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Xiaohui Lyu. Studies on Collaborative Transportation in Less than Truckload Transportation. Business administration. Université de Technologie de Troyes; Université Jiaotong (Xi'an, Chine), 2020. English. NNT: 2020TROY0019 . tel-03808696

HAL Id: tel-03808696

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Studies on Collaborative Transportation in Less than Truckload Transportation



Fig.1 A simple example in collaborative logistics

Fig.2 The framework of the exchange mechanism

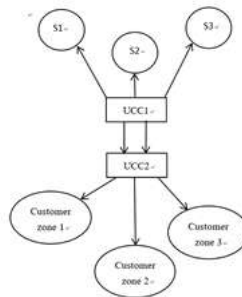


Fig.5 The network of multi-echelon transportation

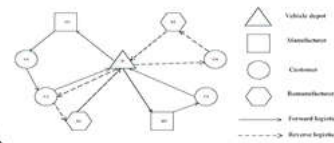


Fig.4 Transportation planning in forward and reverse logistics

Champ disciplinaire :
Sciences pour l'Ingénieur

2020TROY0019

Année 2020

Thèse en cotutelle avec Xi'an Jiaotong University - Xi'an - Chine

THESE

pour l'obtention du grade de

DOCTEUR

de l'UNIVERSITE DE TECHNOLOGIE DE TROYES

EN SCIENCES POUR L'INGENIEUR

Spécialité : OPTIMISATION ET SURETE DES SYSTEMES

présentée et soutenue par

Xiaohui LYU

le 12 novembre 2020

**Studies on Collaborative Transportation
in Less than Truckload Transportation**

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PHD THESIS
to obtain the degree of
DOCTOR of UNIVERSITY
of TECHNOLOGY of TROYES

presented and defended by
LYU Xiaohui

**Studies on Collaborative Transportation in
Less than Truckload Transportation**

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November 12th 2020

*To my Mother, my Father,
for their unlimited support, encouragement, and love.*

Acknowledgements

This work has been carried out within Laboratory of Industrial Systems Optimization (LOSI) at University of Technology of Troyes (UTT). It is funded by China Scholarship Council (CSC) under a project of Cai Yuanpei.

I would like to express my deepest gratitude, appreciation and heartfelt thanks to my supervisors Prof. Haoxun Chen and Prof. Nengmin Wang for their careful guidance and invaluable advice. All of the challenging hours working alongside them have strengthened my desire to succeed in my PhD study. Their lasting commitment to quality and excellence has shaped and influenced my professional attitude.

I also would like to express my special thanks to Dr. Yang Zhen for his helpful comments and suggestions in mathematical modeling, which have helped me to improve my ability to solve optimization problems encountered in my PhD study.

I would like to thank all researchers, secretaries and colleagues in LOSI, and the staffs of the doctoral school of UTT. With whom I had several stimulating and enjoyable conversations about research, technology and life. I would like to thank all my friends for keeping in touch with me even when we were in different countries during my stay in France. Most of all, I would like to thank my parents for their love, supports, and encouragements which have motivated me to never give up.

Résumé

Une planification efficace d'opérations de transport est importante pour les expéditeurs et les transporteurs afin de réduire leurs coûts logistiques en raison des prix élevés des carburants et d'une concurrence croissante sur le marché de transport. La collaboration entre expéditeurs ou transporteurs peut améliorer leur rentabilité en réduisant les repositionnements de véhicules vides et en augmentant les taux de remplissage des véhicules.

Cette thèse étudie trois problèmes soulevés dans la logistique collaborative en transport de chargement partiel. Tout d'abord, un problème de collaboration entre les expéditeurs en logistique bidirectionnel de livraison et de collecte est étudié et un algorithme GRASP-ILS est proposé, qui est efficace en termes de qualité de la solution et de temps de calcul. Des expériences numériques démontrent que cette collaboration entre expéditeurs peut réaliser une réduction de coûts significative par rapport à l'exploitation individuelle de chaque expéditeur sans coopération. Ensuite, un mécanisme itératif d'échange de demandes est proposé pour la collaboration entre transporteurs dans le transport à un seul échelon. Des expériences numériques montrent que ce mécanisme d'échange à plusieurs tours surpasse considérablement les autres mécanismes d'enchères dans la littérature. Enfin, un algorithme de décomposition de Benders est développé pour résoudre un problème de génération d'enchères dans l'achat de services de transport à plusieurs échelons. Les mécanismes et algorithmes d'enchères proposés peuvent aider les transporteurs et les expéditeurs à améliorer leur rentabilité grâce à une collaboration efficace entre eux.

Mots clés: Logistique collaborative; Transport-Planification; Problème de tournée de véhicules; Vente aux enchères; Algorithmes; Programmation mathématique

Abstract

Effective transportation planning is important for shippers and carriers to reduce their logistics costs because of high fuel prices and an increasing competition in the transportation market. Collaboration among shippers or carriers can improve their profitability by reducing empty vehicle repositions and increasing vehicle fill rates.

This thesis studies three problems raised in collaborative logistics in less than truckload transportation. Firstly, a problem of collaboration among shippers in forward and reverse logistics is investigated and an algorithm GRASP-ILS is proposed, which is effective in terms of both solution quality and computation time. Numerical experiments demonstrate that this shipper collaboration can realize significant cost savings compared with the isolated operation of each shipper without cooperation. Then, an iterative request exchange mechanism is proposed for carrier collaboration in a single echelon transportation. Numerical experiments show that this multi-round exchange mechanism significantly outperforms other auction mechanisms in the literature. Finally, a Benders decomposition algorithm is developed to solve a bid generation problem in the procurement of multi-echelon transportation services. The proposed auction mechanisms and algorithms have the potential to help carriers and shippers improve their profitability through effective collaboration among them.

KEY WORDS: Collaborative logistics; Transportation planning; Vehicle routing problem; Auctions; Algorithms; Mathematical programming

CONTENTS

French Abstract.....	II
English Abstract.....	III
1 General Introduction.....	1
1.1 Research background	1
1.2 Research problems and contributions.....	2
1.3 Organization of this thesis	4
2 Literature review	6
2.1 Collaborative logistics.....	6
2.1.1 Shipper collaboration	6
2.1.2 Carrier collaboration.....	7
2.2 Centralized planning approaches for collaborative transportation.....	7
2.3 Decentralized planning approaches for collaborative transportation	9
2.3.1 Auction-based mechanisms	9
2.3.2 Bid generation problems	10
2.4 Vehicle routing problems.....	11
2.4.1 Vehicle routing problems in single-echelon transportation	11
2.4.2 Vehicle routing problems in multi-echelon transportation	13
3 Shipper collaboration in forward and reverse logistics	15
3.1 Introduction	15
3.2 Problem description and mathematical model	18
3.3 GRASP-ILS algorithm	20
3.3.1 Algorithm framework.....	21
3.3.2 Generation of initial solutions	22
3.3.3 Insertion operations	23
3.3.4 Local search.....	24
3.3.5 Perturbation procedure	26
3.4 Computational experiments.....	27
3.4.1 Test instances.....	27
3.4.2 Parameter setting for CPLEX and GRASP-ILS.....	27
3.4.3 Comparison results and interpretations	28
3.4.4 Cost savings for shipper collaboration	38
3.5 Brief summary.....	43
4 A multi-round exchange mechanism for carrier collaboration in less than truckload transportation.....	45
4.1 Introduction	45
4.2 Problem description and request exchange mechanism.....	46
4.2.1 Adjustment of the parameter for selecting outsourcing requests	48

CONTENTS

4.2.2 Transfer payment rule.....	49
4.3 Decision Problems for Request Exchange	49
4.3.1 Outsourcing Bundles Selection	51
4.3.2 Insourcing Bundles Selection.....	53
4.3.3 Winner determination problem.....	55
4.4 Computational Study.....	57
4.4.1 Test instances.....	57
4.4.2 Comparison of three auction mechanisms on an illustrative instance.....	58
4.4.3 Sensitivity analysis of auction parameters	59
4.4.4 Evaluation of the request exchange mechanism.....	61
4.4.5 Comparison with other mechanisms	65
4.5 Brief summary.....	72
5 A benders decomposition algorithm for bid generation problem in the procurement of multi-echelon transportation services.....	73
5.1 Introduction	73
5.2 Problem description and mathematical model	74
5.2.1 Node-based formulation	75
5.2.2 Path-based formulation.....	78
5.3 Benders Decomposition (BD) algorithm.....	80
5.3.1 Basic Benders Decomposition Algorithm	81
5.3.2 Benders reformulation.....	82
5.3.3 Improved benders decomposition algorithm.....	84
5.4 Computational experiments.....	85
5.4.1 Test instances.....	86
5.4.2 Evaluation of different acceleration strategies for BD.....	86
5.4.3 Evaluation of the BD algorithm	91
5.5 Brief summary.....	95
6 Conclusions and perspectives.....	97
6.1 Summary of research results	97
6.2 Perspectives for future research	98
ANNEX A Extended French abstract.....	100
A.1 Introduction Générale.....	100
A.2 Revue de Littérature	103
A.3 La collaboration des expéditeurs dans la logistique de livraison et de collecte	108
A.4 Un mécanisme d'échange à plusieurs tours pour la collaboration des transporteurs dans le transport de chargement partiel.....	112
A.5 Un algorithme de décomposition de Benders pour l'achat de services de transport à plusieurs échelons.....	116
A.6 Conclusions et perspectives.....	120
References	123

List of Figures

1-1 The organization of the thesis	5
3-1 Isolated transportation planning of each shipper in forward and reverse logistics.....	15
3-2 Collaborative transportation planning of all shippers in forward and reverse logistics...	16
4-1 The performance of MRE with different values of profit sharing	60
4-2 The performance of MRE with different combinations of (α^0, δ)	61
4-3 The performance of MRE with different values of NR	61
5-1 The transportation network in a multi-echelon transportation.....	75

List of Tables

3-1 The comparison of the first improvement and the best improvement	26
3-2 The comparison of two strategies	26
3-3 Parameter tuning according to instance size	28
3-4 Notations of performance indicators and their description	28
3-5 Detailed Results for GRASP-ILS and CPLEX	29
3-6 Summarized comparison results of GRASP-ILS and CPLEX	33
3-7 Computational results for GRASP-ILS, GRASP and ILS	34
3-8 Summarized comparison results of GRASP-ILS, GRASP and ILS	37
3-9 Summarized results of deviations among GRASP-ILS, GRASP and ILS.....	38
3-10 Summarized results of the impact of customer geographical distribution on cost savings	39
3-11 Summarized results of the impact of the number of requests on cost savings	39
3-12 Cost savings for instances of different sizes	40
4-1 The detailed iterative process of the proposed auction	58
4-2 The detailed iterative process of the first auction proposed by Berger and Bierwirth (2010)	59
4-3 The detailed iterative process of the second auction proposed by Berger and Bierwirth (2010)	59
4-4 Comparison of two strategies for insourcing bundles of requests	62
4-5 Results of MRE with two insourcing strategies on 3×3 instance set	63
4-6 Results of MRE with two insourcing strategies on 3×5 instance set	63
4-7 Comparison results of WDP with complete information and incomplete information....	63
4-8 Comparison results of MRE with complete information and incomplete information on 3×3 instance set	64
4-9 Comparison results of MRE with complete information and incomplete information on 3×5 instance set	64
4-10 Summarized comparison results for the instance set of Berger and Bierwirth (2010) ..	65
4-11 Comparison results for the instances of Berger and Bierwirth (2010).....	66
4-12 Summarized comparison results for the instances of Gansterer and Hartl (2016).....	68
4-13 Detailed comparison results for the instances of Gansterer and Hartl (2016)	69
5-1 Comparison between basic BD algorithm and the BD algorithm with multiple-cuts acceleration strategy.....	87
5-2 Comparison of Pareto-optimal acceleration strategies.....	88
5-3 Comparison of acceleration strategies for benders decomposition method.....	89
5-4 Summarized comparison results of CPLEX and benders decomposition algorithm	92
5-5 Comparison of CPLEX and basic benders decomposition method	92

List of Tables

5-6 Comparison results of CPLEX and benders decomposition method for large size instances	95
5-7 Detailed comparison results of CPLEX and benders decomposition method for large size instances	95
.....	95

List of Abbreviations

Acronym	Meanings
ALNS	Adaptive large neighborhood search
BD	Benders decomposition algorithm
BGP	Bid generation problem
CA	Combinatorial Auction
GRASP	Greedy randomized adaptive search procedure
ILS	Iterated local search
LB	Lower bound
LNS	Large neighborhood search
LTL	Less-than truckload
MIP	Mixed Integer Programming
PDP	Pickup and delivery
PDPTW	PDP with time windows
RCL	Restricted Candidate List
TL	Truckload
TS	Tabu search
UCC	Urban consolidation center
UB	Upper bound
VNS	Variable neighborhood search
VRPSL	Vehicle routing problem with split loads
VRSPD	Vehicle routing problem with simultaneous pickup and delivery
WDP	Winner Determination Problem
2E-VRP	Two-echelon vehicle routing problem
2E-CVRP	Two-echelon capacitated vehicle routing problem

