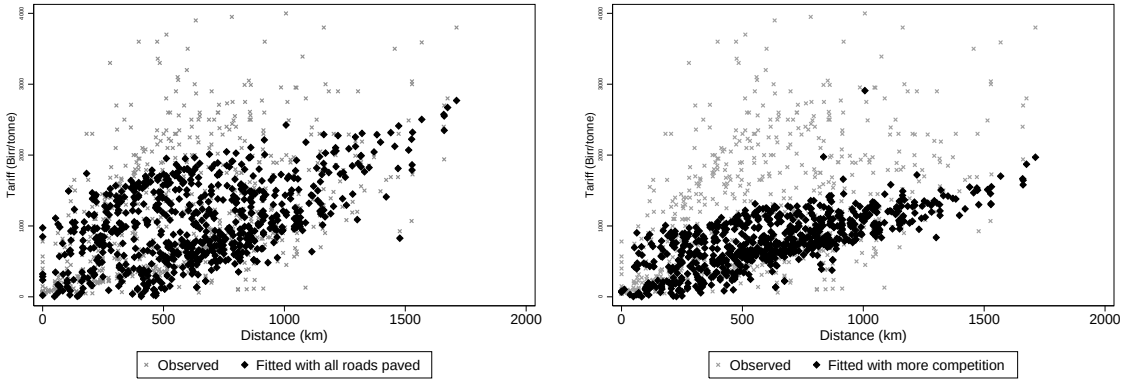
4.5.4.1 Counterfactuals and development policies

Using the regression models 1.4 and 2.4, we can predict what would be the transportation service tariffs when improving the road conditions or when increasing the competition intensity. We have therefore estimated the total transportation costs incurred by unpaved roads and lack of competition. To account for better road conditions, we have computed the predicted transportation tariffs as if all the international corridors were paved and as if all the domestic lanes were in good condition. To account for more competition intensity, we have computed the predicted transportation tariffs if the competition intensity variable values were replaced by the maximum value between the actual number of bids and the third quartile of the number of bids for each network segment ($\ln(\#bids)$ equal to 3.23 for the international corridors, and $\ln(\#bids)$ equal to 3.04 to for the domestic lanes).

In Figure 4.8, the grey crosses correspond to the effective transportation tariffs and the black diamonds are the predicted values obtained when all roads are paved on the left chart, and when increasing competition intensity on the right chart. The results depicted in this figure indicate that increasing the level of competition has a greater impact on reducing transportation tariffs than does paving all the roads of the network. By computing the counterfactual costs, we see that paving the roads would reduce shipping costs by 18%, and improving competition would reduce them by 44% on the international corridors. Similarly for the domestic roads, better road conditions would reduce shipping costs by 12% and more competition by 39%. This nevertheless neglects the possibility for better roads to stimulate competition.

These findings are consistent with the results of Teravaninthorn and Raballand (2010), highlighting the low level of competition as one of the blocks toward achieving lower transportation tariffs in Africa. Large investments in infrastructures are not sufficient to improve transportation markets, since the lack of competition can result in high markups for

transportation services. Improving road infrastructures in more competitive environment is more likely to yield lower transportation tariffs, as we found in results for the international corridors compared to the domestic lanes. The development of the physical infrastructures is recognized to be fundamental for economic growth and poverty reduction. Our results suggest that government authorities responsible for economic development in Ethiopia should consider that policies that facilitate competition in transportation markets are as important as investments in the transportation infrastructure.



(a) Predicted tariffs if the network segments were all paved.

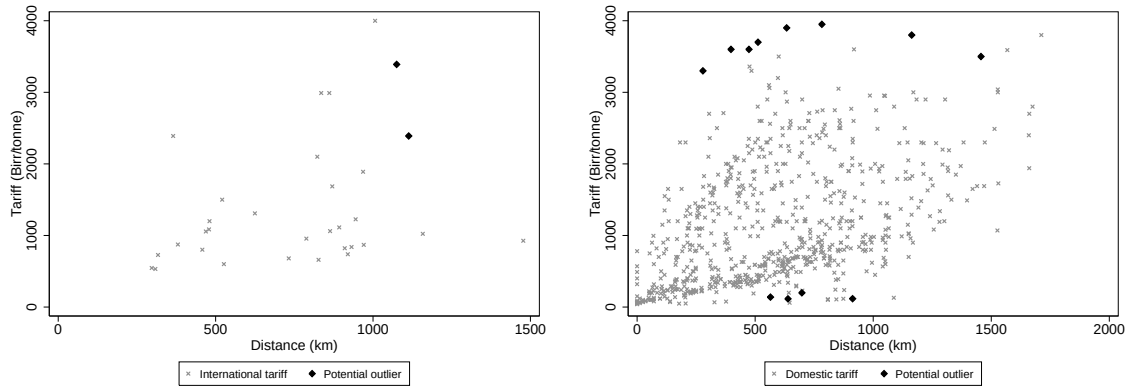
(b) Predicted tariffs if roads the network segments more competitive.

Figure 4.8: Illustration of the predicted tariffs in "what if" scenarios for international corridors and domestic lanes.

4.5.4.2 Managerial tool

Models 1.4 and 2.4 highlight the importance of the transportation tariff structures for the international corridors and domestic lanes in Ethiopia. These models can thus be used to identify the tariffs that deviate from the pricing tendencies in the WFP transportation network. In order to test for outliers, we have identified the outlying $\ln(tariff)$ observations by using a common diagnostic tool suggested in the literature (see Neter et al., 1996). The potential outliers are the cases with deleted standardized residuals large in absolute value identified by means of the Bonferroni test procedure. Figure 4.9 illustrates the lanes for which there appear to be systematic differences in pricing. In this figure the light grey crosses correspond to the effective transportation tariffs and the black diamonds are the transportation network segment suspected to be outliers. These potential outliers are the lanes for which the actual transportation tariffs deviate considerably from the estimates provided by Model 1.4 for the international corridors and by Model 2.4 for the domestic lanes.

The tariffs of the corridors and lanes corresponding to the black diamonds in Figure 4.9 should be examined carefully. The deviations in tariffs for these lanes may be explained by factors that have not been taken into account in our models and they may even be legitimate. However, if this is not the case, this indicates a need for managerial intervention. The lanes with a significant positive deviation are likely to be especially lucrative for carriers and may be characterized by large markups. The lanes with a significant negative deviation may indicate tariffs that are not effectively covering carrier costs, which would prevent carriers to offer reliable transport capacity at the bid price. The WFP should really consider renegotiating its tariffs on these network segments or ensure that the actual tariffs will not be challenged by the contracted carriers.



(a) International corridors

(b) Domestic lanes

Figure 4.9: Illustration of the WFP potential outliers of transportation tarrifs.

4.6 Conclusions

This study constitute a first attempt to analytically understand the main drivers in the truckload pricing structure in an African country. It uses a data set that contains bids and effective transportation tariffs in Ethiopia. The data were provided by the WFP, one of the major shippers in the country. The regression models presented reveal that major determinants of tariffs for the transportation services in Ethiopia are road conditions and the market structure. In order to determine lanes that may require managerial intervention, useful information is provided by the proposed regression equations to model tariffs. In order to gain a better understanding of the transportation market in Africa, further analyses should be conducted and more transparency in the market is required. However, more data are required to conduct deeper analyses, but access to data in developing countries is often an issue. Still, we view our analysis as an important step on the

right direction and we hope it will be followed by other similar studies in other African countries.

Acknowledgements

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4.7 Appendix 1: Variables and cross-correlation tables

In this appendix, we first present descriptive statistics of the socio-economic variables (Table 4.V). We then present the variables extracted from the data sources for the 32 international corridors and the 731 domestic lanes (Tables 4.VII and 4.VIII). We also provide the cross-correlation tables for the socio-economics variables and for the continuous variables of the two transportation markets. Table 4.VI presents the correlation coefficients of the socio-economics variables extracted from the CSAE. Table 4.IX presents the correlation coefficients of the variables associated with the international corridors and Table 4.X presents the correlation coefficients of the variables associated with the domestic lanes for which the distance is known.

Table 4.V: Data on Ethiopia economic activities and population

Distribution of number of manufactures per major industrial group (Central Statistical Agency of Ethiopia, 2010)	*n*	%
Food products and beverages	562	25.51
Tobacco products	1	0.05
Textiles	47	2.13
Wearing apparel, except fur apparel	41	1.86
Tanning and dressing of leather; footwear, luggage and handbags	89	4.04
Wood and products of wood and cork, except furniture	48	2.18
Paper and products and printing	127	5.76
Chemicals and chemical products	75	3.4
Rubber and plastic products	87	3.95
Other non-metallic and mineral products	608	27.6
Basic iron and steel	18	0.82
Fabricated metal products, except machinery and equipment	120	5.45
Machinery and equipment	5	0.23
Motor vehicles, trailers and semi-trailers	12	0.54
Furniture and manufacturing	363	16.48
Distribution of agricultural production (Central Statistical Agency of Ethiopia, 2009)	*Quintal*	%
Grain Crops	104,713,967	95.07
Vegetables	3,763,778	3.42
Coffee	1,665,791	1.51
Distribution of major livestocks (Central Statistical Agency of Ethiopia, 2008)	*n*	%
Cattle	49,297,898	51.25
Sheep	25,017,217	26.01
Goat	21,884,223	22.75
Population (Federal Democratic Republic of Ethiopia Population Census Commission, 2008)	*n*	
Population	72,840,864	

Table 4.VI: Cross-correlation table for the regional socio-economic factors

Variables	*population*	*grain*	*vegetable*	*coffee*	*agriculture*	*cattle*	*sheep*	*goat*	*livestock*	*manufacture*
Demographic										
population	1.000									
Agriculture										
grain	0.949	1.000								
	(0.000)									
vegetable	0.820	0.633	1.000							
	(0.002)	(0.037)								
coffee	0.845	0.788	0.814	1.000						
	(0.001)	(0.004)	(0.002)							
agriculture	0.958	0.999	0.661	0.807	1.000					
	(0.000)	(0.000)	(0.027)	(0.003)						
Livestock										
cattle	0.986	0.978	0.777	0.865	0.985	1.000				
	(0.000)	(0.000)	(0.005)	(0.001)	(0.000)					
sheep	0.952	0.965	0.661	0.678	0.964	0.952	1.000			
	(0.000)	(0.000)	(0.027)	(0.022)	(0.000)	(0.000)				
goat	0.937	0.960	0.624	0.705	0.959	0.948	0.964	1.000		
	(0.000)	(0.000)	(0.040)	(0.015)	(0.000)	(0.000)	(0.000)			
livestock	0.982	0.985	0.728	0.797	0.989	0.992	0.981	0.976	1.000	
	(0.000)	(0.000)	(0.011)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)		
Manufacture										
manufacture	0.333	0.261	0.263	0.246	0.265	0.275	0.242	0.227	0.261	1.000
	(0.317)	(0.439)	(0.434)	(0.467)	(0.431)	(0.413)	(0.473)	(0.502)	(0.438)	

Table 4.VII: Summary of the variables for the 32 international corridors

Variable	Description	Type	Mean	Std deviation	Median	Min.	Max.
Transportation tariff							
tariff	Effective market tariff	Continuous	1,405.27	902.59	1,058.51	532	3,999
ln(*tariff*)	ln of the effective market tariff	Continuous	7.08	0.56	6.96	6.28	8.29
Linehaul cost drivers							
Distance							
distance	Total distance (km)	Continuous	756.14	289.68	831.21	297.06	1,477.29
Road conditions							
paved	Paved distance (km)	Continuous	507.8	285.31	435.99	19.37	1,136.18
unpaved	Unpaved distance (km)	Continuous	248.33	239.95	227.25	0	1,094
Somali risk perception							
high somali	High WFP risk perception	Categorical	4/32	–	–	–	–
not specified somali	No risk specified by the WFP for corridors ending in Somali	Categorical	12/32	–	–	–	–
not specified other	No risk specified by the WFP for corridors not ending in Somali	Categorical	16/32	–	–	–	–
Estimated tonnage							
high	High WFP estimation for tonnage to transport	Categorical	9/32	–	–	–	–
low	Low WFP estimation for tonnage to transport	Categorical	12/32	–	–	–	–
not specified	No estimated tonnage specified by the WFP in the RFQ	Categorical	11/32	–	–	–	–
Market structure							
Competition intensity							
ln(#*bids*)	ln of the number of bids	Continuous	2.79	0.46	2.91	1.95	3.26
Market dispersion							
bid dispersion	Standardized interquartile range	Continuous	0.22	0.15	0.17	0.09	0.63
Market concentration							
carrier destination	Number of active carrier at desdination	Continuous (discrete)	57.78	21.17	62	12	82
hhi destination	Bid based Herfindahl-Hirschmann index at destination	Continuous	0.04	0.02	0.04	0.03	0,1
Socio-economics							
Demographic							
population destination	Population in the region of destination (1 unit = 10,000 people)	Continuous (discrete)	979.59	893.56	443.91	34.28	2,715.85
Economic activities							
manufacture destination	Number of manufactures in the region of destination	Continuous (discrete)	164.28	200.20	43	12	887
agriculture destination	Agricultural production at destination region (1 unit = 10,000 quintals)	Continuous	1,289.402	1,966.337	75.51	10.71	5,326.89
livestocks destination	Livestocks at destination region (1 unit = 10,000 animals)	Continuous	1,185.00	1,380.28	315.79	0	3,899.13