Glossary of Notations

Notation	Definition
x_{ij}^v	Binary variable which equals 1 if and only if $arc(i, j)$ is passed by vehicle $v \in NV, i, j \in N, i \neq j$
y_i	Binary variable which equals 1 if and only if request i is outsourced
lp_{ki}^v	The load of new products picked up from product depot $k \in NP$ by vehicle $v \in NV$ before node $i \in N$ is visited
lr_{ki}^v	The load of used products delivered to recycle depot $k \in NR$ by vehicle $v \in NV$ after node $i \in N$ is visited
Q_i^k	Load of vehicle $k \in K$ when leaving node i
T_i^k	The time at which vehicle $k \in K$ leaves node i
$w_{O_l}^-$	Binary variable which equals 1 if and only if carrier $l \in M$ acts as a seller and a bundle of requests $O_l \in B_l$ is outsourced by the carrier
$w_{I_l}^+$	Binary variable which equals 1 if and only if carrier $l \in M$ acts as a buyer and a set of bundles of requests I_l is insourced (acquired) by the carrier
$v_i^{k,l}$	Binary variable which equals 1 if and only if request $i \in R$ is served by vehicle $k \in K^l, l = \{0, 1, 2\}$
M	The set of carriers in an alliance
R_o	The set of reserved requests for the carrier considered
R_e	The set of selective requests for the carrier considered
R	The set of requests, $R = R_o \cup R_e$
$\theta_{i,R}$	The binary parameter indicating whether request i is included in the set of requests R
p_i	The price that the supplier pays to the carrier of request $i \in R$

1 General Introduction

1.1 Research background

The importance of freight transportation is amplified today by the rapid boom in E-commerce. For instance, Amazon delivered 3.3 billion packages globally in 2019 (CNBC, 2019) and in China over 50 billion packages were delivered across the country in 2018 (National Bureau of Statistics of China, 2019). E-commerce logistics providers are facing numerous challenges, including higher customer expectations of short delivery cycles of orders, individually scheduled delivery time windows and a considerable amount of failed delivery attempts and product returns (Allen et al., 2017). Moreover, due to frequent e-commerce activities, the competitiveness among logistics service providers is gradually intensified. In this context, logistics operators, online retailers, and other parties involved in e-commerce supply chains have devoted adequate efforts to do the internal potential to keep up with consumer expectations and remain cost-competitive. Despite efforts by transport companies, the average truck load factor is low and the frequency of empty running is high. Overall, according to Eurostat (2017), at total transport level, most trucks in Europe fell in the range between 15% and 30% empty journeys. The average load of a truck is much lower than its capacity and particularly low in city distribution. Moreover, freight transportation (in developed countries) is responsible for nearly 15% of greenhouse gas emissions.

In order to survive under the increasing pressure to operate more efficiently and to satisfy customer demands, one of the promising solutions is the collaboration among shippers and carriers. Collaborative transportation is achieved by either sharing transport capacities or transportation orders (Verdonck, et al., 2013). For example, DHL, Baxter, Boots (www.boots.com), and UCB (www.ucb.com) considers horizontal collaboration in transport and logistics (Taneja & Kalita, 2014). In Belgium and Netherlands, the European logistics center of gravity, there have been at least fifty formally established horizontal logistics partnerships (Cruijssen, Dullaert, & Fleuren, 2007). Collaboration among carriers or shippers may improve the statistics and generate economic benefits for the carriers involved as well as social and environmental benefits. The results of horizontal logistics collaboration are impressive: double-digit efficiency improvements of up to 30% have been reported (Audy, Lehoux, D'Amours, & Rönnqvist, 2012; Vanovermeire et al., 2014; Gansterer and Hartl, 2018).

In the collaboration network, it is based on an E-commerce information platform which is similar with eBay or Taobao. Many service platforms as the third-party exchange service provider allows shippers and carriers to share their key information such as transportation needs and capacities and facilitates the trading between shippers and carriers (George and Xu, 2013). For instance, in Europe, Timocom (www.timocom.de) is an established provider of an electronic marketplace for freight exchange. The company acts as auctioneer and charges auction participants a fee. In China, Cainiao Network provides sellers and buyers with

real-time information about the logistics activities to improve the delivery efficiency. Information sharing plays an important role in collaborative transportation (Özener et al., 2011; Gansterer, Hartl and Savelsbergh, 2020). In terms of information sharing, two planning approaches have been proposed to solve the collaborative transportation problem in the literature: centralized planning and decentralized planning (Dai et al., 2011; Lyu et al., 2020). In a centralized framework, a decision-maker with complete information of all players determines the optimal reassignment of requests with the objective of minimizing the total transportation cost or maximizing the total transportation profit. In a decentralized framework, multiple self-interested players form an alliance and exchange their transportation requests with limited information sharing to achieve the optimal efficiency.

Because the demands in e-commerce context are fragment, we focus on less than truckload transportation (LTL). Given the current study for collaborative transportation, in this thesis, we try to address problems encountered in collaborative transportation from two aspects: the complete information sharing in a centralized planning approach and the incomplete information sharing in a decentralized planning approach. In a centralized planning approach, we focus on using transportation optimization algorithms to reassign requests among alliance players. Whereas in a decentralized planning approach, auction-based mechanisms are developed to exchange requests among players to achieve the optimal efficiency.

1.2 Research problems and contributions

In this thesis, we study collaborative transportation in two environments: complete information sharing and incomplete information sharing. In the scenario of complete information sharing, we consider collaborative transportation in a single echelon transportation. In the scenario of incomplete information sharing, we consider two environments: collaboration in a single echelon transportation and collaboration in a multiple-echelon transportation.

First of all, growth in e-commerce has led to high levels of product returns. For example, while brick-and-mortar return rates average between 8% and 10%, ecommerce return rates come in at more than 20%. During the holiday shopping season, the ecommerce return rate can jump as high as 30% (Callarman, 2019). In the e-commerce environment, logistic service provides deliver new products to customers in the forward logistics and the returned products are collected from customers and transported to the e-tailers in the reverse logistics. As the logistic service providers in forward and reverse logistics usually have the same or overlapping customers, serving the forward and reverse transportation requests together by the same set of vehicles of a carrier can improve the utilization of these vehicles and consequently realize significant transportation cost savings. Many literature in vehicle routing optimization considers reverse logistics, but no literature in collaboration transportation studies collaboration in forward and reverse logistics. Therefore, the first problem we study is carrier collaboration in forward and reverse logistics, in which carriers

share their complete information, such as transportation requests and vehicle capabilities.

Second, realizing the full benefits of a collaboration is challenging. Although, carriers and shippers want to achieve the full benefits of a collaboration, they may not be willing to share the necessary information. Trust is a central issue for selfish individuals in collaborative relationships, especially in horizontal collaborations where competing entities collaborate. It is of necessity to design a proper mechanism that facilitates the successful collaboration among carriers who are self-interested and aim to maximize their own profits. Therefore, we design an effective combinatorial auction in carrier collaboration in less than truckload transportation.

Third, two main distribution strategies exist in the transportation network: direct shipping and multi-echelon distribution. In direct shipping, vehicles starting from a depot transport their freight directly to the customers, while in multi-echelon systems the freight is delivered from the origin to the customers through intermediate depots. With the increasing demands of shorter cycles of orders, the strategy of direct shipping shows inefficiency. There is very few literature that considers the collaboration in a multi-echelon transportation. Therefore, we study a bid generation problem arising in a multi-echelon transportation.

The goal of this thesis is to fill the above research gaps and provide practical managerial insights. Our study is devoted to solve the following three problems:

1) Shipper collaboration in forward and reverse logistics. This chapter studies shipper collaboration in forward and reverse logistics, in which multiple shippers with forward or/and reverse logistics operations consolidate their transportation requests. In the forward and reverse logistics, manufacturers deliver new products to their customers and used products are collected from customers and transported to remanufacturers for repair or reproduction. This gives rise to a new vehicle routing problem with pickup and delivery requests and three different types of depots (product depots, vehicle depots and recycle depots). A hybrid approach combining greedy randomized adaptive search procedure (GRASP) and iterated local search (ILS) is proposed to find a near optimal solution of the problem. Numerical experiments on a large set of randomly generated instances with different problem sizes demonstrate that shipper collaboration in forward and reverse logistics can realize significant cost savings compared with the isolated operation of each shipper without cooperation, and the proposed approach is effective in the sense that it can find a high quality solution in a reasonable computation time.

2) A multi-round exchange mechanism for carrier collaboration in less than truckload transportation. This chapter proposes an iterative request exchange mechanism to solve carrier collaboration in less than truckload transportation. In each iteration, each carrier first provides multiple bundles of requests to offer and their corresponding transfer payments. Each carrier then determines which bundles of requests to acquire from one or multiple carriers. Multiple bundles of requests can be exchanged among carriers in each iteration. In each round of the auction, each carrier updates its outsourcing bundles of requests based on the feedback information from previous iterations. Numerical experiments show that this multi-round exchange mechanism provides 11.80% more profit compared to other

mechanisms.

3) A benders decomposition algorithm for the bid generation problem in collaborative transportation. This chapter addresses the bid generation problem in a three-echelon transportation for transportation service procurement realized through Combinatorial auction. In transportation service procurement, shippers want to procure a certain amount of transportation service from a set of potential carriers that have reserved requests. Each request is associated with an origin, a destination, a quantity, time windows and a price for serving the request paid by its corresponding shipper. The delivery of freight from its origin to its destination is through three echelons. The first echelon consists of transferring freight from pickup points to the intermediate facilities (urban consolidation centers), the second echelon consists of transferring freight between intermediate facilities in two different cities, whereas in the third echelon, the freight is transferred from these intermediate facilities to the final customers, within their time windows. We propose one arc-based mathematical formulation and one path-based formulation for our problem. A benders decomposition algorithm is developed for the path-based formulation. The basic decomposition algorithm is enhanced through the acceleration strategies of Multi-cuts and Pareto-optimal cuts. Extensive computational experiments were performed to evaluate the efficiency and computational results indicate that the benders decomposition algorithm can obtain optimal solutions for small size and medium size instances and achieve the average gap of 0.99% for large instances.

1.3 Organization of this thesis

Chapter 1 mainly introduces our research background and generally describes the problems studied in this thesis. Chapter 2 provides an overview of current-art of collaborative transportation planning. A general review is given firstly to the field of collaborative logistics. Then the literature review focuses on significant contributions and important review papers on the centralized planning approaches and decentralized planning approaches. Chapter 3 investigates a problem of collaboration among shippers in forward and reverse logistics in a centralized framework. Chapter 4 focuses on an iterative request exchange mechanism for carrier collaboration in a single echelon transportation. Chapter 5 solves the bid generation problem raised in a multi-echelon collaborative transportation. At last, Chapter 6 concludes this thesis and present the perspectives of future works opened in the field of collaborative transportation planning. The thesis framework is illustrated in Fig.1-1.

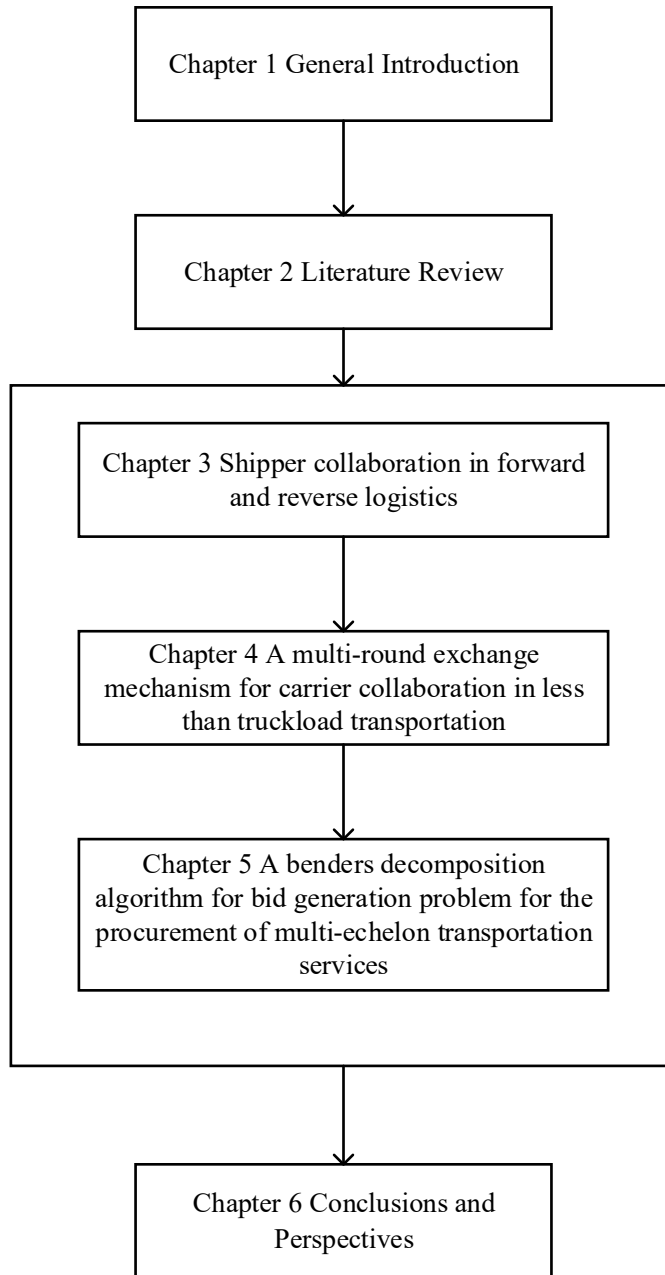


Fig.1-1 The organization of the thesis

2 Literature review

2.1 Collaborative logistics

There are two types of collaborative transportation: vertical collaboration and horizontal collaboration. Vertical collaboration is the collaboration when two or more organizations from different levels or stages in transport chain share their responsibilities, resources, and performance information to serve relatively similar end customers. Horizontal collaboration refers to the collaboration among multiple actors at the same level in logistics operations such as the collaboration among shippers (manufacturers) and the collaboration among carriers (Cruijssen et al., 2007; Verdonck et al., 2013; Gansterer and Hartl, 2018; Cleophas et al., 2019).

Two types of collaboration exist in collaborative transportation: shipper collaboration and carrier collaboration. Shipper collaboration considers the situation of a single carrier and multiple shippers. The collaboration among shippers is realized by consolidation of their transportation requests to be offered to carriers. In carrier collaboration, multiple carriers who provide similar transportation services formed an alliance to exchange self-owned transportation requests to increase profit and optimize the utilization of transportation resources.

There are two modes of road transportation: truckload (TL) transportation and less than truckload (LTL) transportation. In TL transportation, goods are transported from one origin to one destination by fully loaded trucks, whereas in LTL transportation goods are transported from multiple origins to multiple destinations by partially loaded trucks.

Two planning approaches have been proposed to solve the collaborative transportation problem in the literature: centralized planning and decentralized planning. In a centralized framework, a decision-maker with complete information of all actors determines the optimal reassignment of requests among carriers with the objective of minimizing the total transportation cost or maximizing the total transportation profit. In a decentralized framework, multiple self-interested actors form an alliance and exchange their transportation requests with limited information sharing to achieve the optimal efficiency.

In the next subsection, we will review the current study of collaborative transportation in two aspects: shipper collaboration and carrier collaboration.

2.1.1 Shipper collaboration

Shipper collaboration considers the situation of a single carrier and multiple shippers. The collaboration among shippers is realized by consolidation of their transportation requests to be offered to carriers. Some studies on shipper collaboration addressed the collaboration among shippers with truckload shipments. Ergun et al. (2007a, b) introduced a full truckload shipper collaboration problem and formulated it as a lane covering problem, which is to identify a set of tours that cover all given set of lanes with the minimum

transportation cost subject to length or total travel time constraints. Two linear programming models were proposed in a centralized framework to obtain the minimum transportation cost for the shipper alliance in forest transportation: the first one is based on direct flows between supply and demand points and the second considers backhauling (Frisk et al., 2010). Literature on shipper collaboration with LTL shipments is quite limited. Dai and Chen (2009) presented a general mathematical model for collaborative logistics in LTL transportation, which extends the lane covering model to one with pickup and delivery requests. A Lagrangian relaxation method was proposed to solve the model. Yilmaz & Savaseneril (2012) studied a collaboration problem of small shippers with stochastic shipment requirements. Computational experiments showed that the shippers always benefit from the collaboration. Audy et al. (2011) showed that significant cost-savings and delivery time reduction could be achieved through collaborative transportation among manufacturers in forward logistics. Sprenger and Monch (2012) proposed a greedy heuristic method to solve a cooperative transportation planning problem in forward logistics and demonstrated that the cooperative strategy outperforms the non-cooperative one with cost savings of 20% in average. The current literature on shipper collaboration shows that joint planning and design of routes among shippers in a centralized planning framework is a major source of cost savings.

2.1.2 Carrier collaboration

In carrier collaboration, multiple carriers who provide similar transportation services formed an alliance to exchange self-owned transportation requests to increase profit and optimize the utilization of transportation resources. The requests reassignment in carrier collaboration can be realized by using a centralized approach based on a single mathematical programming model (e.g. Hernández and Peeta, 2011; etc.) or by using a decentralized approach such as combinatorial auctions (e.g. Berger and Bierwirth, 2010; Li et al., 2015; Gansterer, M., and Hartl, 2016; etc.). Joint route planning is generally considered to be done by carriers (e.g. Liu et al., 2010; Dai and Chen, 2012; Buijs et al., 2016). Houghtalen et al. (2007) studied carrier collaboration and proposed a mechanism for allocating both resources and profits among carriers by appropriately setting prices for the resources. Agarwal and Ergun (2008) considered carrier collaboration in a multicommodity service network and designed a mechanism for allocating benefits among carriers based on a decentralized multicommodity flow game, capacity exchange costs, and inverse optimization. Dai and Chen (2012) proposed a centralized framework for the problem without time windows for pickup and delivery operations of requests, and the global optimal transportation planning problem for the carrier alliance was formulated as a mixed integer programming model.

2.2 Centralized planning approaches for collaborative transportation

Most of the centralized planning approaches for collaborative transportation focus on complex optimization problems. In the centralized planning framework, customer requests from all participating actors are combined and collected in a central pool and efficient route schemes are set up for all requests simultaneously using appropriate vehicle routing

techniques. There are two main distribution strategies in transportation: direct shipping and multi-echelon distribution. In direct shipping, vehicles starting from a depot transport their freight directly to the customers, while in multi-echelon systems the freight is delivered from the origin to the customers through intermediate depots/logistics platforms (Perboli, Tadei and Vigo, 2011). In the next subsection, we will review the literature on collaborative transportation in a single-echelon transportation and a multi-echelon transportation respectively.

Some studies on shipper collaboration addressed the collaboration among shippers with truckload shipments. Ergun et al. (2007a, b) introduced a full truckload shipper collaboration problem and formulated it as a lane covering problem, which is to identify a set of tours that cover all given set of lanes with the minimum transportation cost subject to length or total travel time constraints. Two linear programming models were proposed in a centralized framework to obtain the minimum transportation cost for the shipper alliance in forest transportation: the first one is based on direct flows between supply and demand points and the second considers backhauling (Frisk et al., 2010). Literature on shipper collaboration with LTL shipments is quite limited. Dai and Chen (2009) presented a general mathematical model for collaborative logistics in LTL transportation, which extends the lane covering model to one with pickup and delivery requests. A Lagrangian relaxation method was proposed to solve the model. Yilmaz & Savasaneril (2012) studied a collaboration problem of small shippers with stochastic shipment requirements. Computational experiments showed that the shippers always benefit from the collaboration. Audy et al. (2011) showed that significant cost-savings and delivery time reduction could be achieved through collaborative transportation among manufacturers in forward logistics. Sprenger and Monch (2012) proposed a greedy heuristic method to solve a cooperative transportation planning problem in forward logistics and demonstrated that the cooperative strategy outperforms the non-cooperative one with cost savings of 20% in average. The current literature on shipper collaboration shows that joint planning and design of routes among shippers in a centralized planning framework is a major source of cost savings.

Some literature focuses on carrier collaboration. The time-dependent centralized multiple carrier collaboration problem was addressed by Hernández and Peeta (2011). The authors formulated the problem as a binary multicommodity minimum cost-flow formulation and proposed a branch and cut algorithm for solving it. Weng and Xu (2014) formulated the optimal hub routing problem of merged tasks in collaborative transportation as a multi-depot arc routing problem and proposed two heuristics based on Lagrangian relaxation and Benders decomposition. Hernández et Peeta (2014) study a single-carrier collaboration problem (SCCP) in LTL transportation, in which a carrier seeks to collaborate with other carriers in order to acquire extra transport capacity to service excess demand. Fernandez et al. (2016) introduced a new arc routing problem for the optimization of collaboration among carriers, in which the mathematical model was formulated as a profitable un-capacitated arc routing problem with multiple depots and profits and a branch-and-cut algorithm was proposed to solve it. Buijs et al. (2016) studied the collaborative transport planning for two

logistics service providers through joint route planning.

In a multi-echelon transportation, products collected from multiple shippers need to be transshipped and consolidated in urban consolidation centers (UCC). Collaboration in a multi-echelon transportation needs to jointly deliver products to UCC and organize last-mile deliveries, which helps to achieve a higher overall efficiency (Cleophas, et al., 2019). Thompson and Hassall (2012) demonstrated that collaboration in a multi-echelon transportation can realize significant cost savings and reduce the number of vehicles compared with the isolated operation without cooperation. Wang et al. (2020) proposed a collaborative two-echelon multicenter vehicle routing problem based on a state-space-time network.

2.3 Decentralized planning approaches for collaborative transportation

The decentralized approaches for carrier collaboration include auction based mechanisms and bid generation problems.

2.3.1 Auction-based mechanisms

The decentralized approaches for carrier collaboration include auction based mechanisms and non-auction exchange mechanisms (Gansterer and Hartl, 2018; Cleophas et al., 2018). In the literature, there are mainly three types of auction mechanisms proposed for carrier collaboration. Figliozzi et al. (2003, 2004, 2005, 2006) conducted some important studies of sequential auctions for TL transportation, where transportation requests arrive at a marketplace randomly and carriers bid for them in a sequence of auctions. Figliozzi et al. (2003) presented a framework for a carrier's strategies in an auction-based transportation marketplace, and examined the complexities of different carrier bidding strategies. Under this framework, Figliozzi et al. (2004) evaluated four different vehicle routing strategies on estimation of service costs under various demand conditions. In their subsequent work, Figliozzi et al. (2005) studied the impact of auction settings and bidding mechanisms on the performance of the transportation marketplace. Figliozzi et al. (2006) provided an expression to quantify the opportunity costs in sequential auctions. In the above mentioned papers, sequential auctions are used for truckload transportation service procurement in a dynamic environment.

The second type of auction mechanism is combinatorial auction (CA), in which carriers are allowed to bid on a bundle of transportation requests (Pekec & Rothkopf, 2003). Song and Regan (2003) designed an exchange framework based on CA to solve a dynamic carrier collaboration problem in TL transportation. Schonberger (2006) proposed a CA-based approach to solve the requests reassignment problem in LTL transportation by a two-step procedure. Krajewska and Kopfer (2006) extended the method of Schonberger (2006) by considering the allocation of costs among carriers, which is based on an assumption that the fulfillment costs for any bundle of requests can be exactly evaluated. Similarly, Schwind et al. (2009) developed a single round auction and an iterative auction to exchange requests among profit centers of a single transportation company with complete information sharing.

In line with the previous studies, Berger and Bierwirth (2010) proposed both a single request auction and a CA to solve a carrier collaboration problem called collaborative traveling salesman problem with pickup and deliveries in LTL transportation. Gansterer and Hartl (2016) adopted the same auction method of Berger and Bierwirth (2010) for carrier collaboration with the BGP solved by a heuristic approach for larger instances. To reduce computational complexity, Dai and Chen (2011) proposed a multi-agent and auction-based framework for carrier collaboration in LTL transportation, in which each carrier selects a request to be outsourced and each carrier determines which request to bid in each round of the auction. Dai et al. (2014) introduced a multi-round price-setting based combinatorial auction approach, in which each carrier determines the requests to offer and to bid based on the price of serving each outsourcing request announced by the auctioneer. Wang and Kopfer (2014a) and Wang et al. (2014b) presented a route-based exchange approach, in which carriers generate and submit new routes based on the dual values of a linear relaxation problem. Chen (2016) presented a combinatorial clock-proxy exchange method to solve carrier collaboration with reserved requests in LTL transportation, in which supplementary bids are generated in the proxy phase. For TL transportation, Lai et al. (2017) proposed an iterative auction mechanism, in which each carrier outsources requests to many carriers and each carrier insources only one request from others in each round of the auction.

The third type of auction mechanism is double auction, in which bilateral bidding is allowed and the transportation market is cleared by the third-party auctioneer. As our focus is on combinatorial auctions, readers can refer to Huang and Xu (2013) and Xu et al. (2016) for a more detailed literature review on double auctions. Some studies consider non-auction based request exchange mechanisms for carrier collaboration. Özener, Ergun, and Savelsbergh (2011) devised various effective lane-exchange mechanisms among truckload carriers with the goal of reducing their re-positioning costs, which differ in terms of degrees of information sharing and side payment options. It is easy to perform non-auction methods without bidding procedure, but it is less efficient as no preference information can be obtained from other collaborators. Different from request exchange, some mechanisms focus on the capacity exchange in LTL transportation. Agarwal and Ergun (2010), Houghtalen et al. (2011) proposed a capacity exchange mechanism for carrier collaboration in liner shipping. Hernández et al. (2011) considered the capacity sharing in a dynamic environment.

2.3.2 Bid generation problems

For the BGP in a combinatorial auction for carrier collaboration, each carrier evaluates an exponential number of potential bundles of requests and determines which bundles of requests to bid. Park and Rothkopf (2005) pointed out that the BGP is usually NP-hard. We focus on the BGP in CA. In the literature, two bidding strategies are considered: bidding on one request and bidding on some bundles of requests.