Table 4.VIII: Summary of the variables for the 731 domestic lanes

Variable	Description	Type	Mean	Std deviation	Median	Min.	Max.
Transportation tariff							
tariff	Effective market tariff	Continuous	1,138.84	844.63	900	40	3,950
ln(*tariff*)	ln of the effective market tariff	Continuous	6.69	0.95	6.80	3.69	8.28
Linehaul cost drivers							
Distance							
distance	Total distance (km)	Continuous	589.82	356.33	564.97	0	1,712
Road conditions							
poor	Poor road condition base on % unpaved	Categorical	171/731	–	–	–	–
intermediate	Intermediate road condition base on % unpaved	Categorical	170/731	–	–	–	–
good	Good road condition base on % unpaved	Categorical	184/731	–	–	–	–
unknown	Unknow road condition	Categorical	206/731	–	–	–	–
Somali risk perception							
high	High WFP risk perception in Somali region	Categorical	42/731	–	–	–	–
low	Low WFP risk perception in Somali region	Categorical	25/731	–	–	–	–
none	No risk identified by the WFP in Somali region	Categorical	35/731	–	–	–	–
not specified somali	No risk specified by the WFP in Somali region	Categorical	367/731	–	–	–	–
not specified other	No risk specified by the WFP for other regions than Somali	Indicator	262/731	–	–	–	–
Estimated tonnage							
high	High WFP estimation for tonnage to transport	Categorical	65/731	–	–	–	–
low	Low WFP estimation for tonnage to transport	Categorical	66/731	–	–	–	–
not specified	No estimated tonnage specified by the WFP in the RFQ	Categorical	600/731	–	–	–	–
Market structure							
Competition intensity							
ln(#*bids*)	ln of the number of bids	Continuous	2.45	0.74	2.56	1.1	4.03
Market dispersion							
bid dispersion	Standardized interquartile range	Continuous	0.4	0.22	0.34	0.02	1.34
Market concentration							
carrier origin	Number of active carrier at origin	Continuous (discrete)	25.85	13.7	26	6	46
carrier destination	Number of active carrier at destination	Continuous (discrete)	47.59	19.09	46	23	82
hhi origin	Bid based Herfindahl-Hirschmann index at origin	Continuous	0.08	0.06	0.05	0.03	0.22
hhi destination	Bid based Herfindahl-Hirschmann index at destination	Continuous	0.06	0.03	0.05	0.03	0.13
Socio-economics							
Demographic							
population origin	Population in the region of origin (1 unit = 10,000 people)	Continuous	1097.67	1,1019.39	443.92	34.28	2,715.85
population destination	Population in the region of destination (1 unit = 10,000 people)	Continuous	846.92	783.72	443.92	18.33	2,715.85
Economic activities							
Manufacturing activies							
manufacture origin	Number of manufactures in the region of origin	Continuous	181.09	210.66	44	12	887
manufacture destination	Number of manufactures in the region of destination	Continuous	121.87	172.64	12	8	887
Agricultural activies							
agriculture origin	Agricultural production at origin region (1 unit = 10,000 quintals)	Continuous	1,691.791	2,250.78	75.51	8.77	5,326.88
agriculture destination	Agricultural production at destination region (1 unit = 10,000 quintals)	Continuous	1,044.45	1,747.69	75.51	6.06	5,326.88
livestocks origin	Livestocks at origin region (1 unit = 10,000 animals)	Continuous	1,419.50	1,576.29	315.79	0	3,899.13
livestocks destination	Livestocks at destination region (1 unit = 10,000 animals)	Continuous	1,007.43	1,241.36	315.79	0	3,899.13

Table 4.IX: Cross-correlation table for the international corridors

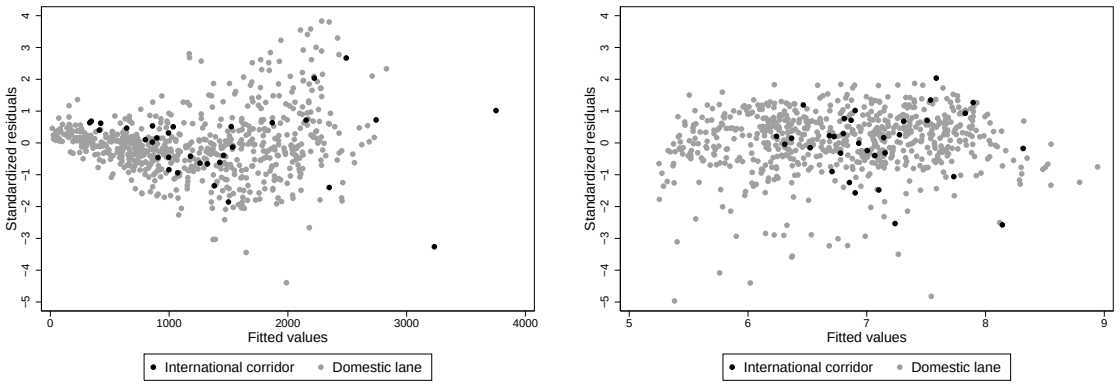
	Tariff	Cost driven			Market structure				Socio-economic			
Variables	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
Tariff												
1. ln(*tariff*)	1.000											
Cost driven												
2. *distance*	0.344	1.000										
	(0.054)											
3. *paved*	–0.207	0.652	1.000									
	(0.255)	(0.000)										
4. *unpaved*	0.662	0.432	–0.402	1.000								
	(0.000)	(0.013)	(0.023)									
Market structure												
5. ln(#*bids*)	–0.751	0.063	0.484	–0.500	1.000							
	(0.000)	(0.732)	(0.005)	(0.004)								
6. *bid dispersion*	0.499	0.094	–0.497	0.705	–0.648	1.000						
	(0.004)	(0.608)	(0.004)	(0.000)	(0.000)							
7. *carrier destination*	–0.344	–0.153	–0.006	–0.178	0.224	–0.236	1.000					
	(0.054)	(0.402)	(0.973)	(0.331)	(0.218)	(0.194)						
8. *hhi destination*		0.618	0.012	–0.473	0.577	–0.697	0.680	–0.735	1.000			
	(0.000)	(0.950)	(0.006)	(0.001)	(0.000)	(0.000)	(0.000)					
Socio-economic												
9. *population destination*	–0.327	0.305	0.521	–0.251	0.425	–0.319	0.240	–0.411	1.000			
	(0.067)	(0.089)	(0.002)	(0.167)	(0.015)	(0.075)	(0.185)	(0.019)				
10. *agriculture destination*	–0.340	0.195	0.456	–0.307	0.409	–0.321	0.187	–0.398	0.967	1.000		
	(0.057)	(0.285)	(0.009)	(0.087)	(0.020)	(0.073)	(0.305)	(0.024)	(0.000)			
11. *livestock destination*	–0.336	0.256	0.506	–0.292	0.435	–0.330	0.188	–0.408	0.986	0.992	1.000	
	(0.060)	(0.157)	(0.003)	(0.105)	(0.013)	(0.065)	(0.303)	(0.020)	(0.000)	(0.000)		
12. *manufacture destination*	–0.440	0.399	0.741	–0.400	0.599	–0.448	–0.058	–0.421	0.564	0.553	0.554	1.000
	(0.012)	(0.024)	(0.000)	(0.023)	(0.000)	(0.010)	(0.755)	(0.016)	(0.001)	(0.001)	(0.001)	

Table 4.X: Cross-correlation table for the domestic lanes

Variables	Tariff 1.	Cost driven 2.	Market structure 3.	4.	5.	6.	7.	8.	Socio-economic 9.	10.	11.	12.	13.	14.	15.	16.
Tariff																
1. ln(*tariff*)	1.000															
Cost driven																
2. *distance*	0.520	1.000														
	(0.000)															
Market structure																
3. ln(#*bids*)	−0.737	−0.170	1.000													
	(0.000)	(0.000)														
4. *bid dispersion*	−0.217	−0.193	−0.002	1.000												
	(0.000)	(0.000)	(0.954)													
5. *carriers origin*	−0.431	0.109	0.750	0.054	1.000											
	(0.000)	(0.003)	(0.000)	(0.147)												
6. *hhi origin*	0.452	−0.175	−0.781	−0.039	−0.878	1.000										
	(0.000)	(0.000)	(0.000)	(0.287)	(0.000)											
7. *carrier destination*	−0.444	0.028	0.532	−0.038	0.348	−0.425	1.000									
	(0.000)	(0.453)	(0.000)	(0.307)	(0.000)	(0.000)										
8. *hhi destination*	0.623	0.117	−0.745	0.097	−0.388	0.476	−0.774	1.000								
	(0.000)	(0.002)	(0.000)	(0.008)	(0.000)	(0.000)	(0.000)									
Socio-economic																
9. *population origin*	−0.264	0.113	0.411	−0.044	0.551	−0.447	0.304	−0.298	1.000							
	(0.000)	(0.002)	(0.000)	(0.233)	(0.000)	(0.000)	(0.000)	(0.000)								
10. *agriculture origin*	−0.275	0.126	0.435	−0.029	0.562	−0.492	0.307	−0.306	0.983	1.000						
	(0.000)	(0.001)	(0.000)	(0.437)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)							
11. *livestock origin*	−0.270	0.133	0.423	−0.036	0.546	−0.477	0.313	−0.312	0.992	0.996	1.000					
	(0.000)	(0.000)	(0.000)	(0.335)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
12. *manufacture origin*	−0.334	0.107	0.547	−0.047	0.641	−0.553	0.368	−0.377	0.560	0.564	0.551	1.000				
	(0.000)	(0.004)	(0.000)	(0.202)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
13. *population destination*	−0.439	−0.150	0.503	−0.038	0.259	−0.296	0.433	−0.516	0.231	0.226	0.234	0.264	1.000			
	(0.000)	(0.000)	(0.000)	(0.306)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
14. *agriculture destination*	−0.456	−0.136	0.524	−0.032	0.274	−0.318	0.394	−0.527	0.240	0.236	0.245	0.281	0.969	1.000		
	(0.000)	(0.000)	(0.000)	(0.383)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
15. *livestock destination*	−0.134	0.530	−0.039	0.277	−0.320	0.402	−0.536	0.242	0.238	0.246	0.283	0.984	0.994	1.000		
	(0.000)	(0.000)	(0.000)	(0.296)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
16. *manufacture destination*	−0.527	−0.148	0.605	−0.054	0.322	−0.377	0.359	−0.603	0.250	0.255	0.260	0.311	0.664	0.653	0.660	1.000
	(0.000)	(0.000)	(0.000)	(0.143)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

4.8 Appendix 2: Heteroscedasticity

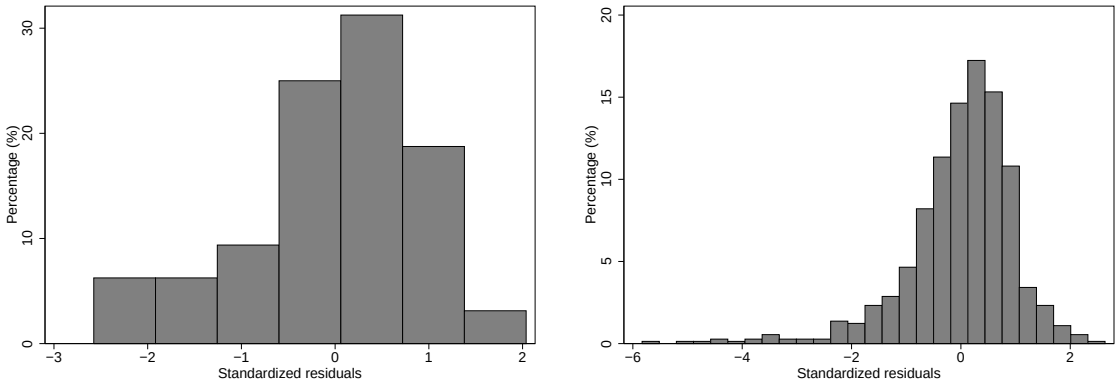
Heteroscedasticity occurs when the error terms from a regression model do not have constant variance, which can be detected by plotting the standardized residuals on the fitted values (Neter et al., 1996). Figure 4.10 shows the scatter plots of the standardized residuals obtained when regressing *tariff* and ln(*tariff*) on the cost driven and market structure variables. Comparing Figure 4.10a and Figure 4.10b, we observe that regressing *tariff* as opposed to ln(*tariff*) generates non-constant error terms (the absolute values of the standardized residuals increase whit the fitted value). Using ln(*tariff*) as a dependent variable into the regression models does not generate significant problem of heteroscedasticity as is the case for *tariff*. The same conclusion can be drawn for the models using the socio-economic variables as shown in Figure 4.12. To complete the analysis of the OLS assumptions, Figure 4.11 and Figure 4.13 show the histograms of the standardized residuals for the different regression models of ln(*tariff*). We observe in these figures that the standardized residuals are close to being normally distributed.