For strategies bidding on individual, non-bundled requests, Dai and Chen (2011) formulated the outsourcing requests selection problem and the bidding requests selection problem in a LTL carrier collaboration auction as selective pickup and delivery problems with time windows (SPDPTW-LTL). They used the CPLEX MIP solver to solve the

SPDPTW-LTL models involved in the auction. Li et al. (2015) and Lai et al. (2017) established an outsourcing request selection model and an insourcing request selection model in a TL carrier collaboration auction based on the concept of marginal profit. The two request selection problems were formulated as selective pickup and delivery problems with time windows in TL transportation (SPDPTW-TL) and were solved by CPLEX MIP solver. Some studies focus on bidding on multiple requests. Based on the prices for serving requests announced by the auctioneer, Dai and Chen (2014) formulated the BGP as a selective pickup and delivery problem with time windows in LTL transportation (SPDPTW-LTL). Different from that of Dai and Chen (2011), Dai and Chen (2014) proposed a SPDPTW-LTL model to determine the requests to outsource and insource simultaneously. They solved the SPDPTW-LTL model by CPLEX MIP solver for small instances. By assuming that each carrier has reserved requests, Li et al. (2016) modeled the BGP as a selective pickup and delivery problem with time windows, profits, and reserved requests (SPDPTWR), and proposed an adaptive large neighborhood search approach (ALNS) to solve it for large size instances. In another stream of research, the BGP is also studied in the literature of transportation service procurement in TL transportation (TSP-TL), where the BGP in TSP-TL is formulated as a minimum cost flow network model. Please refer to review papers of Song and Regan (2002, 2005), Caplice and Sheffi (2013), Sheffi (2014), Chen et al. (2009) and Chang (2009) for more details. After analyzing the literature of BGP in collaborative transportation, we find the BGP in various CAs is mainly a selective pickup and delivery problem with time windows. CPLEX MIP solver is usually used to solve BGP for small instances and meta-heuristics were used to solve BGP for large instances.

2.4 Vehicle routing problems

There are different level research issues in collaborative transportation, including collaboration partners selection, requests reassignment and cost/profit distribution and so on. The problems studies in this thesis are based on the optimization of vehicle routing problem (VRP). Therefore, analyzing the current study on VRP models and algorithms has a great significance to explore the research in collaboration transportation. In this subsection, we will review the VRP based on different distribution networks: VRP in a single echelon transportation and VRP in a multi-echelon transportation.

2.4.1 Vehicle routing problems in single-echelon transportation

Different kinds of VRP are survey in the current study. In this subsection, we review vehicle routing problem with simultaneous pickup and delivery (VRPSPD) and pickup and delivery problem (PDP) related to our work.

In VRPSPD, goods are transported from a depot to linehaul customers and from backhaul customers to the same depot. Due to the complexity of VRPSPD, heuristics and meta-heuristics become dominating methods. Salhi and Nagy (1999) studied a cluster insertion heuristic which inserts two customers in a route each time. Dethloff (2001) presented a mathematical model for VRPSPD in reverse logistics and developed an

insertion-based heuristic to solve it. Nagy and Salhi (2005) proposed a composite heuristic approach for VRPSPD, which includes several routines used for checking feasibility. As lack of an improvement routine, solutions obtained by simple heuristics are often not satisfactory. Crispim and Brandao (2005), Bianchessi and Righini (2007), and Wassan et al. (2008) proposed a hybrid algorithm that combines tabu search (TS) and local search method to solve VRPSPD. Zhang et al. (2014) integrated TS and ant colony approach to solve the time dependent vehicle routing problems with simultaneous pickup and delivery. Except for TS, an ant colony system using two multi-route local search schemes (Gajpal et al.,2009), a genetic algorithm (Tasan et al.,2011), and a hybrid approach combining particle swarm optimization with local search method (Goksal et al.,2013) were studied. Moreover, intensive local search strategies such as large neighborhood search (LNS), variable neighborhood search (VNS) and iterative local search (ILS) have been tried in order to seek a tradeoff between the solution quality and the computation time. Ropke and Pisinger (2006a, 2006b, 2007) designed an adaptive large neighborhood search (ALNS) approach for solving different variants of vehicle routing problems including VRPSPD. This approach selects the neighborhood to search according to its historic performance. Subramanian et al. (2010, 2013) proposed a parallel algorithm embedded with a multi-start meta-heuristic. Li et al. (2015) proposed an ILS method embedded with adaptive neighborhood selection methods for a multi-depot VRPSPD problem. Analyzing the existing literature on VRPSPD, meta-heuristic algorithms combining with local search methods have been widely implemented for VRPSPD.

Vehicle routing problems with pickup and delivery can be classified into three categories based on the route structure and the demand type (Berbeglia et al., 2007 and Battarra et al., 2014): (1) many to many pickup and delivery, where a commodity may be picked up at one of multiple origins and then delivered to one of multiple destinations; (2) one to many to one pickup and delivery, where goods are either delivered from a single vehicle depot to multiple customers or from multiple customers to a single vehicle depot; (3) one to one pickup and delivery, where a vehicle picks up a load from an origin and delivers it to its destination. As one to one pickup and delivery problem is related to our problem, we focus on one to one PDP. The vast majority of literature concentrates on PDP with time windows (PDPTW). Various heuristic and meta-heuristic algorithms were developed for PDPTW. Lu & Dessouky (2006) introduced different insertion-based heuristics for solving PDPTW. Nanry and Barnes (2000) developed a reactive TS based on three local search moves. Li and Lim (2003) proposed a hybrid approach combining TS and simulated annealing, which restarts the search procedure from the current best solution after a number of iterations without improvement. Pankratz (2005) proposed a grouping genetic algorithm for solving PDPTW with a group-oriented genetic coding. Bent and Van Hentenryck (2006) adopted a two-stage hybrid algorithm, in which simulated annealing was used in the first stage to reduce the number of routes, and LNS is used to improve the solution in the second stage of cost minimization. Ropke et al. (2006a, 2006b, 2007) proposed an ALNS approach to solve various vehicle routing problems by transforming them into PDPTW. This approach

could obtain better solutions for many benchmark instances. Lai et al.(2010) used a two stage hybrid meta-heuristic for PDPTW, in which the simulated annealing algorithm was used in the first stage to decrease the number of vehicles and TS was used to decrease the traveling cost in the second stage. Meta-heuristic algorithms combining with local search methods become dominate solution approaches for PDP.

We also review previous studies on the vehicle routing problem with split loads (VRPSL) and the pickup and delivery problem with split loads (PDPSL). Dror and Trudeau (1989) first introduced VRPSL, in which the assumption that each customer is visited only once made on the capacitated vehicle routing problem is relaxed. Mitra (2005, 2008) solved unpaired PDPSL, in which the loads to be split at each node have to be determined. It is a variant of PDP. Nowak et al. (2008, 2009) used the Clarke and Wright Savings Algorithm (CW) and local search to solve the single vehicle paired PDPSL, where a vehicle picks up any portion or all of a load from a specific original node and delivers it to its destination node and each node can be visited by more than once by the same vehicle. For a more detailed literature review on VRPSL, readers can refer to Archetti and Speranza (2012).

2.4.2 Vehicle routing problems in multi-echelon transportation

In this subsection, we mainly review related works on the vehicle routing problem in a multi-echelon transportation.

Multi-echelon (or N -echelon) vehicle routing problems, was first introduced by Gonzalez-Feliu et al. (2008), in which freights are not delivered directly from a central depot but via N echelons to customers. Most of the studies in the multi-echelon vehicle routing and scheduling problem are related to the two-echelon vehicle routing problem(2E-VRP), in which the freights are transported from the central depot to the satellite facilities in the first echelon, and in the second echelon the delivery is from the satellites to the customers.

The two-echelon schemes require more complex planning models compared with those developed for single-echelon schemes. The modeling challenges are related in the two-echelon schemes not only to the operations of vehicles on each echelon, but also to the interactions arising between the two echelons, such as the synchronization and coordination of fleets and terminal operations (Crainic & Sgalambro, 2014). For the two-echelon capacitated vehicle routing problem(2E-CVRP), synchronization constraints are introduced on the meeting of the vehicles at satellites such that once 1st-echelon vehicles have arrived, cargoes on 1st-echelon vehicles are loaded onto 2nd-echelon vehicles as soon as possible. Gonzalez-Feliu (2008) was the first to introduce a flow-based mathematical model for 2E-CVRP. As the 2E-CVRP is a relatively new problem, solution approaches for the 2E-CVRP are limited. Because of the complexity of the problem, the 2E-CVRP was solved mostly by heuristics. Clustering and multi-depot approach based meta-heuristics were presented by Crainic et al. (2008), in which the 2E-CVRP was decomposed into two resulting routing problems: depot to satellite transfer in the first echelon and the satellite to customer delivery in the second echelon. Under the same decomposition framework for the 2E-CVRP, a family of multi-start heuristics was developed by Crainic et al. (2011) and Crainic et al. (2013) proposed a hybrid meta-heuristic combing the greedy randomized

adaptive search procedure (GRASP) combined with path relinking. Perboli, Tadei, and Vigo(2011) developed a flow-based mathematical model, several valid inequalities and proposed two math heuristics based on the model to solve it. The adaptive large neighborhood search (ALNS) algorithm for the 2E-CVRP was presented by Hemmelmayr et al. (2012). Breunig et al. (2016) implemented large neighborhood search (LNS) to solve the 2E-CVRP with unlimited fleet size and achieved better results than Hemmelmayr et al. (2012). Zeng et al. (2014) applied a hybrid heuristic which is composed of a GRASP with a route-first cluster second splitting algorithm and a variable neighbourhood descent (VND) to solve the 2E-CVRP. Exact algorithms for the 2E-CVRP include the branch and cut algorithm (Feliu et al., 2008; Perboli and Tadei, 2010; Jepsen et al., 2013), a hybrid exact algorithm (Baldacci et al., 2013) and the constraint logic programming with the mathematical programming algorithm (Sitek and Wikarek, 2014). According to our knowledge, the exact algorithm can solve the instances with up to six satellites and 100 customers can be solved. For detailed reviews on the 2E-VRP, please refer to Gonzalez-Feliu (2011) and Cuda et al. (2015).

A limited number of solution approaches for the variants of the 2E-VRP with time windows are proposed in the literature. Gonzalez-Feliu and Perboli et al. (2011) reviewed the 2E-VRP, of which some variants include: the 2E-VRP with time windows; the 2E-VRP with satellites synchronization; the 2E-VRP with pickup and delivery; the multi-depot 2E-VRP; and the 2E-VRP with direct delivery. Kergosien et al. (2013) considered a real-life logistic problem arising in the hospital as a 2E-VRP with time windows and a heterogeneous fleet and proposed a genetic algorithm and a tabu search algorithm to solve it. The problem of 2E-VRP with arc time windows was introduced and the memetic algorithm was proposed to solve it by Cetinkaya, Karaoglan, and Gokcen (2013). Soysal, Bloemhof-Ruwaard, and Bektaş (2015) focused on a time-dependent 2E-VRP that accounts for vehicle type, travelled distance, vehicle speed, load, multiple time zones and emissions. Grangier et al. (2016) presented the 2E-VRP that considered time window constraints and synchronization constraints, and an ALNS algorithm was adopted to solve this problem. Li, Zhang, et al. (2016) formulated the two-echelon time-constrained vehicle routing problem (2E-TVRP) in linehaul-delivery systems as a mixed integer nonlinear programming model, in which vehicle routes on two echelons are interacted by time constraints. The savings-based algorithm combined with the local search phase was adopted to solve it.

3 Shipper collaboration in forward and reverse logistics

3.1 Introduction

Effective transportation planning is important for shippers and carriers to reduce their logistics costs because of high fuel prices and an increasing competition in the transportation market. Collaboration among shippers or carriers can improve their profitability by reducing empty vehicle repositions and increasing vehicle fill rates. In this chapter, we focus on shipper collaboration, which involves multiple shippers whose transportation requests are served by a single carrier. Through collaboration, the shippers may be able to identify and submit routes with less asset repositions to the carrier for obtaining more favorable rates. In our problem, shippers may include both manufacturers who distribute new products to customers (retailers) and remanufacturers who collect used products from the customers for disassembling and remanufacturing and then sell remanufactured products in a secondary market. Collaborative planning of forward logistics operations of manufacturers and reverse logistics operations of remanufacturers can reduce their logistics costs and improve their service levels to customers.

Manufacturers with forward logistics operations and remanufacturers with reverse logistics operations usually have the same or overlapping customers. Serving their forward and reverse transportation requests together by the same set of vehicles of a carrier can improve the utilizations of these vehicles and consequently realize significant transportation cost savings. This can be illustrated by a simple example in Figure 3-1 and Figure 3-2. In this example, two manufacturers ($M1$ and $M2$), two remanufacturers ($R1$ and $R2$), and one carrier with a single vehicle depot (D) are involved. It is assumed that all forward and reverse transportation requests are served by vehicles of the carrier initially located at depot D . In the non-collaboration scenario, each shipper (a manufacturer or a remanufacturer) subcontracts its transportation requests to the carrier individually, as shown in Figure 3-1. In this scenario, one vehicle is required to deliver new products of manufacturer $M1$ to its customers $C1$ and $C2$, one vehicle is required to deliver new products of manufacturer $M2$ to its customer $C3$, one vehicle is required to collect used products from customer $C2$ to remanufacturer $R1$, and one vehicle is required to collect used products from customer $C4$ to remanufacturer $R2$.

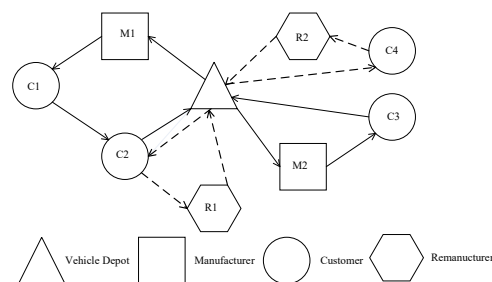


Fig. 3-1 Isolated transportation planning of each shipper in forward and reverse logistics

We assume here that the total delivery or collection load of each vehicle is far less than its capacity such that the vehicle has available capacity to serve more requests after it serves its assigned delivery or pickup requests. In such situation, it is possible to use only one vehicle to serve all delivery and pickup requests of the manufacturers and the remanufacturers as shown in Figure 3-2. In this figure, two manufacturers with forward logistics operations and two remanufacturers with reverse logistics operations collaborate by consolidating their delivery and pickup requests and subcontracting these requests to one vehicle of the carrier. In this collaboration scenario, the delivery and pickup requests of customer *C2* are served simultaneously by this vehicle, and instead of returning to its depot, the vehicle proceeds to serve other transportation request with its available capacity after visiting remanufacturer *R1* and customer *C3*. Because of the decrease of the number of vehicles used and the increase of the vehicle utilization, the total transportation cost of all manufacturers and remanufacturers paid to the carrier in the collaboration scenario will be less than that in the non-collaboration scenario. Thus, by forming a shipper coalition and consolidating their transportation requests, the manufacturers and remanufacturers can capture the benefits of complementarities of their delivery/pickup requests to achieve the economics of scope and scale, reduce their transportation costs and improve the vehicle utilization of the carrier.

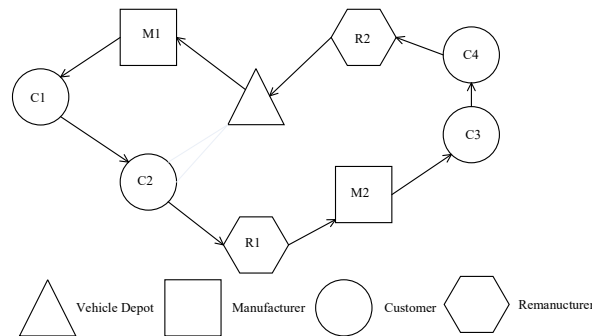


Fig.3-2 Collaborative transportation planning of all shippers in forward and reverse logistics

Most of the research in shipper collaboration pays attention to forward logistics, in which only manufacturers form an alliance and only delivery requests are consolidated together. As reverse logistics becomes more and more important in sustainable development of economy and society, we study shipper collaboration in both forward and reverse logistics, in which shippers of two types (manufacturers and remanufacturers) share customers and have complementary transportation requests. For example, Apple Inc. launched an iPhone trade-in program, under which new cell phones are shipped to retailers or customers from its manufacturing factories (forward logistics) and used or damaged mobile phones are retrieved and transported to remanufacturers for repairing (reverse logistics) and finally resold in secondary markets. By consolidating their forward and reverse transportation requests and proposing a globally optimized transportation plan, the shippers together can ask for more favorable rates when subtracting the service of these requests to a carrier. Our objective is to find an optimal transportation plan for all shippers so that their total transportation cost is minimized. To our best knowledge, no previous work studied such shipper collaboration problem in forward and reverse logistics. We adopt the centralized method to solve the

shipper collaboration problem in this paper. Different from Audy et al. (2011) and Sprenger and Monch (2012), who only considered collaboration among manufacturers in forward logistics, we consider collaboration among manufacturers and remanufacturers in both forward and reverse logistics. In this problem, customers may have different types of transportation requests generated by forward and reverse logistics. Some customers may only have delivery requests generated by forward logistics, where new products are shipped to customers from manufacturing factories (product depots). Some customers may supply used products to remanufacturers (recycle depots) for repair and reproduction in reverse logistics. The other customers may have both delivery and pickup requests as mentioned above. Moreover, manufacturers, remanufacturers, vehicle depots may be dispersed geographically at different locations. Therefore we consider three different kinds of depots. This gives rise to a new vehicle routing problem with pickup and delivery requests and three different types of depots (product depots, vehicle depots and recycle depots) in forward and reverse logistics (VRPPD-FRL).

As customers have pickup and delivery requests in VRPPD-FRL, it is related to the vehicle routing problem with simultaneous pickup and delivery (VRPSPD) introduced by Min (1989) and the pickup and delivery problem (PDP). However, our problem is different from the classical VRPSPD and PDP defined in the literature: (1) Three types of depots: each vehicle route starts from and ends at the same vehicle depot; it visits product depots to load new products before it visits the corresponding customers to deliver the products; On the same vehicle route, used products are collected and transported to recycle depots after picking up them at customers. (2) Three types of customers may exist at the same time in the transportation network: customers with only delivery requests, customers with only pickup requests, customers with simultaneous pickup and delivery requests. (3) Multiple requests may share the same product depot and recycle depot: all the customers demanding the same product are supplied by the same manufacturer, and the same used product recycled from customers are transported to the same remanufacturer. (4) each product depot (manufacturing location) and each recycle depot (remanufacturing location) in our problem may be visited by vehicles multiple times, but can be visited by each vehicle at most once. Thus, VRPPD-FRL is a new variant of vehicle routing problem, which was never studied in the literature before. The new characteristics of VRPPD-FRL make our problem more complicated than VRPSPD and PDP.

As our problem VRPPD-FRL is a new variant of capacitated vehicle routing problem with pickup and delivery, which is NP-hard, we propose a meta-heuristic that combines the greedy randomized adaptive search procedure (GRASP) and iterative local search (ILS) to find a near-optimal solution of the problem. Competitive results have been reported in the literature on using hybrid GRASP-ILS algorithms to solve different variants of vehicle routing problems such as the capacitated vehicle routing problem by Prins (2009) and the vehicle routing problem with time windows, synchronization and precedence constraints by Haddadene et al. (2016). By adapting GRASP and ILS to the new characteristics of our problem, we propose a GRASP-ILS meta-heuristic to solve the problem near optimally. Our

experimental results demonstrate that the hybrid GRASP-ILS algorithm is more effective and robust than GRASP and ILS.

The main contributions of this paper include: (1) Shipper collaboration in forward and reverse logistics is considered for the first time; (2) A new variant of vehicle routing problem with pickup and delivery requests and three types of depots is studied and a mixed integer programming model is formulated for the problem. (3) An effective GRASP-ILS algorithm well adapted to new characteristics of the problem is proposed to solve the NP-hard vehicle routing problem with precedence constraints of each request and split loads at product depots and recycle depots. The performance of GRASP-ILS is evaluated by numerical experiments, which demonstrate the effectiveness of the algorithm and the significance of cost savings that can be achieved by shipper collaboration in forward and reverse logistics.

The rest of this chapter is organized as follows. In section 3.2, a mixed integer programming model is formulated to model VRPPD-FRL. In section 3.3, a meta-heuristic GRASP-ILS algorithm is proposed to find a near optimal solution of VRPPD-FRL. Computational results on a large set of randomly generated instances are reported and analyzed in section 3.4. Brief summary is drawn in section 3.5.

3.2 Problem description and mathematical model

We consider shipper collaboration in forward and reverse logistics, where a set of manufacturers denoted by M_1 and a set of remanufacturers denoted by M_2 form an alliance M with $M = M_1 \cup M_2$ by consolidating their pickup and delivery requests and jointly planning the vehicle routes to serve these requests together. Let NC_m denote the set of customers of manufacturer or remanufacturer $m \in M$, $NC = \bigcup_{m \in M} NC_m$ denote the customer set of the alliance, s_i and t_i denote the product depot and the recycle depot of customer $i \in NC$, respectively. Each manufacturer $m \in M_1$ wants to deliver new products with quantity d_i from product depot s_i to its customer $i \in NC_m$ and each remanufacturer $m \in M_2$ wants to collect used products with quantity p_i from its customer $i \in NC_m$ to recycle depot t_i . To find an optimal transportation plan for all shippers, a new variant vehicle routing problem VRPPD-FRL with the objective to minimize the overall transportation costs of the collaboration alliance is proposed. VRPPD-FRL aims to schedule a fleet of homogeneous vehicles to serve customer requests of all the shippers so that each customer is visited exactly once under the vehicle capacity constraints, the maximum traveling length constraints of each vehicle, and the pairing and precedence constraints. Each vehicle starts from and ends with the same vehicle depot. In our collaborative transportation planning problem, each product depot and recycle depot can be visited many times by the vehicle fleet, because different customers with demand of the same product are supplied by the same product depot, and the same used products recycled from different customers are transported to the same recycle depot.

Assumptions:

1) Trans-shipments are not allowed between vehicles and each customer must be served only once by a vehicle.

2) As multiple shippers may share the same product depot and recycle depot, the new product quantity available at a product depot or the used product quantity at a recycle depot can be more than the vehicle capacity. Therefore, we allow each product depot and recycle depot can be visited many times by the vehicle fleet, but can be visited at most once by each vehicle.

3) Each delivery request has only one specific product depot and each pickup request has only one designated recycle depot.

4) Each route starts from and terminates with the same vehicle depot.

Notations

M	set of shippers in the alliance, $m \in M$
O	set of vehicle depots
NC	set of customers of the shipper alliance, $NC = \bigcup_{m \in M} NC_m$
NP	set of product depots of the shipper alliance, $NP = \bigcup_{m \in M_1} \bigcup_{i \in NC_m} \{s_i\}$
NR	set of recycle depots of the shipper alliance, $NR = \bigcup_{m \in M_2} \bigcup_{i \in NC_m} \{t_i\}$
N	$N = O \cup NC \cup NP \cup NR$
c_{ij}	distance between node i and node $j, i, j \in N, i \neq j$
NV	set of vehicles in the shipper alliance
Q	capacity of the homogeneous vehicle

Decision variables

x_{ij}^v	1 if $arc(i, j)$ is passed by vehicle $v \in NV, i, j \in N, i \neq j$; 0 otherwise
lp_{ki}^v	the load of new products picked up from product depot $k \in NP$ of vehicle $v \in NV$ before node $i \in N$ is visited
lr_{ki}^v	the load of used products delivered to recycle depot $k \in NR$ of vehicle $v \in NV$ after node $i \in N$ is visited
q_i^v	the position of node $i \in N$ in the route of vehicle $v \in NV$

With these notations, the problem can be formulated as follows:

$$\min \sum_{v \in NV} \sum_{i \in N} \sum_{j \in N, j \neq i} c_{ij} x_{ij}^v \quad (3-1)$$

S.t.

$$\sum_{j \in N, j \neq i} x_{ij}^v \leq 1, \quad \forall i \in O, v \in NV \quad (3-2)$$

$$\sum_{v \in NV} \sum_{j \in N, j \neq i} x_{ij}^v = 1, \quad \forall i \in NC \quad (3-3)$$

$$\sum_{j \in N, j \neq i} x_{ij}^v = \sum_{j \in N, j \neq i} x_{ji}^v, \quad \forall i \in N, v \in NV \quad (3-4)$$

$$\sum_{j \in N, j \neq i} x_{ij}^v \leq \sum_{j \in N, j \neq s_i} x_{s_i, j}^v, \quad \forall i \in NC, v \in NV \quad (3-5)$$

$$\sum_{j \in N, j \neq i} x_{ij}^v \leq \sum_{j \in N, j \neq t_i} x_{j, t_i}^v, \quad \forall i \in NC, v \in NV \quad (3-6)$$

$$lp_{kj}^v \geq lp_{ki}^v + \sum_{h \in NC, s_h = j} \sum_{i \in N} x_{ih}^v \cdot d_h \cdot \alpha_{jk} - Q \cdot (1 - x_{ij}^v), \quad \forall i \in N, j, k \in NP, i \neq j, v \in NV \quad (3-7)$$

$$lp_{kj}^v \geq lp_{ki}^v - d_j \cdot \beta_{jk} - Q \cdot (1 - x_{ij}^v), \quad \forall i \in N, j \in NC, k \in NP, i \neq j, v \in NV \quad (3-8)$$

$$lr_{kj}^v \geq lr_{ki}^v - \sum_{h \in NC, t_h = j} \sum_{i \in N} x_{ih}^v \cdot p_h \cdot \alpha_{jk} - Q \cdot (1 - x_{ij}^v), \quad \forall i \in N, j, k \in NR, i \neq j, v \in NV \quad (3-9)$$

$$lr_{kj}^v \geq lr_{ki}^v + p_j \cdot \beta_{jk} - Q \cdot (1 - x_{ij}^v), \quad \forall i \in N, j \in NC, k \in NR, i \neq j, v \in NV \quad (3-10)$$

$$lp_{ji}^v + lr_{ki}^v = 0, \quad \forall i \in O, j \in NP, k \in NR, v \in NV \quad (3-11)$$

$$0 \leq \sum_{k \in NP} lp_{ki}^v + \sum_{k \in NR} lr_{ki}^v \leq Q, \quad \forall i \in N \setminus O, v \in NV \quad (3-12)$$

$$q_j^v \geq q_i^v + 1 - N(1 - x_{ij}^v), \quad \forall i \in N, j \in N, j \neq i, v \in NV \quad (3-13)$$

$$\sum_{i \in N} \sum_{j \in N, j \neq i} c_{ij} x_{ij}^v \leq L, \quad v \in NV \quad (3-14)$$

$$x_{ij}^v \in \{0, 1\}, \quad \forall i, j \in N, v \in NV \quad (3-15)$$

$$0 \leq lp_{ki}^v \leq Q, \quad \forall i \in N, k \in NP, v \in NV \quad (3-16)$$

$$0 \leq lr_{ki}^v \leq Q, \quad \forall i \in N, k \in NR, v \in NV \quad (3-17)$$

$$1 \leq q_i^v \leq N, \quad \forall i \in N, v \in NV \quad (3-18)$$

The objective function (3-1) minimizes the total transportation costs. Constraints (3-2) ensures that each vehicle starts from and ends to the vehicle depot. Constraints (3-3) indicate that each customer can be exactly visited for one time. Constraints (3-4) ensure that if a vehicle visits a node, it must leave this node. Constraints (3-5) and (3-6) guarantee that once a customer is visited by a vehicle, its corresponding product depot and recycle depot must also be visited by the same vehicle. Constraints (3-7) and (3-8) are the load flows at each product depot node. Constraints (3-9) and (3-10) are the load flows at each recycling depot node. Constraints (3-11) ensure that each vehicle starts from and ends to the vehicle depot in an empty load. Constraints (3-12) are the vehicle capacity constraints. Constraints (3-13) guarantee the sub-tour elimination. Constraints (3-14) indicate that the travel distance of each vehicle cannot exceed its maximum traveling length. Constraints (3-15)-(3-18) indicate the natures of all variables and their upper and lower bounds.