(a) *tariff* as dependent variable.

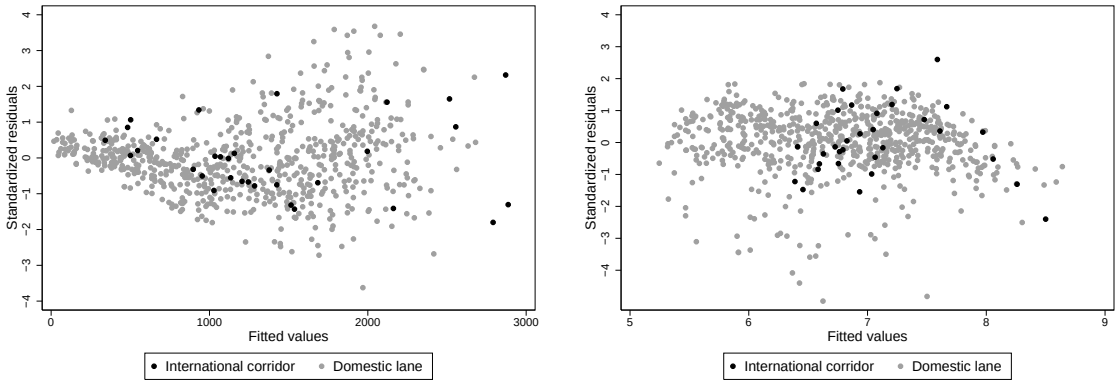
(b) ln(*tariff*) as dependent variable.

Figure 4.10: Scatter plots of standardized residuals on fitted values for models using market structure variables.



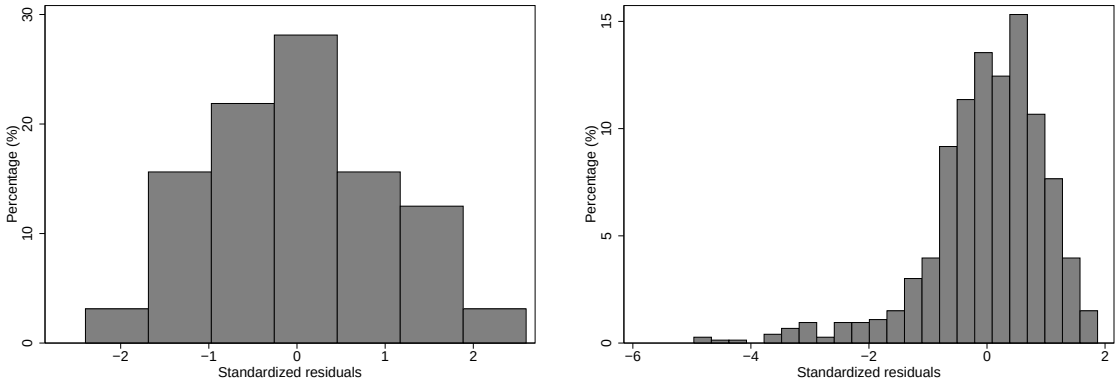
(a) International corridors. (b) Domestic lanes.

Figure 4.11: Histograms of standardized residuals for models of ln(*tariff*) as the dependent variable using market structure variables.



(a) *tariff* as dependent variable. (b) ln(*tariff*) as dependent variable.

Figure 4.12: Scatter plots of standardized residuals on fitted values for models using soci-economic variables.



(a) International corridors. (b) Domestic lanes.

Figure 4.13: Histograms of standardized residuals for models of ln(*tariff*) as the dependent variable using socio-economic variables.

4.9 Appendix 3: Regressions to explain bid values

Table 4.XI shows the specifications obtained when regressing the carrier bids on the cost driven factors, the market structure measures and by controlling for carrier specificities through variables.

Table 4.XI: Bid regression models

VARIABLES[j]	(1) International ln(*bid*) (Birr/tonne)	(2) domestic ln(*bid*) (Birr/tonne)
Cost driven		
Distances		
paved (km)	0.000404***	
	(5.13e-05)	
unpaved (km)	0.000939***	
	(7.26e-05)	
distance (km)		0.00139***
		(1.62e-05)
Road conditions[k]		
poor		0.295***
		(0.0193)
intermediate		0.0436***
		(0.0131)
good		–0.146***
		(0.0106)
Risk perception[l]		
none		–0.0154
		(0.0241)
low		0.378***
		(0.0319)
high	0.610***	0.501***
	(0.0480)	(0.0262)
notspecified	0.0551	0.144***
	(0.0344)	(0.0131)
Tonnage estimates[m]		
low	–0.113***	–0.0929***
	(0.0302)	(0.0132)
high	–0.241***	–0.210***
	(0.0339)	(0.0155)
Market structure		
Competition intensity		
ln(#*bids*)	–0.744***	–0.388***
	(0.0429)	(0.0158)
Market dispersion		
bid dispersion	–0.682***	–0.443***
	(0.147)	(0.0225)
Market concentration		
carrier origin		0.00113*
		(0.000611)
carrier destination	–0.00341***	–0.00412***
	(0.000616)	(0.000295)
Constant	9.075***	7.537***
	(0.162)	(0.0463)
n	562	10,377
R-squared	0.852	0.772
Adj. *R*-squared	0.845	0.771
Max. VIF value	2.39	5.20

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[j]Carrier indicator variables are also included in the models but not shown in Table 4.XI.
[k]The category of reference is “unknown"
[l]The category of reference is “not specified" for regions other than Somali.
[m]The category of reference is “not specified".

Chapitre 5

Tactical Network Planning for Food Aid Distribution in Kenya

Chapter information

M.-È. Rancourt, J.-F. Cordeau, G. Laporte et B. Watkins. Tactical Network Planning for Food Aid Distribution in Kenya. Technical Report, *Cahier du CIRRELT–2013–09*, Montreal, February 2013.

Abstract

In Sub-Saharan Africa, the annual seasonal patterns cause frequent and regular shocks which make the population more vulnerable to food insecurity. Kenya is affected by periodic droughts at the beginning and at the end of two irregular rainy seasons, which have a profound effect on seasonal food crises. This project aims at providing a mathematical programming based methodology for the design of food aid distribution networks in Kenya. It can also be applied to other developing countries. We present a location model to determine a set of distribution centers, where the food is directly distributed to the beneficiaries, for the region of Garissa in Kenya. Our model takes into account the welfare of all stakeholders involved in the response system: the government of Kenya, the World Food Programme, the Red Cross, and the beneficiaries. We describe how we have combined need assessment and population data to plan food distribution in Garissa. We also show how we have used GIS data on the road network to establish a set of potential distribution centers. In addition to the results obtained by solving our primary model, we present the several sensitivity analyses and variants of the basic covering model.

Keywords: Food aid, network design, location problem, stakeholder welfare.

5.1 Introduction

According to the United Nations World Food Programme (2012a), hunger and malnutrition pose the largest risks to worldwide health. Many developing countries suffer from food shortages, but Sub-Saharan Africa is the only region in the world that is constantly suffering from widespread chronic food insecurity and persistent threats (Shaw, 2009). Seasonalities have always had an important impact on hunger and poverty in rural Africa. The annual patterns of the two dry and two rainy seasons cause frequent and regular shocks which make people vulnerable to food insecurity and hamper their opportunities to move out of poverty. Relatively little attention has been paid to the implications of seasonalities on food insecurity and rural poverty, despite the fact that they generate short-term hunger and seasonal food crises every year (Devereux, 2012). Because seasonalities are repetitive, rural households and communities have developed coping strategies to buffer their effects, like pastoralist livelihood systems (Young, 1992).

Food aid is an instrument used to reduce insecurity in poor nations. Although food aid has often been criticized (see Bourn and Blench, 1990; Barrett, 2006; Margolies and Hoddinott, 2012), it remains an important component of humanitarian operations. Food aid management entails humanitarian operations evolving within highly complex supply chains. As mentioned by Van Wassenhove (2006) and Christopher and Tatham (2011), logistics is now being recognized to be an integral part of relief operations. In the last decade, humanitarian organizations have started adopting supply chain management methodologies to increase their performance and enhance coordination between the actors involved in assistance operations. For example, the World Food Programme (WFP) has made continuous efforts to expand its logistics capacity and to improve the efficiency of its transportation operations, which has enabled it to acquire an acknowledged expertise in moving large amounts of food commodities, often in difficult circumstances, throughout the developing world (see Shaw, 2011).

Haddow and Bullock (2004) have distinguished four phases for disaster management operations of humanitarian organisations: response, recovery, mitigation and preparedness. Figure 5.1 provides an overview of the cycle of these phases and their meanings. In disaster management, one typically considers that the shocks (disasters) occur before the response phase. These shocks are typically unpredictable and devastating, and they only last a relatively short period of time, like in the case of earthquakes and tsunamis. Our problem is related to preparedness and planning continuous relief operations rather than

to the immediate response (see Kovács and Spens, 2007; Çelik et al., 2012, for a distinction between disaster relief and development aid work). For long-term development operations, such as food aid distribution in Sub-Saharan Africa, the context is different because the shocks grow over longer periods and are more predictable, even though emergencies can also occur (the 2011 famine in the Horn of Africa for example). However, the four phases of disaster management are still appropriate and applicable to the context of food security, but they overlap over time. Like the consequences of sudden-onset disasters, long-term development issues also engender human suffering, often coupled with economic damage or poverty, even if the causes cannot usually be attributed to one specific catastrophe.

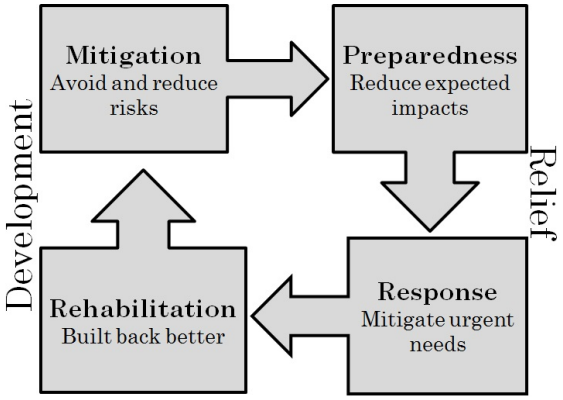


Figure 5.1: Disaster management lifecycle (Source: Tomasini and Wassenhove, 2009).

In this context, where the welfare of the stakeholders is related to economical or accessibility concerns, managing tactical food aid supply chains is a complex task. Humanitarian organisations operate with limited resources which depend primarily on donations. It is therefore of critical importance for these organisations to effectively design their supply chain and transportation plans in order to reach as many affected people as possible during crises. Humanitarian logistics shares several characteristics with its industrial counterpart. Multiple relevant location and transportation problems encountered in the context of food distribution are defined on networks and share a common structure with classical distribution management problems. Indeed, Tzeng et al. (2007) have compared general physical distribution systems for business with relief distribution systems. They have suggested that the points located in non-devastated areas where the commodities are collected act as supply nodes (depots), whereas the devastated areas where relief is provided to victims act as demand nodes (customers). Van Wassenhove (2006) pinpoints the cross-learning potential for both humanitarian and private sectors in emergency food relief operations and the benefits of potential collaborations. This has motivated us to analyze the food aid distribution problem in developing coutries through the use of a mathematical programming based methodology, an approach not commonly used in this context. As mentioned by White et al. (2011) operations research can make important

contributions to the improvement of decision making in developing countries although it is of limited use to help reduce poverty. We believe that the results obtained by exploiting such a methodology can provide a valuable perspective for decision makers responsible food relief management.

Our study is motivated by the case of food aid distribution in a region of Kenya (Figure 5.2), Garissa District and its surroundings, but our contribution is of general applicability for developing countries that are struggling with food insecurity. To our knowledge, this project constitutes the first attempt to solve location models which could serve as a basis for the development of a decision support system for the design of last-mile food aid supply chains. It makes use of real seasonal need assessment data, geographic information systems, and data related to demographics and road infrastructure. Although food aid is often associated with rapid and short-term disaster relief, there are cases in poor and low rainfall areas where food aid is more predictable since it addresses regular and seasonal food insecurity. Maxwell1 and Watkins (2003) have argued that in such cases, it makes sense to invest in the optimization of the distribution network. The Garissa District is one such area and serves as a relevant example for medium-term network optimization.

Figure 5.2: Map of Kenya (Source: Nation Online, 2012).