3.3 GRASP-ILS algorithm

As GRASP is a powerful heuristic to generate good and diversified initial solutions and

ILS is an effective method to escape from local optima and explore more solution spaces, we propose a hybrid approach GRASP-ILS that combines GRASP and ILS to find near optimal solutions for the studied shipper collaboration problem. The hybridization of GRASP-ILS takes advantages of both GRASP and ILS. GRASP is a powerful heuristic to generate good and diversified initial solutions, which are important for finding high quality final solutions by local search improvement. ILS is an effective local search based method which makes a good trade-off between solution quality and computation time. Considering the new characteristics of our problem, we make some adaptations of GRASP-ILS to solve it. We first introduce the main procedural framework of GRASP-ILS in section 4.1, and then present successively the generation of initial solutions by GRASP, the insertion operations and the feasibility check procedure used in ILS, in section 4.2, 4.3, 4.4, respectively. Finally, we will describe the main components of ILS, i.e., the local search and the perturbation procedure in section 4.5 and 4.6, respectively.

3.3.1 Algorithm framework

The main procedural framework of the hybrid GRASP-ILS is sketched in Algorithm 3-1. The main loop (lines 2-17) describes a solution construction phase performed by using a GRASP method and a solution improvement phase made by an iterative local search ILS that together may find a solution better than the current best solution S^* . In each iteration of the main loop, an initial solution S^0 is first generated by using a randomized constructive heuristic *GenerationInitialSolution()* detailed in subsection 3.3.2. This solution is improved by a local search procedure *LocalSearch()* (line 4). The resulting solution is further improved by an ILS (line 5-12). Each ILS iteration calls a perturbation procedure *Perturbation()* and a local search procedure *LocalSearch()*. Note that the local search procedure used in GRASP (line 4) is the same as that used in ILS (line 8). In Algorithm 3-1, np and ni are the maximum number of iterations of GRASP and ILS, respectively. The local search procedure and the perturbation procedure will be described in subsection 3.3.4 and 3.3.5, respectively.

GRASP-ILS is a hybridization of a GRASP with an ILS, combing the advantages of both methods. GRASP (Greedy Randomized Adaptive Search Procedure), first proposed by Feo and Bard (1989), is a multi-start local search meta-heuristic. Each iteration of GRASP contains mainly two phases: 1) the construction phase which constructs a feasible solution in a greedy and random way; 2) the local search phase which aims at improving the feasible solution obtained in the construction phase. This construction-improvement scheme is repeated for a given number of iterations. ILS (Iterated Local Search), introduced by Lourenco et al. (2003), is a simple but effective method for various combinatorial optimization problems. By randomly perturbing the current local optimal solution using a perturbation procedure in each iteration, the ILS tries to diversify the search space every time when a local optimal is reached, the new solution obtained by the perturbation is then improved by a local search.

Algorithm 3-1 Hybrid GRASP-ILS

```

1   $f^* := +\infty$ 
2  for  $i:=1$  to  $np$  do
3     $S^0 := \text{GenerationInitialSolution}()$ 
4     $S^0 := \text{LocalSearch}(S^0)$ 
5    for  $j:=1$  to  $ni$  do
6       $S := S^0$ 
7       $S := \text{Perturbation}(S)$ 
8       $S := \text{LocalSearch}(S)$ 
9      if  $f(S) < f(S^0)$  then
10        $S^0 := S$ 
11     end if
12   end for
13   if  $f(S^0) < f^*$  then
14      $f^* := f(S^0)$ 
15      $S^* := S^0$ 
16   end if
17 end for
18 Output the best solution  $S^*$  found so far

```

3.3.2 Generation of initial solutions

A GRASP is proposed to generate multiple feasible solutions of VRPPD-FRL in an iterative manner. In each iteration of the GRASP, routes are constructed one by one until all customers have been routed. At each step of its iteration, one element is selected randomly from a Restricted Candidate List (RCL) with a limited size and added to the current solution.

The RCL is a set of unrouted customers with a size of $nrcl$. To obtain the RCL, the minimal cost for inserting each unrouted customer into the currently constructed route r^l is calculated. The RCL consists of $nrcl$ unrouted customers with the smallest insertion costs on route r^l . The candidates in the RCL are sorted in an increasing order of their minimal insertion costs. The GRASP then randomly select one element from the RCL and insert it into the route r^l . Update the route r^l and repeat the above process until no more customer can be feasibly inserted into r^l , which implies the insertion of a new customer into r^l will violate the vehicle capacity constraint or the maximum traveling length constraint of each route. A feasible solution is obtained if all customers have been routed. Otherwise, a new route containing only the vehicle depot is created and the above process will be repeated. The construction phase of GRASP for generating an initial solution is described in pseudo-code in Algorithm 3-2.

Algorithm 3-2 Construction of Feasible Solution

```

1   $l := 0$ ,  $r^l := \{\text{the vehicle depot}\}$ , initialize candidate set CL;
2  while ( $CL \neq \emptyset$ )
3      Construct a RCL of unrouted customers according to  $r^l$ ;
4      Randomly select an unrouted customer from the RCL and insert it into the route  $r^l$ ;
5      If no more unrouted customer can be feasibly inserted into  $r^l$ , then
6           $l := l + 1$ 
7           $r^l := \{\text{the vehicle depot}\}$ 
8      End if
9  End while
10 Output a feasible solution

```

3.3.3 Insertion operations

We use insertion operations both in the generation of initial solutions and in the local search improvement procedures in ILS. In our problem, the delivery and pickup request of each customer has a vehicle visiting order of “product depot—customer—recycle depot” and some customers share the same product depot or recycle depot, which makes VRPPD-FRL more complicated than PDP. For the PDP, a pair nodes corresponding to the pickup and delivery locations of a request are inserted into an existing route. For VRPPD-FRL, when a customer is inserted into a route we must also insert its product and recycle depots unless one or both of them have been in the route in case that previously inserted customers have the same product or/and recycle depots as the customer. The first step for inserting a customer i into a route r^l is to identify whether its product depot s_i and recycle depot t_i are already in the route. We search s_i forward and t_i backward in route r^l . Depending on different situations, inserting customer $i \in RCL$ into the route r^l has the following four possibilities: 1) insert customer node i only as product depot node s_i and recycle depot node t_i have been in r^l ; 2) insert i and s_i when t_i has been in r^l ; 3) insert i and t_i as s_i has been in r^l ; 4) insert i , s_i and t_i together. The computation of the insertion cost of each customer thus must consider the following four cases:

1) Customer node i is inserted between position k and $k+1$ on the route r^l , $k = s_i + 1, s_i + 2, \dots, t_i - 1$. In this case, the insertion cost of this node, denoted by $c_1(r^l, i, k)$, can be computed as follows:

$$c_1(r^l, i, k) = c_{k,i} + c_{i,k+1} - c_{k,k+1} \quad (3-18)$$

2) Product depot node s_i is first inserted between position j and $j+1$, $j = 1, 2, \dots, t_i - 1$, and customer node i is then inserted between k and $k+1$, $k = j+1, j+2, \dots, t_i - 1$, on route r^l . The cost of inserting (s_i, i) on route r^l , denoted by $c_2(r^l, s_i, i, j, k)$, can be computed as follows:

$$c_2(r^l, s_i, i, j, k) = c_{j, s_i} + c_{s_i, j+1} - c_{j, j+1} + c_{k, i} + c_{i, k+1} - c_{k, k+1} \quad (3-19)$$

3) Customer node i is first inserted between j and $j+1$, $j = s_i + 1, s_i + 2, \dots, t_i - 1$, and recycle depot node t_i is then inserted between k and $k+1$, $k = j+1, j+2, \dots$, on route r^l . The cost of inserting (i, t_i) on route r^l , denoted by $c_3(r^l, i, t_i, j, k)$, can be computed as equation (3-20).

$$c_3(r^l, i, t_i, j, k) = c_{j, i} + c_{i, j+1} - c_{j, j+1} + c_{k, t_i} + c_{t_i, k+1} - c_{k, k+1} \quad (3-20)$$

4) Product depot node s_i is first inserted between j and $j+1$, $j = 1, 2, \dots$, customer node i is then inserted between k and $k+1$, $k = j+1, j+2, \dots$, and recycle depot node t_i is finally inserted between l and $l+1$, $l = k+1, k+2, \dots$, on route r^l . The cost of inserting (s_i, i, t_i) on route r^l , denoted by $c_4(r^l, s_i, i, t_i, j, k, l)$, can be computed as follows.

$$c_4(r^l, s_i, i, t_i, j, k, l) = c_{j, s_i} + c_{s_i, j+1} - c_{j, j+1} + c_{k, i} + c_{i, k+1} - c_{k, k+1} + c_{l, t_i} + c_{t_i, l+1} - c_{l, l+1} \quad (3-21)$$

In the above four cases, only feasible customer insertion is allowed in our implementation. That is, the capacity and maximum traveling length constraints of each vehicle must be respected. Further, for each inserted customer, the vehicle that visits it must follow the visiting order of “designated product depot—customer—designated recycle depot”, and the nodes of three types (product depot, recycle depot, and customer node) associated with each request must be inserted into their best positions with the minimal total insertion cost. In the next section, we will describe how to check the feasibility of insertion of a node of each type efficiently in detail.

3.3.4 Local search

The local search part of GRASP and ILS plays an important role in improving the quality of the final solution. Usually, the local search procedure explores all or part of the neighborhoods of the current solution and then moves to the best one or the first one that is better than the current solution. The order to search different neighborhood structures is important to jump out from the trap of local optima and save computation time. The method that randomly switches and explores solution space among multiple neighborhood structures, has been proved its great potential in reducing computation time and in obtaining better solutions by Subramanian et al. (2010). To make the search more flexible and to improve its efficiency, we search the neighborhood structures in a random way in the local search phase of our GRASP-ILS.

Six neighborhood structures ($N_1 \sim N_6$) are used in the local search. Each neighborhood structure contains all feasible solutions that can be reached by performing one of the moves $M_1 \sim M_6$ as shown in the following. The first three neighborhoods correspond to three inter-route moves ($M_1 \sim M_3$), respectively, whereas the others correspond to intra-route moves ($M_4 \sim M_6$). Each neighborhood move involves one or two requests. These moves are:

M_1 —transfer a request from one route to another one.

M_2 —exchange two requests between two different routes.

- M_3 —transfer two requests from one route to another one.
- M_4 —change the positions of the nodes of one request in one route.
- M_5 —exchange the positions of two adjacent customers in one route.
- M_6 —exchange the positions of two non-adjacent customers in one route.

In our problem, a request includes three nodes: product depot, customer node, recycle depot. Different from PDP, as many customers share the same product depot or recycle depot, when removing one request into the route, we should first justify whether the remaining requests on the route satisfies the pairing constraints and then performs the removal of one or two requests. In our implementation, when a new solution is obtained by performing one of the above mentioned moves except for M_5 , we first check its feasibility. If the move considered is infeasible, we modify the solution by inserting the product depot or/and recycle depot into the right place. If a better solution is found, we then move to this new solution. The pseudo-code of the local search procedure is presented in Algorithm 3-3. In each iteration, we first randomly choose a neighborhood structure to improve the initial solution. If an improved solution is found, we preserve this neighborhood structure in the neighborhood list. Otherwise, we delete this neighborhood structure from the current list. The local search procedure is terminated until the neighborhood list is empty.

Algorithm 3-3 Local search

- 1 Initialize the neighborhood structures $N = \{N_1, N_2, \dots, N_5, N_6\}$;
 - 2 **While** $N \neq \phi$ **do**
 - 3 Randomly select a neighborhood structure from N and enumerate neighborhood solutions in it
 - 4 **If** an improved solution is found, **then**
 - 5 Replace the current solution by the new solution
Update N
 - 6 **Else**
 - 7 Remove this neighborhood structure from N
 - 8 **End if**
 - 9 **End while**
 - 10 Output the current solution
-

To save computation time, when performing the inter-route moves, we begin with the longest route that contains the largest number of nodes, because the longer a route, the higher the possibility that the route can be improved. When choosing two routes to make inter-route moves, we adopt the gravity center of mass concept to compute the coordinates of the virtual center for each route. Given a route r^l , the coordinates of its virtual center are calculated by

$$C_{lx} = \sum_{i \in r^l} \max\{d_i, p_i\} * x_i / \sum_{i \in r^l} \max\{d_i, p_i\}, C_{ly} = \sum_{i \in r^l} \max\{d_i, p_i\} * y_i / \sum_{i \in r^l} \max\{d_i, p_i\} \quad (3-22)$$

where C_{lx} , C_{ly} denote the x -coordinate and the y -coordinate of the virtual center of route r^l respectively, and x_i, y_i denote the x -coordinate and the y -coordinate of node i on route r^l . In our implementation, the Euclidean distance between the virtual centers of the two routes is

used to evaluate their closeness. Once a route is randomly selected, the route that is the closest to it is selected as the other route in performing an inter-route move.