5.1.1 Literature review

The surge of natural disasters over the last decade has led to a growing interest in the humanitarian applications of quantitative research in the field of humanitarian logistics. Van Wassenhove and Martinez (2012) show that significant improvements can be achieved by using an operations research methodology to adapt supply chain practices to humanitarian logistics for two applied cases of field vehicle fleet management. Altay and Green (2006) and Simpson and Hancock (2009) have provided exhaustive surveys of operations research-based projects which have contributed to disaster related research in the last decades. Johnson and Smilowitz (2012) have introduced the area of community-based OR, which addresses problems common to humanitarian logistics, such as vulnerable populations, fairness and sustainability objectives. Ergun et al. (2011) have summarized several contributions adressing key problems from the humanitarian and public sectors and have suggested solution approaches.

A number of algorithms have been proposed to deal with location problems related to disaster management issues. Tzeng et al. (2007) have used fuzzy multi-objective programming to create an emergency relief distribution model and have proposed a framework for data collection. They have also tested their methodology on a real case study based on earthquake response in Taiwan. Recently, Naji-Azimia et al. (2012) have modelled the distribution of survival goods to people in disaster areas as a generalization of the covering tour problem and have proposed a heuristic tested on randomly generated data. Campbell and Jones (2011) have studied the problem of prepositioning supplies in the context of preparation for disaster by considering risk and inventory levels. They have first solved the problem analytically for one depot and then incorporated their results into a heuristic for a p-median problem.

White et al. (2011) have provided a broad overview of operations research applications in developing countries and have also discussed its relevance for long-term development. We refer the reader to Çelik et al. (2012) for a recent complete tutorial on humanitarian logistics. These authors have highlighted the importance of long-term development issues although most of the operations research-based methodologies developed for the field of humanitarian logistics are related to disaster management problems.

Three projects have been conducted in collaboration with the World Food Programme regarding food aid planning. De Angelis et al. (2007) have proposed a routing and scheduling for emergency air deliveries of food aid in Angola. Aviles et al. (2008) have implemented an inventory management tool and have solved a mathematical model of the WFP country-level supply chain (location of commodity pre-positioning depots). By testing their approaches on historic and simulated data, these authors have shown that benefits in increased service levels and decreased costs could be achieved with better in-

ventory management policies and a redesigned supply chain. Alvarenga et al. (2010) have designed a simulation tool to generate an optimal shipment schedule which takes into account transportation lead times, transportation capacities, land transportation storage and handling costs while considering the current state of the supply chain network. This tool first simulates port operations, and then optimizes the truck shipping routes and schedules for food shipments to the main warehouses of a country. However, to our knowledge, none of the projects presented in this literature review directly applies to food aid network planning at the last-mile distribution level.

The problem considered in this paper is related to long-term humanitarian operations and consists in designing a tactical network for food aid distribution. This problem can be modeled as an uncapacitated facility location problem, which has been largely studied by location scientists. Mathematical models and classification schemes for location problems have been reviewed by ReVelle et al. (2008) and Daskin (2008). Melo et al. (2009) have presented applications of facility location models to supply chain network design arising in various industries and have highlighted the current state-of-the-art contributions. Although many sophisticated exact branch-and-bound algorithms have been developed (see Erlenkotter, 1978; Koerkel, 1989), a number of simple heuristics have also been proved to be very successful (see Kratica et al., 2001; Michel and Van Hentenryck, 2004). In this project, we solve the problem with a general purpose mixed integer programming solver. However, the main challenge of the project lies more in modeling the problem, carrying out data collection and processing, and performing analyses for a real case study than on algorithmic development. Data collection and processing is fraught with difficulties in developing countries like Kenya. It was facilitated by the fact that the fourth author runs a consulting company involved in projects related to food aid distribution in Kenya, and the first author made a one-month field trip in August 2012 to gather first-hand information.

5.2 Problem context and motivation

We now present the context of food aid distribution in Kenya. We describe the humanitarian operations activities associated with the food distribution supply chain, and we explain the roles of the main stakeholders involved in the process.

5.2.1 Seasonalities and assessment

Rainfalls are highly variable in Kenya; there are two rainy seasons and two intervening dry seasons. The long rain season lasts from March until June, and is followed by a long dry season from June to October. The second rainy season is shorter and lasts from

October to December, followed by another dry period from December to March. All parts of the country are subject to periodic droughts at the beginning and at the end of the two rainy seasons, which has a profound effect on settlement patterns and on the Kenyan population affected by nutrition crises. The severity of the droughts has a deep influence on the ability of the affected population to recover from food insecurity, which drives the food aid needs for the following periods. The most vulnerable regions of Kenya are the arid and semi-arid regions in which agro-pastoralism and pastoralism are the dominant livelihood systems (see Bourn and Blench, 1999).

To account for the effects of seasonalties, the Kenya Food Security Steering Group (KFSSG) conducts a need assessment for food aid twice a year, after each rainy season. The KFSSG is a joint group of specialists from the Government of Kenya (GoK), the United Nations (UN), non-governmental organizations (NGOs), and district level teams (see Government of Kenya, 2012a). The assessments consist in determining the number of beneficiaries and the ratio entitlements at the district and division levels across the country. The ratio entitlement corresponds to the percentage of a standard food ration that the beneficiaries are entitled to receive, and is calculated on the basis of their nutritional requirements. This ratio depends on the severity of the seasonal food scarcity. A full ratio entitlement, commonly called a food basket, is made up of 400 g of cereal, 60 g of pulses, 25 g of oil (fortified with vitamine A and D), 50 g of fortified blended food (corn soya blend), 15 g of sugar, and 15 g of iodized salt. To determine the number of beneficiaries and the ratio entitlement, the KFSSG analyzes the available information on the food security situation and other relevant indicators, such as price data, field assessment and livelihood economic contexts. The results of the assessment are valid for a six-month period, i.e. until the following assessment plan is implemented.

The pastoralist populations practice seasonal migrations depending on resource availabilities for their livestock. They allow them to exploit more land in order to suit their food production and survive in arid regions, but the women and the children who remain in pastoralist settlements are often left behind with few resources. Pastoralist households are indeed among the most vulnerable groups in this society. Sanford and Habtu (2000) expose the shortcomings of early warning and response systems in the pastoral areas. The need to develop service delivery models which meet the particular demands of the pastoral communities and the effects of seasonal food scarcity is of critical importance. Managing food aid supply chains in such complex environments is a real challenge for humanitarian organisations. This project aims to provide a methodology for designing and managing tactical food aid distribution networks. Our study takes into account the results of the 2012 short rains assessment for the district of Garissa and its surroundings, a district characterized by semi-arid lands and pastoralist populations.

The district of Garissa is important for food aid in Kenya. Over the period ranging from September 2004 to August 2011, during each six-month period, an average of 83,483 people of this district have received food aid. This corresponds to about 5% of the 1,823,588 people who have received food aid in Kenya, making it the sixth most important district out of the 28 in which aid is distributed, behind Turkana, Wajir, Makueni, Mandera and Kitui. On average, 35% of the district population has been receiving aid. During the most difficult period, this number reached 62%. Only five districts have a higher percentage of the population receiving aid (the district receiving the most is Marsabit, with 60% on average).

Importantly, the district of Garissa has been receiving aid more consistently than the country as a whole. Indeed, the variation in the number of its beneficiaries is lower than it is at the national level: the coefficient of variation in the number of beneficiaries across six-month periods in Garissa is 0.45, and 0.51 at the country level. Only Turkana, Marsabit, Samburu, Mandera, Wajir, Tana River and Kwale, receive aid more consistently. These are all semi-arid regions prone to drought. As suggested by Maxwell1 and Watkins (2003), in Garissa like in these other districts, the relatively stable number of beneficiaries has led to a fixed distribution system which justifies the need for an optimized network.

5.2.2 Food aid supply chain

Sub-Saharan African in-country food aid supply chains are composed of several main warehouses (MWs) located in strategic regions where primary storage infrastructure is available. The MWs serve mostly as storage facilities and transshipment hubs (Figure 5.3a). The food is then transported to distribution centers (DCs) from the MWs, where it is informally stored and directly handed out to the beneficiaries. The DCs are temporary depots such as shelters, schools, and community facilities which are often located in remote regions, depending on the population needs (Figure 5.3b). The beneficiaries must walk to the DCs in order to receive food assistance. For ongoing aid operations, the MWs are usually fixed warehouse infrastructures located in strategic locations in the country, whereas the DCs are temporary depots whose locations may vary over time. These informal warehouses must be located in places accessible to the population. Each MW is used for supplying a specific region in the country, and each DC is supplied from the MW that serves its region. Determining where to locate the DCs in order to reach the vulnerable populations and planning how much food aid should be delivered to these distribution points is of primary importance for supply chain responsiveness and cost effectiveness.

(a) Main warehouse.

(b) Distribution center.

Figure 5.3: Photographs of a MW and of a DC.

5.2.3 Stakeholder's responsibilities

Several agents are involved in the food aid supply chain in Kenya. Here we explain who are the different stakeholders involved in the supply chain (World Food Programme, Kenya Red Cross Society, Community Relief Committee, and beneficiaries) and what their responsibilities are. We will focus on the supply chain activities at the regional level, i.e. on the logistics operations engaged once the food is stored at the regional MW. There also exist several ethical, social, and economic implications associated with food aid distribution which are neither analyzed nor discussed in this paper since they lie beyond the scope of this project.

5.2.3.1 The World Food Programme

The WFP is in full charge of the international transportation movements, the transport of food aid from Mombassa port to the MWs, and the transshipments between the MWs. Once the food supplies arrive at an MW, the cooperating lead partner agency manages the transportation operations from the MW to the DCs, as well as the food distribution to the population. Humanitarian organisations usually contract with trucking companies to move cargo across the network, and such secondary transport operations are generally very costly. While not taking the lead for contracting with transporters, the WFP fixes the transportation rates and reimburses the cooperating lead partner agency for transportation costs. The WFP is also engaged in offering guidance on logistics activities, such as storage and handling of commodities, as well as providing training on food aid distribution practices, reporting and warehousing when necessary.

5.2.3.2 The Kenya Red Cross Society

In the district of Garissa and its surroundings, the Kenya Red Cross Society (KRCS) acts as the cooperating lead partner for food assistance, which implies that it is responsible for the reception and storage of food at the MW. As mentioned above, the KRCS is also mandated to organize secondary transport operations and to distribute commodities provided by the WFP or the GoK to the beneficiaries. The KRCS must maintain records and facilitate monitoring for all commodities received at the MW and distributed at the DCs. The KRCS must also take reasonable measures to ensure that food assistance reaches the beneficiaries within a reasonable delay and in the condition in which it has been received. In order to be qualified for conducting food aid distribution, the KRCS staff receives a training on the community based food aid targeting and distribution system (World Food Programme and Government of Kenya, 2005). The KRCS acts as facilitator and monitor to ensure that the principles established for food aid distribution in Kenya are properly followed during the settlement process following the assessment, and during the monthly food distribution operations. The organization thus continuously assists the community during the different phases of the food aid distribution.

5.2.3.3 Community Relief Committee

The community members of each DC elect a Community Relief Committee (CRC) comprised of seven to 17 members. After being trained by the KRCS, the CRC becomes mainly in charge of the beneficiary registration and of the food aid distribution. The CRC is thus responsible for the targeting of the beneficiaries, record keeping as well as setting arrangements to call beneficiaries during the monthly distributions, and dealing with absences and complaints. The CRC must make arrangements to provide accessible temporary storage, to receive and handle the food, and to ensure security at the DC. The purpose of the relief committee is to give more responsibilities to the community and enhance information transparency. The CRC acts as a link between the KRCS and the community, including the beneficiaries. This system aims to provide a better understanding of the food distribution mechanisms for the people receiving assistance and to help the beneficiaries make decision for themselves rather than being controlled by agencies remote from their environment. An important component for ensuring better access to information is the participation of women within the relief committee since humanitarian organisations strive to encourage the presence of the women in assistance projects (see World Food Programme and Government of Kenya, 2005).

5.2.3.4 Beneficiaries

The beneficiaries are the people within the communities who receive food assistance through different aid programmes. Ideally, they should be targeted because they are the most vulnerable people in the community. They must travel and collect their food at their assigned DC on the day of the distribution. As far as possible, the organizations hand-out food aid to women. For the food distribution to be successful, the community should get involved in the process and should participate in the meetings organized by the KRCS and the CRC.

5.3 Problem formulation

We propose a mathematical programming based methodology to determine where to locate the DCs, how much food to deliver to them and which populations they should serve. The regional food aid distribution network can be formulated on a directed graph $G = (V, A)$, where V is a set of nodes and A is a set of arcs. The set V can be partitioned into $\Big\{\{v_0\}, V_1, V_2\Big\}$, where v_0 is an MW supplying a specific affected region, V_1 is a set of population agglomerations, and V_2 is a set of potential locations for DCs. The number of tonnes of food required by the population located at node $v_i \in V_1$ is equal to q_i. Let us also define W_i as the set of potential DCs located within a coverage radius $\bar{r}$ km of v_i, with $v_i \in V_1$ and $W_i \subseteq V_2$. The route taken by a transporter to go from v_0 to $v_j \in V_2$ is represented by an arc (v_0, v_j), and the path taken by the population v_i to walk up from $v_i \in V_1$ to $v_j \in V_2$, is represented by an arc (v_i, v_j).

5.3.1 Mathematical model based on social welfare costs

The model must take into account the anticipated food assistance needs and must optimize the social welfare of all the stakeholders involved in the food distribution. We define the following variables:

x_{ij} : the proportion of population at v_i needing a hand-out from a DC at v_j, with $i \in V_1$, and $v_j \in W_i$;

y_j : a binary variable equal to 1 if and only if DC v_j is in operation during the planning horizon, with $v_j \in V_2$.

The tactical food aid network design problem is formulated as follows:

Model 1

$$\text{minimize} \quad \sum_{i \in V_1} \sum_{j \in W_i} \alpha_{ij}\, x_{ij} + \sum_{i \in V_1} \sum_{j \in W_i} \beta_j\, q_i\, x_{ij} + \sum_{j \in V_2} \gamma_j\, y_j$$

subject to

$$\begin{aligned}
\sum_{j \in W_i} x_{ij} &= 1 && i \in V_1 && (5.1)\\
x_{ij} &\leq y_j && i \in V_1,\ j \in W_i && (5.2)\\
x_{ij} &\geq 0 && i \in V_1,\ j \in W_i && (5.3)\\
y_j &\in \{0,1\} && j \in V_2. && (5.4)
\end{aligned}$$

The objective is to minimize the weighted cost of all the stakeholders involved in the food distribution process at the regional level. The first term of the objective function is the total access cost for the beneficiaries to travel and collect their food at the DCs, the second term is the supply cost paid by the WFP for transporting the food from the MW to the DCs, and the last term accounts for the DC managing and hand-out costs which are under the KRCS responsibility. The coefficient α_{ij} represents the cost borne by the population at v_i needing a hand-out from DC at v_j; the coefficient β_j represents the cost per tonne borne by the WFP to transport food destined to the DC located at v_j; the coefficient γ_j represents the fixed cost of locating a DC at v_j. The determination of these coefficients is explicited in Section 5.3.2.2. Constraints (1) ensure that the demand of each population is satisfied, while constraints (2) stipulate that the population points can only be served from open DCs. Constraints (3) and (4) are standard non-negativity and integrality constraints. Note that since there is no capacity constraint, there is always an optimal solution in which each population is assigned to a single DC. The integrity constraints for the population assignement variables x_{ij} are therefore relaxed in Model 1.

5.3.2 The case of Garissa and its surroundings

We now explain how the graph G was constructed for the region of Garissa and its surroundings. We describe how the different parameters were determined through the use of geographic information system data. We also explain how the parameters in the objective function were determined, which entails the evaluation of all the corresponding stakeholder welfare costs.

5.3.2.1 Network

To discretize the population locations on the map, we used gridded population proxies based on satellite data (see Jordan et al., 2010, and Figure 5.4). The population nodes $v_i \in V_1$ correspond to the centroids of delimited landscape areas of one square kilometer. The potential geographical grid points for the DC potential locations, which constitute the set V_2, are those points close enough to a road (within a distance less than 200 meters) and which are also sufficiently populated to constitute a CRC (their population must be at least 20 people per square kilometer). Indeed, the DCs must be close to the road in order to be accessible by truck, and they must be sufficiently populated so that the security of the DC can be ensured by the surrounding community. For DC potential locations we have also considered points of interests, such as schools, community centers, and health facilities. This information can be retrieved from government data publicly available online and can be manipulated through a GIS (Government of Kenya, 2012b).

In our case, the demand of the system corresponds to the food aid needs. Each population point $v_i \in V_1$ has p_i inhabitants and has a food aid need q_i expressed in tonnes to be satisfied during a six-month planning horizon, which is the result of a specific need assessment. In order to compute the need of each population grid point in Garissa and its surroundings, we have considered that these needs were uniformly distributed among the population across the numbers detailed in the short rain assessment of 2012 for the smallest administrative level given.

We have also used population and Kenyan road network shapefile information to determine the following distances:

- for all $v_i \in V_1$, the distance d^*_{ij} (obtained by mean of PostGIS) from a grid population point v_i to its closest road;
- for all $v_i \in V_1$ and $v_j \in V_2$, the geographical distance d^g_{ij} (obtained by mean of PostGIS) from a population grid points v_i to a potential DC v_j;
- for all $v_j \in V_2$, the road distance d^r_{0j} (obtained by mean of Google API) from the Garissa MW to a potential DC v_j.

5.3.2.2 Objective function

In the context of food aid distribution, several costs affect both the beneficiaries and the humanitarian organisations involved. These stakeholders, the beneficiaries, the KRCS and the WFP, have their own responsibilities in the supply chain, which translate into different objectives. In order to determine a global social welfare function, we have evaluated the values of all these responsibilities in terms of Kenya shillings (KSh). For the

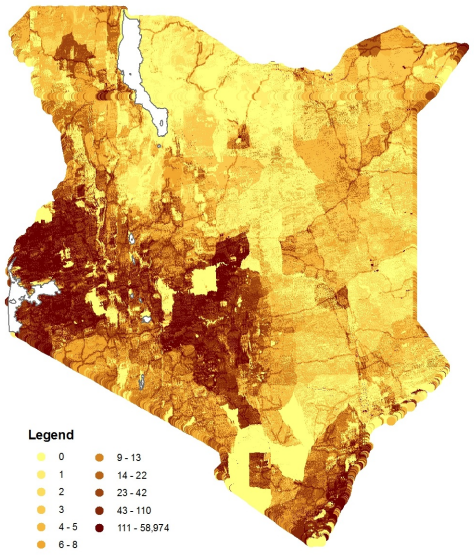


Figure 5.4: Population data for Kenya (Jordan et al., 2010).

humanitarian organizations, these are management, transportation, and hand-out costs; for the beneficiaries, these are access costs.

Beneficiary access costs

The beneficiary access costs are opportunity costs measured by evaluating the productive activities sacrificed for collecting food assistance. The access cost is thus a value associated with the time taken by a beneficiary to walk from her location to her assigned DC. We have assumed that the beneficiaries use a least duration path to walk from v_i to v_j at an off-road pace of 4 km/h. The walking time from v_i to v_j is thus equal to the 0.25 h/km, times the geographical distance. To evaluate the value of walking time, we have used the minimum wage rate for unskilled labor (Minister for Labor, 2012), which is less that two dollars per day. Moreover, the beneficiaries must pay for transportation to bring their food ration back home, which is usually done by paying an individual who operates a trailer attached to a donkey (Figure 5.5a). Using statistics presented in monitoring reports from WFP, we have determined that the cost of donkey transportation can be approximated by the linear function 20 KSh + 2.5 KSh/km $\times$ *distance*. The total access cost α_{ij} per kilometer of a beneficiary located at node v_i and collecting her food ration entitlement at DC v_j is obtained by adding up her opportunity costs and the donkey transportation cost.

WFP supply costs

Humanitarian organisations contract with trucking companies to transport food aid across the network (Figure 5.5b). For transportation operations between the MW to the DCs,

the WFP sets a fixed price per tonne, which depends on the distance between the MW and the delivery location. The WFP offers a constant price per tonne c_0 for the DCs located within a short distance of the MW. For the locations that are further from the MW, the WFP sets constant prices c_1 and c_2 per km-tonne, depending on the distance to the MW. For confidentiality reasons, we are not allowed to reveal the current cost function, but only a generic one. The long-haul transportation costs in KSh per tonne to serve DC v_j from Garissa MW v_0 can be represented by the following step function:

$$\beta_j \quad = \quad \begin{cases} c_0 & \text{if } d^r_{0j} \in [0, \bar{d}_0] \\ c_1\, d^r_{0j} & \text{if } d^r_{0j} \in (\bar{d}_0, \bar{d}_1] \\ c_2\, d^r_{0j} & \text{if } d^r_{0j} > \bar{d}_1. \end{cases}$$

KRCS location and hand-out costs

The KRCS must mobilize staff to ensure that food distribution proceeds according to the established practices of the World Food Programme and Government of Kenya (2005). The CRC training and the beneficiary registration validation require about two days of work for the KRCS facilitators at each DC, which should be considered as a fixed cost for the six-month planning horizon. There are also monthly costs for the food distribution monitoring functions, such as advertising, dispatch and distribution supervision, which require two days of work per month per DC. The KRCS location and hand-out cost at each DC v_j are thus the cost of labor γ_j for ensuring that food distribution is made properly during the planning horizon (Figure 5.5c).

(a) Donkey transportation.

(b) Ground transportation.

(c) Monitoring activities.

Figure 5.5: Photographs of some stakeholder activities.

5.3.3 Descriptive statistics

We now provide an overview of the data through some relevant descriptive statistics. Table 5.I summarizes the population grid point data for the district of Garissa and its surroundings. It shows that for the region of interest, the average population per square

kilometer is 9.57 and the average distance from the population centroids to their closest routes is 11.03 km. Most of the population grid points are scarcely populated (the median is equal to 3), which explains why the average distance to the closest route is quite large. The food aid allocation statistics for the 12 covered divisions from Garissa MW are given in the last line of Table 5.I. This information was required to determine the structure of the food aid network in order to design the response system by means of mathematical programming.

Table 5.I: Summary of Garissa and its surroundings

Description	n	Mean	Std. Dev.	Median	Min.	Max.
Population per km^2	47,241	9.57	159.32	3	0	13,793
Distance to closest route (km)	47,241	11.03	9.34	8.49	0	50.34
Population per division	12	50,120.2	34,977.8	37,049	3987	121,822
Six-month food need per division (tonnes)	12	521.3	154.73	555.65	287.35	768.24

Table 5.II summarizes the relevant information on the food aid distribution network in Garissa. The set V_2 of potential DCs, which consists in the population grid points close to a route and densily populated, contains 1,460 elements. The average travel distance from Garissa MW to these potential DC is 106.32 km. There are 24,453 population grid points (V_1) with at least two inhabitants (Figure 5.6a). The average estimated food aid allocation per beneficiary in these population points is of 24.38 kg for the six-month period (Figure 5.6b). The average distance from the population points to their closest potential DC is 11.85 km and the median is 8.71 km, which indicates that there is at least one potential DC located close to most of the population points.

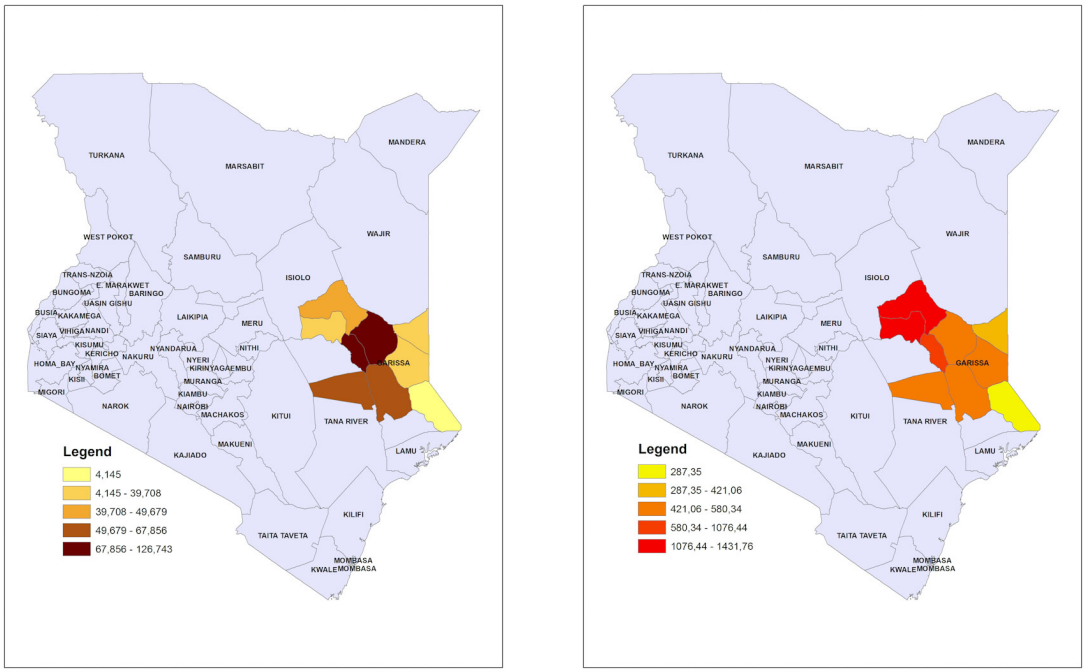
Table 5.II: Summary of food aid distribution network

Description	n	Mean	Std. Dev.	Median	Min.	Max.
Potential DC nodes (V_2)	1,460					
Road distance to MW (km)	1,460	106.32	71.41	107.16	0.05	268.93
Population nodes (V_1)	24,453					
Six-month food need per beneficiary (kg)	24,453	24.38	24.42	11.36	3.96	115.34
Euclidian distance to closest potential DC (km)	24,453	11.85	10.91	8.71	0	54.48

5.3.4 Covering models

The problem can also be modeled by means of a covering formulation. This allows us to determine how many DCs are required to cover all the beneficiaries within a coverage radius $\bar{r}$ or what portion of the population would be covered by fixing the number of DCs to a given value p. We thus define the following variables:

y_j : a binary variable equal to 1 if and only if DC v_j is in operation during the planning horizon, with $v_j \in V_2$;



(a) Population map.