In the literature, best improvement strategy and first improvement strategy are usually used in local search. We did numerical experiments to compare the best improvement strategy and the first improvement strategy. The comparison results are shown in Table 3-1.

Table 3-1 The comparison of the first improvement and the best improvement

Instance	Best improvement		First improvement	
	CPU	Gap	CPU	Gap
I40	827.63	5.20	29.22	5.18
O40	796.54	0.62	35.18	0.58

As the comparison results in Table 3-1 show that finding the best neighborhood solution in each iteration by applying the best improvement strategy requires much time with no significant improvement of the final solution in comparison with the first improvement strategy, we choose the first improvement strategy in the local search of our algorithm.

Furthermore, in the exploration of M_3 , the general strategy is to consider all possible exchanges of two customer nodes in one route, this may be quite time-consuming. Instead, we adopt a speedup strategy in the exploration of M_3 , in which we just exchange the positions of two neighboring customer nodes. We compare the speedup strategy with the general strategy. The comparison results are shown in Table 3-2.

The experimental results in Table 3-2 show that compared with the speedup strategy, the general strategy of considering all possible exchanges of two customer nodes in one route brings no significant improvement except for a much longer computation time in the exploration of M_3 . For this reason, in our implementation, we only consider the exchange of customer node pairs $(i, i+1)$ and $(i, i+2)$ in each route according to the vehicle visiting order of nodes.

Table 3-2 The comparison of two strategies

Instance	General strategy		Speedup strategy	
	CPU	Gap	CPU	Gap
I40	327.63	5.18	29.22	5.18
O40	296.54	0.61	35.18	0.58

3.3.5 Perturbation procedure

The perturbation procedure in GRASP-ILS aims at jumping into an attraction basin adjacent to the current local optimal. The perturbation procedure in GRASP-ILS is implemented after GRASP and in each iteration of ILS. The goal of the perturbation procedure is to diversify the solutions. As the perturbation procedure affects the performance of ILS, the level of perturbation is important. A strong perturbation of the current solution may behave like a random restart, which can reduce the probability to reach the global optimal solution, whereas a small perturbation may fall back into the local optimum (Lourenco et al. 2003). In our implementation of the perturbation procedure, three routes are first randomly selected and two successive moves of M_1 are then performed among these

three routes. Different from the perturbation procedure proposed by Renaud et al. (2002), we conduct move M_1 twice between two routes arbitrarily chosen out of the three routes until the perturbation procedure gets a new feasible solution. For example, given three routes r^l, r^m, r^n , we perform M_1 between r^l and r^m and then between r^m and r^n . If a new feasible solution is not obtained, we conduct two successive moves M_1 between r^m and r^l and then r^l and r^n . Thus, the number of combinations for perturbation is six for three selected routes.

3.4 Computational experiments

As the problem we study is new, there is no benchmark instance in the literature that can be directly used to evaluate the performance of the proposed GRASP-ILS and identify the cost savings of collaboration. To this end, we generate randomly instances for VRPPD-FRL with different sizes and different geographical distributions of customers of the shippers based on the scheme of generating instances in Berger and Bierwirth (2010). These instances are used to evaluate the performance of our GRASP-ILS and analyze the effect of geographical distributions of customers of the shippers on the cost savings of collaboration. The proposed GRASP-ILS algorithm was coded in C++. Numerical experiments were carried out on a personal computer with Intel Core i5-3210M and 4.0GB of RAM under Microsoft Windows 7 operating system. The commercial optimization software CPLEX 12.6 with default setting was used as the MIP solver.

3.4.1 Test instances

We consider three shippers (two manufacturers and one remanufacturer) in VRPPD-FRL. Three geographical distributions of customers of the shippers are considered as in Berger and Bierwirth (2010), which correspond to the customer areas of the shippers are adjacent, overlapping, and identical, respectively. The three instance sets generated corresponding to the three geographical distributions of customers are denoted by A, O and I , respectively, with each set containing 40 instances. Each instance set includes 10 instances with 20 requests, 10 instances with 40 requests, 10 instances with 60 requests and 10 instances with 100 requests. Each instance is named with *Customer area—number of requests— $|NP|$ — $|NR|$* . The nodes of the instances are taken from the Euclidean TSP R101 of Solomon (2005) randomly. The coordinates of the vehicle depot, two product depots and one recycle depot are (35, 40), (30, 60), (18, 24) and (55, 60), respectively. The quantity of new products to be delivered to each customer and the quantity of used products to be collected from each customer are uniformly distributed in interval [0,100]. In all 120 instances, the capacity of each vehicle is set to $Q = 200$, and the maximum travelling length for each route is 200. The maximum number of vehicles of each shipper is set to 8. The transportation distance c_{ij} between each node i and j is their Euclidean distance rounded to an integer.

3.4.2 Parameter setting for CPLEX and GRASP-ILS

In our numerical experiments, model VRPPD-FRL is solved by the MIP solver of CPLEX 12.6 with default setting. For instances with different numbers of requests, different

computation time limits are set for the solver since even for an instance with 40 requests, CPLEX cannot solve it optimally within an acceptable time. For the instances with 20 requests, the time limit is set to 10,800 seconds, whereas for the instances with 40 requests, 60 requests or 100 requests, the time limit is set to 21,600 seconds.

The parameters were set based on preliminary experiments by making a tradeoff between solution quality and CPU time. To achieve the best performance, a limited number of parameters combinations were considered and tuned. The parameters of GRASP-ILS include the size of the restricted candidates list (*nrcl*) in the constructive heuristic of GRASP, the maximum number of initial solutions generated by GRASP (*np*), and the maximum number of calls to ILS (*ni*). The best values of the parameters that allow to obtain a good compromise between solution quality and running time are shown in Table 3-3.

Table 3-3 Parameter tuning according to instance size

Parameter	Value			
	20 requests	40 requests	60 requests	100 requests
<i>np</i>	10	10	15	15
<i>ni</i>	5	10	15	20
λ	0.5	0.5	0.75	0.75

3.4.3 Comparison results and interpretations

To evaluate the performance of GRASP-ILS, we compare the results obtained by GRASP-ILS with those of CPLEX solver, GRASP and ILS. All meta-heuristics were executed 10 times on each instance.

To facilitate the presentation of numerical results, the notations of the performance indicators considered and their descriptions are given in Table 3-4.

Table 3-4 Notations of performance indicators and their description

Notations	Description
<i>UB</i>	The best cost obtained by CPLEX solver in a preset running time
<i>LB</i>	The lower bound obtained by CPLEX solver in a preset running time
<i>Ini</i>	The cost of the best initial solution obtained by GRASP-ILS
<i>Zmin</i>	The best cost of 10 runs for each meta-heuristic
<i>Zavg</i>	The average cost of 10 runs for each meta-heuristic
<i>Dev</i>	The standard deviation of the costs obtained in ten runs by each meta-heuristic.
<i>Imp_{Ini}</i>	The improvement of best cost over <i>Ini</i> . For CPLEX solver <i>Imp_{Ini}</i> is calculated by $(UB - Ini)/UB * 100\%$ For meta-heuristics, <i>Imp_{Ini}</i> is calculated by $(Z_{min} - Ini)/Z_{min} * 100\%$
<i>Gap_{LB}</i>	The percentage gap between the best cost and LB. For CPLEX solver, <i>Gap_{LB}</i> is calculated by $Gap_{LB} = (UB - LB)/UB * 100\%$ For meta-heuristics, <i>Gap_{LB}</i> is calculated by $(Z_{min} - LB)/Z_{min} * 100\%$
<i>Imp_{Cplex}</i>	The improvement of the best cost obtained by meta-heuristics over the best cost obtained by CPLEX solver. <i>Imp_{Cplex}</i> is calculated as: $(UB - Z_{min})/UB * 100\%$

Table 3-4 (continued)

Notations	Description
$Imp_{GRASP-ILS,GRASP}$	The improvement of $Z_{min,GRASP-ILS}$ over $Z_{min,GRASP}$. It is calculated as: $(Z_{min,GRASP} - Z_{min,GRASP-ILS}) / Z_{min,GRASP-ILS} * 100\%$
$Imp_{GRASP-ILS,ILS}$	The improvement of $Z_{min,GRASP-ILS}$ over $Z_{min,ILS}$. It is calculated as: $(Z_{min,ILS} - Z_{min,GRASP-ILS}) / Z_{min,GRASP-ILS} * 100\%$
N_V	The average total number of vehicles used in the transportation
$Cost_N$	The total transportation cost of the shippers without collaboration obtained by CPLEX
$Cost_C$	The total transportation cost of the shippers with collaboration, which is the best objective value of CPLEX solver and GRASP-ILS.
ϕ	The cost savings in percentage achieved by the collaboration among the shippers. ϕ is defined as: $(Cost_N - Cost_C) / Cost_N * 100\%$
CPU_{avg}	The average execution time in seconds for meta-heuristics

1) Results of comparison between GRASP-ILS and CPLEX

As VRPPD-FRL is highly combinatorial, for most instances of medium size or large size tested, the solver of CPLEX cannot even find a feasible solution in a reasonable computation time. For instances with 40 requests, 60 requests or 100 requests, we use the best initial solution obtained by GRASP-ILS as an initial solution to CPLEX in the same way as that of Liu and Xie (2013). From this initial solution, CPLEX can eliminate a part of the search space and thus improve its computational efficiency. Detailed results for comparison between GRASP-ILS and CPLEX solver are shown in Table 3-5.

Table 3-5 Detailed results for GRASP-ILS and CPLEX

Instance	CPLEX				GRASP-ILS		
	Ini	LB	UB	CPU	Zmin	CPU	Imp _{Cplex}
I20-2-1-0	/	459.26	459.26	6727.61	459.26	6.24	0.00
I20-2-1-1	/	366.66	366.66	142.44	366.66	2.23	0.00
I20-2-1-2	/	478.19	478.19	1360.56	478.19	6.64	0.00
I20-2-1-3	/	360.24	360.24	128.19	360.24	1.86	0.00
I20-2-1-4	/	383.24	383.24	8933.10	383.24	1.67	0.00
I20-2-1-5	/	343.70	343.70	369.21	343.70	1.41	0.00
I20-2-1-6	/	344.51	344.51	366.51	344.51	1.59	0.00
I20-2-1-7	/	354.59	354.59	266.03	354.59	1.75	0.00
I20-2-1-8	/	351.37	351.37	2202.84	351.37	1.40	0.00
I20-2-1-9	/	476.32	476.32	514.23	476.32	6.97	0.00
Avg				2101.07		3.18	0.00
O20-2-1-0	/	240.46	240.46	817.75	240.46	2.18	0.00
O20-2-1-1	/	260.84	260.84	727.20	260.84	1.84	0.00
O20-2-1-2	/	250.62	250.62	945.73	250.62	2.50	0.00
O20-2-1-3	/	254.79	254.79	1213.25	254.79	1.50	0.00
O20-2-1-4	/	273.79	273.79	563.98	273.79	2.03	0.00
O20-2-1-5	/	269.61	269.61	2227.00	269.61	1.46	0.00

3 Shipper collaboration in forward and reverse logistics

Table 3-5(continued)

Instance	CPLEX				GRASP-ILS		
	Ini	LB	UB	CPU	Zmin	CPU	Imp _{Cplex}
O20-2-1-6	/	260.31	260.31	1456.89	260.31	1.64	0.00
O20-2-1-7	/	245.95	245.95	1323.50	245.95	1.69	0.00
O20-2-1-8	/	240.28	240.28	685.00	240.28	1.70	0.00
O20-2-1-9	/	229.92	229.92	813.89	229.92	2.70	0.00
Avg				1077.42		1.92	0.00
A20-2-1-0	/	362.31	362.31	987.80	362.31	1.59	0.00
A20-2-1-1	/	444.80	444.80	1188.06	444.80	7.26	0.00
A20-2-1-2	/	329.67	329.67	2358.72	329.67	1.37	0.00
A20-2-1-3	/	363.62	363.62	1206.36	363.62	4.06	0.00
A20-2-1-4	/	343.77	343.77	2440.98	343.77	1.66	0.00
A20-2-1-5	/	287.74	287.74	1266.59	287.74	1.99	0.00
A20-2-1-6	/	338.23	338.23	821.69	338.23	1.56	0.00
A20-2-1-7	/	290.21	290.21	985.11	290.21	1.40	0.00
A20-2-1-8	/	314.20	314.20	1324.84	314.20	2.13	0.00
A20-2-1-9	/	323.60	323.60	921.38	323.60	1.93	0.00
Avg				1350.15		2.49	0.00
I40-2-1-0	764.73	733.02	554.38	21600	706.64	31.77	3.60
I40-2-1-1	617.81	617.81	432.47	21600	600.90	30.07	2.74
I40-2-1-2	776.04	776.04	526.08	21600	729.24	31.07	6.03
I40-2-1-3	718.16	702.54	545.94	21600	651.55	26.00	7.26
I40-2-1-4	720.41	716.43	519.91	21600	699.59	26.37	2.35
I40-2-1-5	748.66	748.66	475.02	21600	647.36	27.67	13.53
I40-2-1-6	615.92	615.92	435.58	21600	590.24	29.90	4.17
I40-2-1-7	664.83	662.64	432.11	21600	612.68	28.53	7.54
I40-2-1-8	634.10	594.85	447.33	21600	573.59	32.61	3.57
I40-2-1-9	611.25	604.84	466.03	21600	598.44	28.16	1.06
Avg				21600		29.22	5.18
O40-2-1-0	590.88	494.73	486.52	21600	494.73	30.31	0.00
O40-2-1-1	484.61	443.19	390.45	21600	434.04	36.80	2.06
O40-2-1-2	452.71	445.80	401.58	21600	445.80	34.44	0.00
O40-2-1-3	604.15	529.67	456.10	21600	523.35	36.44	1.19
O40-2-1-4	551.18	550.47	458.60	21600	549.35	37.96	0.20
O40-2-1-5	627.43	576.14	486.90	21600	573.11	34.70	0.53
O40-2-1-6	496.89	492.06	422.04	21600	489.14	39.24	0.59
O40-2-1-7	545.21	532.03	492.50	21600	528.80	31.72	0.61
O40-2-1-8	441.62	427.55	427.55	21600	427.55	32.20	0.00
O40-2-1-9	611.65	582.21	485.50	21600	578.85	37.98	0.58
Avg				21600		35.18	0.58
A40-2-1-0	595.16	581.93	463.33	21600	550.20	26.67	5.45
A40-2-1-1	617.54	617.54	428.57	21600	597.17	29.64	3.30
A40-2-1-2	685.71	593.58	508.05	21600	582.03	32.10	1.95
A40-2-1-3	511.22	511.22	383.62	21600	505.21	31.86	1.18
A40-2-1-4	574.55	569.49	460.72	21600	567.77	33.23	0.30