(b) Food allocation map (tonnes).

Figure 5.6: Population and food aid allocation maps for each division of Garissa District and its surroundings.

z_i : a binary variable equal to 1 if and only if population v_j is covered by at least one DC during the planning horizon, with $v_i \in V_1$.

We also define the following parameters:

π_{ij} : a binary parameter equal to 1 if and only if the distance from the population v_i to DC v_j does not exceed $\bar{r}$, with $v_i \in V_1$ and $v_j \in V_2$.

A first problem is to maximize the need coverage with p DCs:

Model 2

$$\text{maximize} \quad \sum_{j \in V_2} p_i \, z_i$$

subject to

$$z_i \leq \sum_{j \in V_2} \pi_{ij}\, y_j \qquad \forall i \in V_1 \tag{5.5}$$

$$\sum_{j \in V_2} y_j = p \tag{5.6}$$

$$z_i \in \{0,1\} \qquad \forall i \in V_1 \tag{5.7}$$

$$y_j \in \{0,1\} \qquad \forall j \in V_2. \tag{5.8}$$

A second problem of interest is to minimize the number p of DCs to cover all the beneficiaries within a coverage radius $\bar{r}$:

Model 3

$$\text{minimize} \quad p$$

subject to

$$\sum_{j \in W_i} \pi_{ij}\, y_j \geq 1 \qquad \forall i \in V_1 \tag{5.9}$$

$$\sum_{j \in V_2} y_j = p \tag{5.10}$$

$$y_j \in \{0,1\} \qquad \forall j \in V_2. \tag{5.11}$$

5.4 Computational results

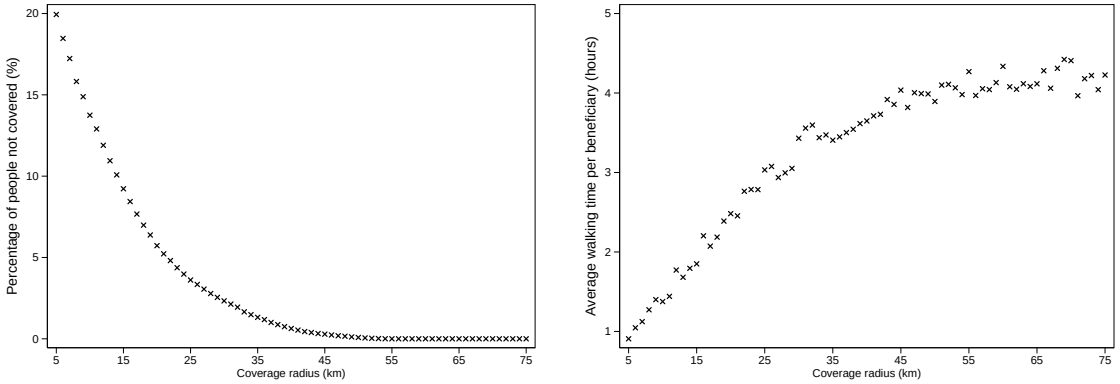
In this section, we describe the computational results obtained by solving different optimization problems for the case of Garissa and its surroundings. We first provide the results of some sensitivity analyses before illustrating optimal response systems.

5.4.1 Sensitivity analyses

The objective of this section is to better understand the impact of the response system structure on the stakeholder welfare. To this end, we have conducted several sensitivity analyses by varying some parameters and solving the problems formulated in Section 5.3. These were solved by means of CPLEX 12.8.0 and by setting the optimality gap to 2%. We consider that this is a reasonable gap given the precision of the data.

We have first assessed the impact of the coverage radius on the percentage of people covered by the response system. In Model 1, we assume that a population without any

DC within a distance $\bar{r}$ is not taken into account in the optimization problem, which implies that this population is not covered by the response system. We have also assessed the results on the average walking time per beneficiary to ensure that the solution did not result in having beneficiaries walking too far when the coverage radius was fixed to a large value. Figure 5.7 shows the results obtained with Model 1 for different values of $\bar{r}$. We note from Figure 5.7a that in order to cover all the population, the coverage radius must be set to at least 55 km. Nevertheless, according to the results shown in Figure 5.7b, the average walking time per beneficiary remains acceptable even when the coverage radius becomes larger, and the increase in average walking time tends to stabilize when it becomes larger than 35 km. This means that even if the coverage radius is large, the optimal solution mostly assigns the populations to their closest DC.



(a) Percentage of the population not covered as a function of the coverage radius.

(b) Average walking time per beneficiary as a function of the coverage radius.

Figure 5.7: Percentage of the population not covered and average walking time per beneficiary as a function of the coverage radius.

Figure 5.8 shows the values of the objective function as well as the values of its different terms obtained by solving Model 1 and varying the coverage radius from 5 km to 75 km. For each $\bar{r} \in \{5, 6, ..., 75\}$, the black dots correspond to the value of the objective function (total cost), the grey diamonds correspond to the WFP supply cost, the grey "x" correspond to the beneficiary opportunity cost, and the grey squares correspond to the KRCS hand-out cost. We have observed that the most important part of the total cost is borne by the WFP for transporting the food from the MW to the DCs. This finding is consistent with the affirmation of Trunick (2005) who observed that approximately 80% of disaster relief efforts relate to logistics activities. The beneficiary opportunity costs are also important compared with the KRCS hand-out costs, which constitute the smallest component of the total cost. These results show the importance of transportation costs in the response system, even when the beneficiary opportunity cost is taken into account. This implies that an organization like the WFP has an interest in being actively involved

in the DC selection process. We also note that the reduction in supply cost becomes less significant when the coverage radius is larger than 45 km. Considering that the minimum radius needed to cover all the population is 55 km, there is no benefit in solving the problem with a larger covering radius.

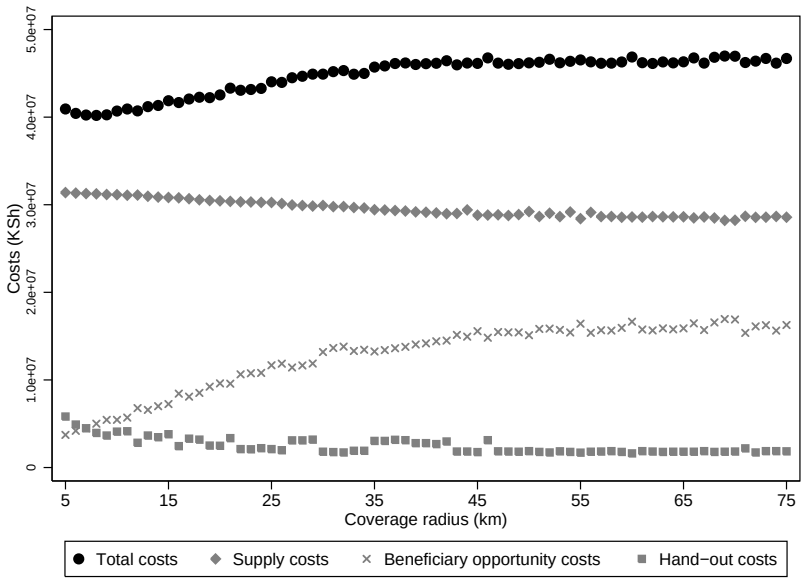
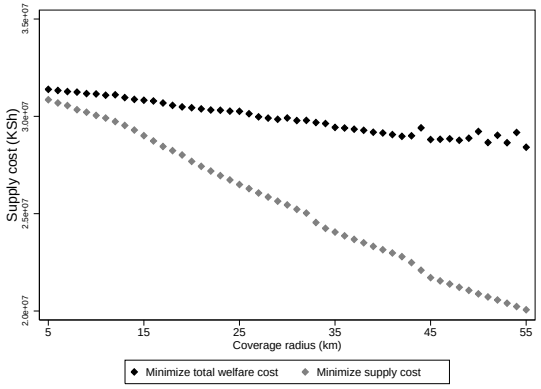


Figure 5.8: Stakeholder costs as a function of the coverage radius.

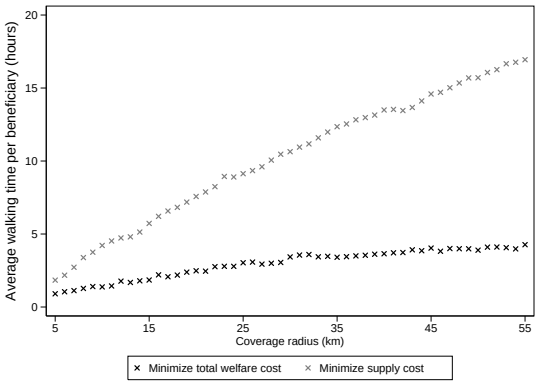
In Model 1, the objective function is a weighted sum of the three stakeholder objectives. In order to determine the behaviour of each term, we have solved the problem by minimizing each objective separately, thus yielding three cases: 1) $\alpha_{ij} = 0$ and $\gamma_j = 0$ (Figures 5.9a, 5.9b, 5.9c, and 5.9d); 2) $\alpha_{ij} = 0$ and $\beta_j = 0$ (Figures 5.10a, 5.10b, 5.10c, and 5.10d); 3) $\beta_{ij} = 0$ and $\gamma_j = 0$ (Figures 5.11a, 5.11b, 5.11c, and 5.11d). Case 2 is equivalent to solving Model 3, i.e. minimizing the number of open DCs to cover the population with a coverage radius $\bar{r}$. We note that CPLEX could not solve case 2 for $\bar{r} = \{33, 34, 40, ..., 55\}$ because of excessive branching.

Comparing Figures 5.11c, 5.9c and 5.10c, we note that optimizing the total welfare cost, as opposed to a single-objective function, yields larger percentages of increase for the KRCS hand-out cost, the beneficiary opportunity cost and the WFP supply cost, respectively. However, cases 1 and case 2 yield solutions that make the beneficiaries walk significantly more to go and collect their food, as shown in Figures 5.9d and 5.10d. The average walking time per beneficiary becomes unacceptable when the covering radius exceeds 15 km, as shown in Figures 5.9b and 5.10b. Note that the percentage increase in WFP supply cost remains less than 10% for covering radii smaller than 20 km. Figure 5.11 illustrates the results obtained when only the beneficiary opportunity cost is considered in the network design.

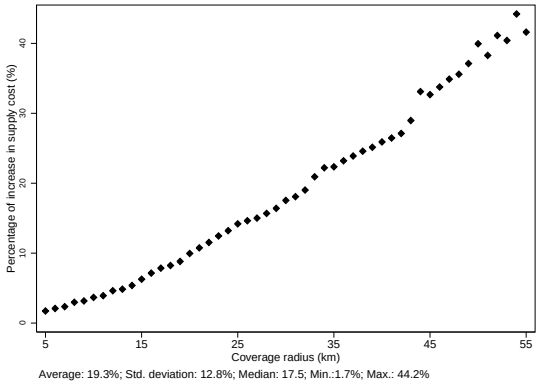
These results show that including the beneficiary opportunity costs into the network optimization does not have a substantial impact on the financial costs incurred by the operational agencies, but increases the accessibility of the beneficiaries. Currently, the opportunity cost of beneficiaries is not sufficiently considered in the academic literature and in the WFP emergency costing models. This seems to conflict with the humanitarian principles which tend to emphasize the welfare of the beneficiaries rather than cost reductions.



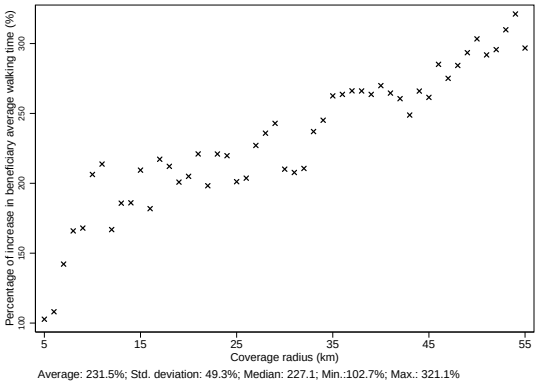
(a) WFP supply costs as a function of the coverage radius.



(b) Average walking time per beneficiary as a function of the coverage radius.



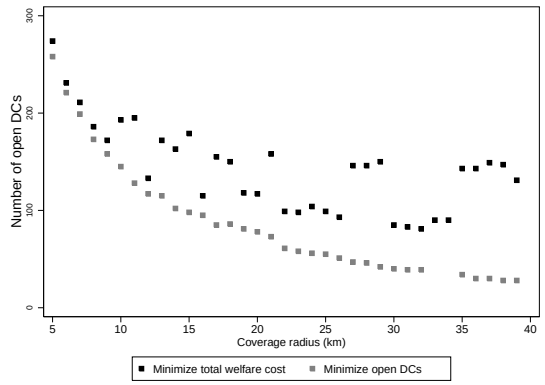
(c) Percentage increase in the WFP supply cost when minimizing total welfare cost (Model 1) as opposed to a single-objective function (case 1), as a function of the coverage radius.



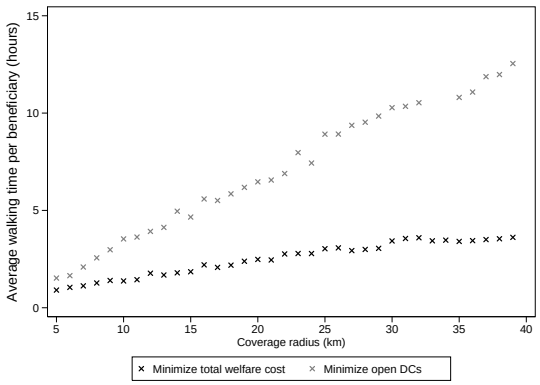
(d) Percentage increase in the average beneficiary walking time when minimizing a single-objective function (case 1) as opposed to the total welfare cost (Model 1), as a function of the coverage radius.

Figure 5.9: Comparing the results of multi-objective and single objective optimizations (case 1).

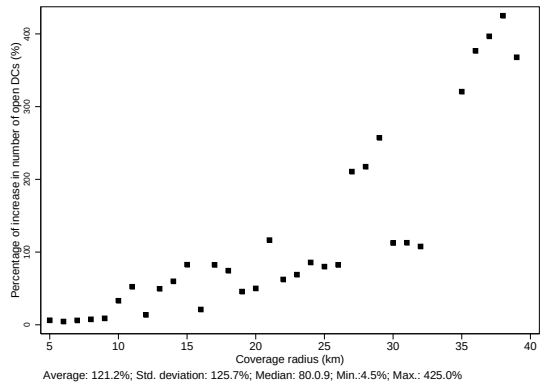
Moreover, to ensure that the beneficiaries are not underestimated in the parameterization of the mathematical model, we have solved Model 1 with various values of the hourly wage rate. In the initial parameterization, we have estimated the beneficiaries' opportunity costs by valuing their time proportionally to the minimum wage rate for unskilled labor ($wage = 22$ KSh/h). We have thus solved Model 1 for each $wage \in \{20, 21, ..., 40\}$



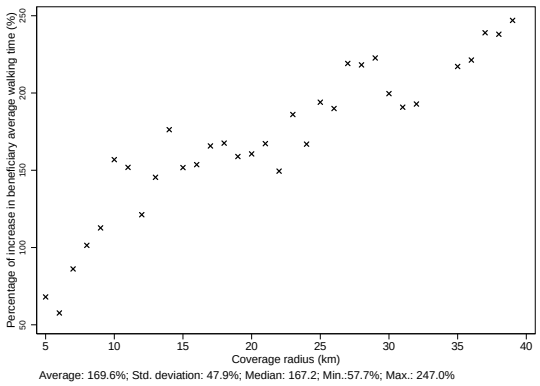
(a) Number of open DCs as a function of the coverage radius.



(b) Average walking time per beneficiary as a function of the coverage radius.



(c) Percentage increase in the KRCS hand-out cost when minimizing total welfare cost (Model 1) as opposed to a single-objective function (case 2), as a function of the coverage radius.

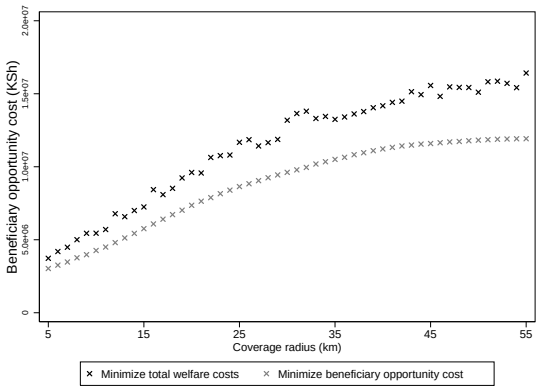


(d) Percentage increase in the average beneficiary walking time when minimizing a single-objective function (case 2) as opposed to the total welfare cost (Model 1), as a function of the coverage radius.

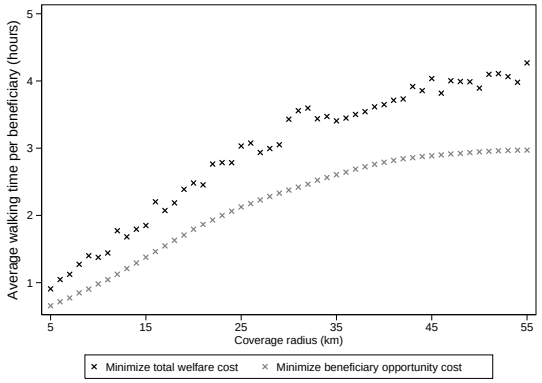
Figure 5.10: Comparing the results of multi-objective and single objective optimizations (case 2).

to evaluate the impact of the value given to the beneficiaries' time on the response system. The results yielded by this experiment are illustrated in Figure 5.12. We note from Figure 5.12a that the total cost of the response systems is mostly due to the increase in beneficiary opportunity costs, which is mostly explained by the increase of α_{ij} since the supply and hand-out costs do not increase significantly when *wage* increases. Figure 5.12b also shows that the average walking time by the beneficiaries does not drop considerably with *wage*. This validates adoption of the minimum wage rate for unskilled labor as the value for the beneficiary opportunity cost.

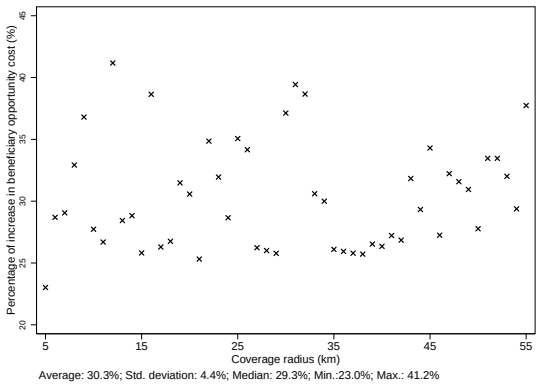
There are currently 156 DCs in Garissa District and its surroundings. In order to compute the maximum number of people that can be covered with 156 DCs, we have solved Model 2 with $p = 156$ and $\bar{r} \in \{5, 6, ..., 55\}$. Figure 5.13a shows the percentage



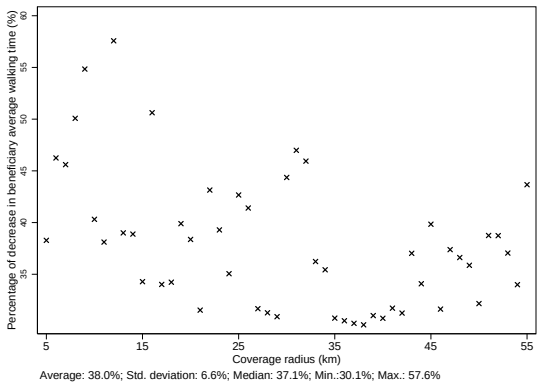
(a) Beneficiary opportunity cost as a function of the coverage radius.



(b) Average walking time per beneficiary as a function of the coverage radius.



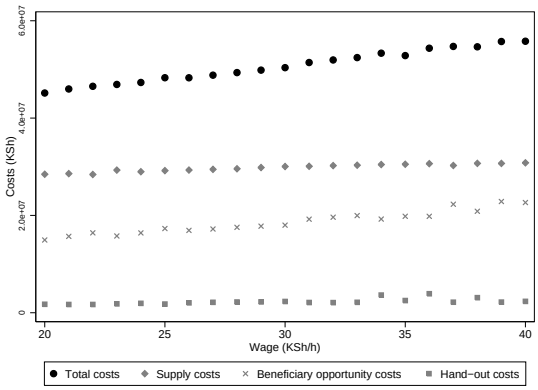
(c) Percentage increase in beneficiary opportunity costs when minimizing total welfare cost (Model 1) as opposed to a single-objective function (case 3), as a function of the coverage radius.



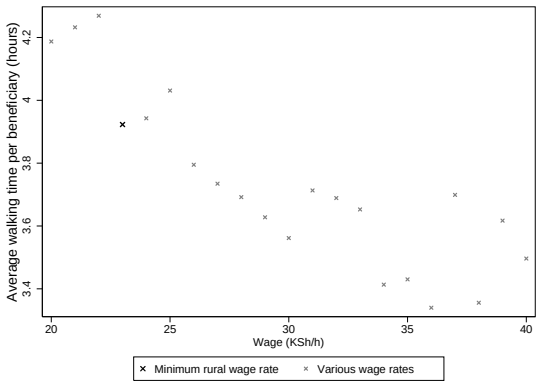
(d) Percentage decrease in the average beneficiary walking time when minimizing a single-objective function (case 3) as opposed to the total welfare cost (Model 1), as a function of the coverage radius.

Figure 5.11: Comparing the results of multi-objective and single objective optimizations (case 3).

of the uncovered population obtained by solving Model 2 with $p = 156$ and Figure 5.13b shows the difference in the number of open DCs obtained by solving Model 1 with 156 open DCs, as in the current situation. Note that, as shown in Figure 5.10a, the minimum number of open DCs obtained with Model 3 is 158 for $\bar{r} = 9$ and 145 for $\bar{r} = 10$, which implies that 156 open DCs do not enable to cover all the population living within a radius of less than 10 km from a DC. Figure 5.13b shows that solving Model 1 is more advantageous for the beneficiaries when a smaller coverage radius is used since Model 1 yields more than 156 open DCs. We therefore believe that the current condition could be improved by considering all the welfare cost in the network design, as we did in Model 1, especially since smaller coverage radii are preferable for the beneficiaries and the DC costs are the least important part of the total welfare cost.

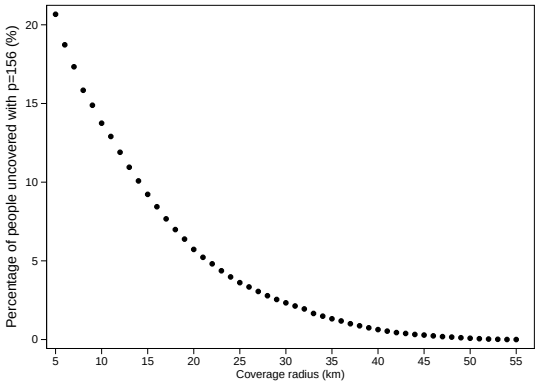


(a) All stakeholders' costs as a function of the coverage radius.

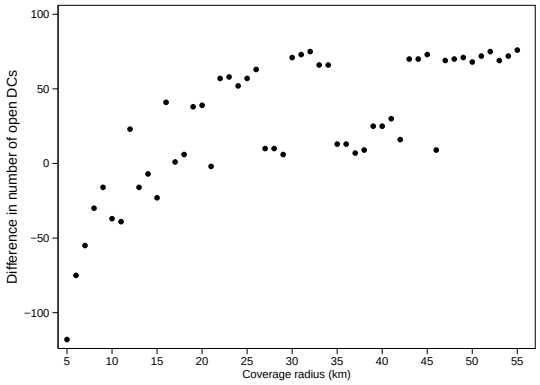


(b) Average walking time per beneficiary as a function of the coverage radius.

Figure 5.12: Impact of beneficiary time value on the response system ($\bar{r} = 55$ km).



(a) Percentage of uncovered population as a function of the coverage radius.



(b) Difference in number of open DCs obtained by solving Model 1 with 156 as a function of the coverage radius.

Figure 5.13: Results obtained by solving Model 2 with $p = 156$.

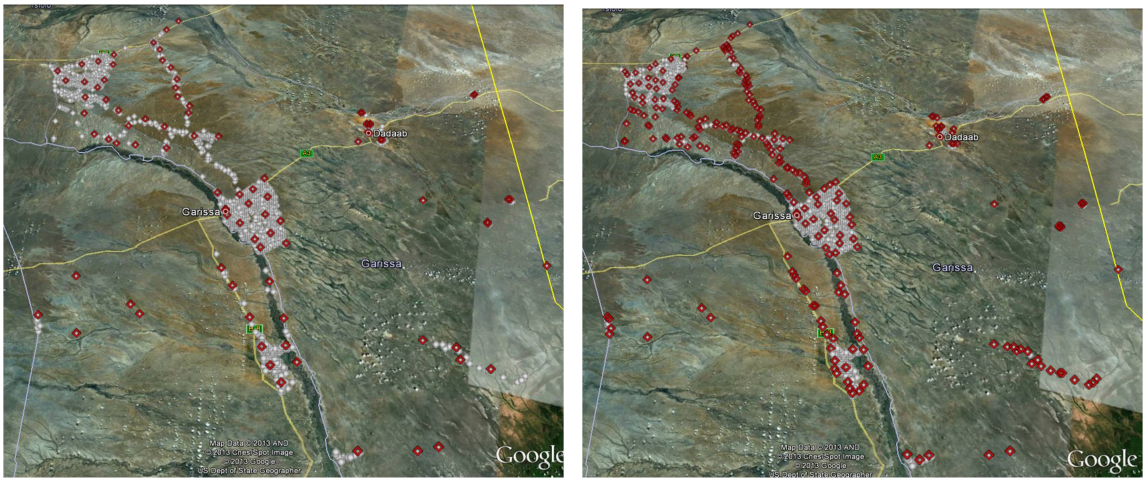
5.4.2 Solution illustrations

We now present some optimal solutions obtained by solving Model 1 with CPLEX, using a 0.1% gap. Table 5.III provides the values of the attributes of three different solutions obtained with $\bar{r} = 5, 10$ and 55 km, and Figure 5.14 illustrates the two extreme case solutions on a map. We do not claim that these solutions are those that should be implemented since it is up to the decision maker to assess the impact of various parameters on the design of the food distribution network while taking into account the interest of the various stakeholders. We believe, however, that a multicriteria optimization tool such as the one we have described helps generate good quality solutions from which the decision

maker can choose. This represents an improvement over the current practice where most decisions are made without a strong analytical support.

Table 5.III: Characteristics of three representative optimal solutions

Solution	Costs				DCs	Beneficiary statistics		CPLEX
$\bar{r}$	Total	Beneficiary	Supply	Hand-out	#	Not covered (%)	Average walk time (hr)	CPU time (sec)
55	46,078,345.46	15,457,251.17	28,688,800.29	1,932,294	91	0	3.99	2,0345.71
25	43,438,031.79	11,029,998.54	30,135,995.25	2,272,038	107	3.62	2.84	2,297.95
5	40,671,491.26	3,688,771.978	31,376,943.28	5,605,776	264	19.94	0.89	10,331.91



(a) Solution with $\bar{r} = 55$ km. (b) Solution with $\bar{r} = 5$ km.

Figure 5.14: Optimal solutions with $\bar{r} = 55$ km and $\bar{r} = 5$ km.

5.5 Conclusions

We have considered a tactical location problem arising in food aid distribution in Kenya. The problem was modeled and solved by means of a mathematical programming methodology. Several sensitivity analyses were conducted to validate the results provided by the model and to study the effects of various parameters on the solutions. We have shown how mathematical programming can be used to design last-mile food aid distribution network using real data for the case of Garissa District in Kenya. Our results show that the most important part of the total cost is related to transporting the food from the district warehouse to the distribution centers. We have also shown the importance of valuing the beneficiary time, which is by itself a new contribution.

This paper bridges part of the gap between theory and practice in the development of humanitarian logistics support decision tools. Solving this problem contributes to the long-term food security of the country. It can also help decision makers handle simultaneously the objective of several decision makers and select a suitable solution

from those that are generated. This approach should be welcome in the context of food aid distribution in developing countries such as Kenya.

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Chapitre 6

Conclusion

Le transport constitue un support essentiel aux systèmes de production de biens et de services. Un système de transport efficace, autant pour la mobilité des personnes que des marchandises, est essentiel au développement économique des sociétés. Néanmoins, toutes les sociétés n'en sont pas au même point en ce qui à trait à l'évolution de leurs services de transport et à la qualité de leurs infrastructures. Cette thèse s'est donc penchée sur deux problématiques importantes reliées au transport de longue distance et se posant dans deux contextes économiques nettement différents : le transport de marchandises en charges partielles en Amérique de Nord et la distribution de denrées alimentaire en Afrique de l'Est. En conséquence, nous avons rédigé cette thèse autour de deux thèmes principaux, comportant chacun deux chapitres.

Cette thèse avait pour but dans une première partie (1) de résoudre un problème riche de planification de tournées de véhicules de longue durée avec des contraintes d'heures de service aux États-Unis et (2) d'incorporer les dimensions de coûts d'opération pour les transporteurs et d'inconvénients pour les chauffeurs dans un cadre de résolution multicritère pour ce problème. Dans la deuxième partie, cette thèse avait pour but (3) d'étudier le marché du transport en Éthiopie afin de déterminer les facteurs qui influencent les tarifs et (4) de résoudre un problème de conception de réseau tactique pour la distribution de denrées alimentaires au Kenya. Nous croyons que les différents outils que nous avons développés peuvent aider les gestionnaires dans leur prise de décision et permettront de mieux comprendre les arbitrages à effectuer entre des critères liés aux différentes parties prenantes dans des problèmes de transport de longue distance. Les résultats de l'ensemble de cette thèse contribuent à améliorer la planification des opérations de transport dans deux contextes particuliers, c'est-à-dire dans une perspective de respect de la réglementation en Amérique du Nord et de développement humanitaire en Afrique de l'Est.

6.1 Contributions et limites de la première partie

Pour le premier problème, nous avons développé une heuristique de recherche avec tabous. Cette heuristique comporte différents algorithmes de planification d'horaires des chauffeurs qui respectent les lois sur les heures de service au États-Unis. Les résultats de tests numériques, effectués sur des instances modifiées de la littérature conçues pour le problème de tournées de véhicules avec fenêtres de temps, ainsi que sur une instance réelle du Groupe Robert, montrent que de meilleures solutions peuvent être obtenues en incorporant plus de flexibilité dans l'affectation des périodes de repos des chauffeurs. Les gains réalisés varient selon la complexité des algorithmes d'ordonnancement et la structure des problèmes. La contribution majeure de ce chapitre est le développement d'une heuristique efficace pour un nouveau problème riche de tournées de véhicules et la démonstration de son rendement sur des instances artificielles et réelles. Pour atteindre notre deuxième objectif, nous avons modifié notre heuristique de recherche avec tabous afin de la faire cadrer dans une approche de résolution multicritère en utilisant une méthode basée sur la distance par rapport à un objectif de référence. Trois objectifs on été considérés : le nombre de véhicules utilisés, les coûts d'opération des transporteurs et les inconvénients des chauffeurs. Notre seconde version de l'algorithme a été testée sur les mêmes instances que celles du chapitre précédent. À partir des résultats obtenus, il a été possible d'évaluer les arbitrages entre les différents objectifs. Nous avons montré que la diminution des inconvénients encourus par les chauffeurs fait augmenter les coûts d'opération des transporteurs dans une proportion moindre. Nous avons aussi confirmé la pertinence de la pratique courante des répartiteurs de minimiser le nombre de véhicules déployés sur la route. En effet, nous avons constaté que les coûts d'opération augmentent lorsque le nombre de véhicules utilisés dépasse la taille de la flotte minimale dans la plupart des cas.

D'un point de vue méthodologique, nous avons proposé un algorithme permettant de soutenir la planification d'un problème complexe de distribution de marchandises en charges partielles aux États-Unis. Bien que ces deux projets aient contribué à un nouveau sujet de recherche, cette première partie de thèse comporte également certaines limites. Nous avons fait un certain nombre d'hypothèses pour simplifier le problème et pour le résoudre dans un temps raisonnable. Par exemple, nous avons ignoré l'incertitude dans les temps de déplacement et dans la disponibilité des chauffeurs, ce qui pourrait pourtant avoir d'importantes conséquences lors de la planification des tournées de véhicules. Il serait donc approprié d'incorporer ces éléments stochastiques dans les modèles et les algorithmes appliqués à ces problèmes.

6.2 Contributions et limites de la deuxième partie

Pour analyser les marchés de transport international et domestique en Éthiopie, notre troisième objectif, nous avons travaillé en collaboration avec le PAM. Nous avons recueilli des données provenant de deux sources : un appel d'offres du PAM et des rapports publiques de l'Agence Centrale de Statistique d'Éthiopie. Nous avons ensuite présenté et interprété des modèles de régression linéaire multiple obtenus pour chaque segment de marché. Nous avons aussi réalisé des analyses de dominance sur les variables explicatives et effectué des calculs contrefactuels pour évaluer différents scénarios. Ces démarches nous ont permis d'identifier les facteurs qui expliquent le mieux la structure des tarifs de transport et de quantifier leur apport aux modèles de régression. Les résultats montrent que les principaux déterminants des tarifs pour les services de transport en Éthiopie sont à la fois l'état des routes et la structure du marché. Néanmoins, nos analyses révèlent que l'intensité de la compétition tend à diminuer les tarifs de transport de manière plus importante que l'amélioration des infrastructures, du moins à court terme. Il semble alors que les investissements dans les infrastructures de transport ne constituent pas une condition suffisante au développement, si l'on considère que le transport n'est pas un secteur distinct de l'économie mais qu'il fait plutôt le lien entre les différents secteurs économiques. D'un point de vue gestion des opérations, nous avons aussi montré comment les modèles de prédiction peuvent être utilisés pour soutenir les processus d'achat de services de transport et améliorer la performance de la chaîne d'approvisionnement des expéditeurs.

Toutefois, comme notre recherche a été effectuée à partir de données provenant d'un seul acheteur de services de transport et à partir de contacts valides pour une période d'un an et demi, il est possible que nos résultats ne soit pas généralisables. Afin de les généraliser, il serait pertinent d'analyser des données qui proviennent de différents acheteurs de services de transport et qui s'étendent sur plusieurs périodes. D'autres analyses pourraient aussi être effectuées afin d'acquérir une meilleure compréhension des marchés du transport en Afrique dans son ensemble. Nous considérons néanmoins que ce chapitre constitue une étape dans la bonne direction.

Pour atteindre notre quatrième et dernier objectif, nous avons résolu un problème de localisation de centre de distribution de denrées alimentaires au Kenya par l'utilisation de la programmation mathématique. De l'information provenant d'une évaluation des besoins d'aide alimentaire subséquente à la saison courte des pluies de 2012, des données maillées sur la population ainsi que des données extraites de systèmes d'information géographique du réseau routier pour la région de Garissa et ses environs ont été recueillies pour résoudre ce problème de conception de réseau. La collecte de données a été facilitée par une observation directe sur le terrain et par la collaboration d'organismes impliqués à différents niveaux dans la distribution de denrées alimentaires au Kenya. Notre modèle

principal a pris en compte les coûts rattachés aux objectifs de tous les acteurs impliqués dans ce système de réponse : le PAM, la Croix-Rouge et les bénéficiaires. L'attribution d'un coût d'opportunité des bénéficiaires dans l'objectif nous a permis de démontrer l'importance de cette valorisation et de quantifier ses impacts sur les coûts de transport et de distribution, ce qui constitue une contribution intéressante. Nous avons aussi effectué diverses analyses de sensibilité et nous avons comparé les résultats du modèle principal à ceux de modèles de couverture classiques pour comprendre les conséquences des paramètres utilisés sur la structure du réseau. Des illustrations graphiques de systèmes de réponse optimaux ont permis de valider la pertinence de notre méthodologie. Toutefois, notre modèle se concentre sur la région de Garissa et se limite à un horizon de planification de six mois. On peut considérer que ces hypothèses sont restrictives compte tenu du contexte dans lequel évoluent les chaînes d'approvisionnement d'aide humanitaire.

6.3 Perspectives de recherche future

Cette thèse a démontré que des outils de recherche opérationnelle peuvent faciliter la résolution et la compréhension de problèmes complexes de distribution autant dans les secteurs commerciaux qu'humanitaire. On peut toutefois envisager certaines avenues de recherche future. Dans le secteur du transport routier en Amérique du Nord, deux nouvelles règles concernant les heures de service seront en application à partir de juillet 2013 aux États-Unis. Pour évaluer leurs impacts sur les coûts d'opération des transporteurs et sur les inconvénients des chauffeurs, il serait pertinent de les incorporer aux algorithmes d'ordonnancement afin d'actualiser l'heuristique de recherche avec tabous. En ce qui concerne notre contribution au problème de distribution de denrées alimentaires en Afrique de l'Est, nous souhaitons étendre ce projet à un niveau plus général. Le réseau de distribution pourrait en effet être élargi afin de considérer le Kenya en entier ou même d'autres pays en voie de développement. De plus, l'aspect périodique du problème pourrait être exploité. Pour ce faire, il faudrait développer des modèles de prévision pour la demande future en denrées alimentaires et développer des méthodes de résolution plus robustes. Par ailleurs, il serait approprié de considérer la possibilité de s'approvisionner dans les marchés locaux favorisant ainsi le développement économique du pays.

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