3 Shipper collaboration in forward and reverse logistics

Table 3-5(continued)

Instance	CPLEX			GRASP-ILS			
	Ini	LB	UB	CPU	Zmin	CPU	Imp _{Cplex}
A40-2-1-5	626.75	626.75	484.73	21600	617.34	28.18	1.50
A40-2-1-6	574.52	572.59	457.56	21600	537.91	32.50	6.06
A40-2-1-7	615.58	552.47	494.52	21600	542.06	30.23	1.88
A40-2-1-8	642.09	630.61	480.02	21600	600.61	27.93	4.76
A40-2-1-9	714.16	698.33	542.39	21600	632.33	27.06	9.45
Avg				21600		29.94	3.58
I60-2-1-0	1075.15	1011.77	647.03	21600	911.77	99.40	9.88
I60-2-1-1	1190.63	1187.76	774.42	21600	987.76	118.70	16.84
I60-2-1-2	950.96	939.23	602.05	21600	877.23	131.62	6.60
I60-2-1-3	1088.70	1082.44	690.16	21600	882.44	137.82	18.48
I60-2-1-4	1047.69	1000.73	685.00	21600	896.87	108.94	10.38
I60-2-1-5	1026.03	1026.03	632.75	21600	996.95	138.59	2.83
I60-2-1-6	1214.28	1143.88	758.39	21600	1043.88	119.96	8.74
I60-2-1-7	993.02	993.02	642.58	21600	944.32	132.32	4.90
I60-2-1-8	946.14	918.94	625.61	21600	818.94	132.87	10.88
I60-2-1-9	1029.63	965.24	687.93	21600	865.24	133.94	10.36
Avg				21600		125.42	9.99
O60-2-1-0	778.81	742.35	556.24	21600	652.35	146.37	12.12
O60-2-1-1	860.37	792.55	585.30	21600	746.22	144.23	5.85
O60-2-1-2	883.39	832.49	606.55	21600	732.49	138.82	12.01
O60-2-1-3	975.67	897.76	686.25	21600	787.76	128.96	12.25
O60-2-1-4	889.25	832.01	565.60	21600	727.32	159.57	12.58
O60-2-1-5	891.08	852.47	631.60	21600	752.74	150.60	11.70
O60-2-1-6	813.00	813.00	542.76	21600	680.46	129.71	16.30
O60-2-1-7	935.69	881.76	640.60	21600	752.96	162.61	14.61
O60-2-1-8	850.19	835.58	571.37	21600	695.58	134.58	16.75
O60-2-1-9	850.23	823.61	562.61	21600	723.61	152.90	12.14
Avg				21600		144.84	12.63
A60-2-1-0	936.24	936.24	594.70	21600	836.54	161.45	10.65
A60-2-1-1	1072.31	1072.31	663.76	21600	911.33	161.93	15.01
A60-2-1-2	859.84	803.79	620.37	21600	703.79	135.40	12.44
A60-2-1-3	950.17	881.73	663.68	21600	781.73	122.15	11.34
A60-2-1-4	912.08	902.08	622.80	21600	793.69	148.34	12.02
A60-2-1-5	908.24	908.24	611.25	21600	740.28	148.01	18.49
A60-2-1-6	919.06	854.71	676.50	21600	754.71	146.15	11.70
A60-2-1-7	942.98	880.28	647.62	21600	780.28	155.59	11.36
A60-2-1-8	799.61	799.61	594.75	21600	751.38	140.81	6.03
A60-2-1-9	817.71	776.45	553.61	21600	705.99	163.67	9.07
Avg				21600		148.35	11.81
I100-2-1-0	1735.62	1680.34	1041.47	21600	1500.16	242.56	10.72
I100-2-1-1	1651.57	1634.89	1015.27	21600	1399.61	244.23	14.39
I100-2-1-2	1668.99	1668.99	907.93	21600	1481.37	264.12	11.24
I100-2-1-3	1764.60	1689.42	1077.17	21600	1406.15	200.51	16.77

Table 3-5(continued)

Instance	CPLEX			GRASP-ILS			
	Ini	LB	UB	CPU	Zmin	CPU	Imp _{Cplex}
I100-2-1-4	1686.00	1686.00	985.47	21600	1471.77	231.05	12.71
I100-2-1-5	1700.66	1700.66	878.73	21600	1465.71	265.97	13.82
I100-2-1-6	1692.38	1691.53	1017.12	21600	1482.92	258.92	12.33
I100-2-1-7	1645.66	1645.66	900.34	21600	1439.77	227.63	12.51
I100-2-1-8	1505.41	1478.50	927.61	21600	1277.58	261.05	13.59
I100-2-1-9	1541.52	1460.33	987.62	21600	1286.29	267.15	11.92
Avg				21600		246.32	13.00
O100-2-1-0	1467.93	1420.49	950.02	21600	1215.92	278.27	14.40
O100-2-1-1	1309.79	1309.79	836.30	21600	1113.13	316.97	15.01
O100-2-1-2	1283.48	1230.45	831.54	21600	1066.12	254.79	13.36
O100-2-1-3	1284.46	1321.90	810.99	21600	1166.47	300.23	11.76
O100-2-1-4	1382.26	1338.36	909.82	21600	1146.62	287.89	14.33
O100-2-1-5	1494.38	1431.12	903.18	21600	1223.53	294.71	14.51
O100-2-1-6	1318.96	1264.83	831.75	21600	1062.43	311.91	16.00
O100-2-1-7	1435.95	1432.51	894.75	21600	1224.31	306.67	14.53
O100-2-1-8	1254.70	1221.48	779.18	21600	971.56	296.99	20.46
O100-2-1-9	1381.18	1339.26	866.90	21600	1098.25	278.80	18.00
Avg				21600		292.72	15.24
A100-2-1-0	1415.28	1404.33	863.94	21600	1212.68	235.67	13.65
A100-2-1-1	1696.07	1627.24	1168.36	21600	1271.73	269.87	21.85
A100-2-1-2	1328.88	1283.69	849.55	21600	1129.63	308.04	12.00
A100-2-1-3	1364.97	1360.34	865.59	21600	1162.85	263.527	14.52
A100-2-1-4	1433.15	1417.56	886.68	21600	1190.23	270.33	16.04
A100-2-1-5	1320.79	1320.79	802.64	21600	1093.48	267.46	17.21
A100-2-1-6	1450.78	1400.91	972.51	21600	1208.76	258.22	13.72
A100-2-1-7	1404.69	1371.23	920.23	21600	1174.24	364.28	14.37
A100-2-1-8	1334.8	1321.19	847.28	21600	1154.51	266.66	12.62
A100-2-1-9	1382.94	1365.60	918.36	21600	1217.18	320.42	10.87
Avg				21600		282.45	14.68

Summarized results for the meta-heuristic GRASP-ILS and CPLEX solver are presented in Table 3-6. We consider several performance indicators: Imp_{Ini} , Gap_{LB} , Imp_{Cplex} , and CPU .

For the instances with 20 requests, CPLEX solver and GRASP-ILS were able to find an optimal solution for each instance. CPLEX solver could obtain an optimal solution in 1509.55 seconds on average, whereas GRASP-ILS consumed much less CPU time to solve each instance to optimality (in 2.53 seconds on average).

For instances with 40 requests, 60 requests or 100 requests, we took the initial solution obtained by GRASP-ILS as an initial solution to CPLEX solver. As no proven optimal solution was obtained, we compare the best solutions of the two methods using the following three performance indicators: Imp_{Ini} , Gap_{LB} and Imp_{Cplex} and the running times of both methods. For the instances with 40 requests, we observe that GRASP-ILS could find a better

solution than CPLEX solver for all of the 30 instances. CPLEX solver consumed 21600.00 seconds on average to improve the initial solution with an average improvement of 3.60% for the final solution. In contrast, our GRASP-ILS could achieve an average improvement of 6.52% in only 31.45 seconds. Furthermore, solutions obtained by GRASP-ILS are better than CPLEX solver with an average improvement of 3.11% in terms of cost.

When the number of requests increases to 60, the resolution of VRPPD-FRL becomes more difficult. The average gap Gap_{LB} for CPLEX solver increases to 30.46%. The improvement of the initial solution by GRASP-ILS increases quickly with the increase of the number of requests, reaching the value of 13.70%. In contrast, the improvement of the initial solution by CPLEX solver is only 3.62%. GRASP-ILS could achieve better solutions than CPLEX solver with an average improvement of 12.47% in terms of cost in 139.54 seconds of average computation time. For the instances with 100 requests, the average Gap_{LB} becomes 37.68%. The average improvement of the initial solution by GRASP-ILS increases to 19.16% in 273.83 seconds of average computation time. In contrast, the improvement of the initial solution by CPLEX solver is only 2.10% in 216,000 seconds of computation time.

Therefore, GRASP-ILS significantly outperforms CPLEX solver in terms of cost. Moreover, GRASP-ILS could generate a better solution in a much shorter time compared with CPLEX solver. Due to the NP-hard nature of VRPPD-FRL, CPLEX solver could not solve the problem in a reasonable time if it has more than 20 requests. On the contrary, GRASP-ILS performs well on larger instances.

Table 3-6 Summarized comparison results of GRASP-ILS and CPLEX solver

Instance	CPLEX			GRASP-ILS			
	Imp_{Ini}	Gap_{LB}	CPU	Imp_{Ini}	Imp_{Cplex}	Gap_{LB}	CPU
I20	---	0.00	2101.07	---	0.00	0.00	3.17
O20	---	0.00	1077.42	---	0.00	0.00	1.92
A20	---	0.00	1350.15	---	0.00	0.00	2.49
Avg		0.00	1509.55		0.00	0.00	2.53
I40	1.44	28.47	21600.00	6.57	5.18	24.58	29.22
O40	6.02	10.78	21600.00	6.37	0.58	10.27	35.18
A40	3.33	20.89	21600.00	6.61	3.58	17.91	29.94
Avg	3.60	20.05	21600.00	6.52	3.11	17.59	31.45
I60	2.74	34.25	21600.00	12.45	9.99	26.73	125.42
O60	4.77	28.38	21600.00	16.85	12.63	18.00	144.84
A60	3.35	28.74	21600.00	14.78	11.81	19.18	148.35
Avg	3.62	30.46	21600.00	13.70	12.47	21.30	139.54
I100	1.62	40.24	21600.00	16.85	13.00	31.27	246.32
O100	2.57	38.25	21600.00	21.11	15.24	23.55	292.72
A100	1.83	34.56	21600.00	19.52	14.68	23.17	282.45
Avg	2.01	37.68	21600.00	19.16	14.31	26.00	273.83

2) Comparison results among meta-heuristics

In this section, we compare results provided by GRASP-ILS with those of GRASP and ILS. By setting the parameter $ni=1$, GRASP-ILS is reduced to meta-heuristic GRASP. If np

is set to 1, we obtain an algorithm ILS with a single initial solution as its input. To be fair in the comparison, the running time is set the same for the three meta-heuristics for each instance. That is, the running time limit for both GRASP and ILS is set equal to the running time of GRASP-ILS for each instance. Detailed results for comparison of the three meta-heuristics for each set of instances tested are presented in Table 3-7.

Table 3-7 Computational results for GRASP-ILS, GRASP and ILS

Instance	GRASP		ILS		GRASP-ILS		
	Zmin	Zavg	Zmin	Zavg	Zmin	Imp _{GRASP}	Imp _{ILS}
I20-2-1-0	459.26	459.26	459.26	459.26	459.26	0.00	0.00
I20-2-1-1	449.88	449.88	366.66	366.66	366.66	22.70	0.00
I20-2-1-2	478.19	478.19	478.19	478.19	478.19	0.00	0.00
I20-2-1-3	449.29	459.44	360.24	415.28	360.24	24.72	0.00
I20-2-1-4	387.33	413.78	387.33	412.08	383.24	1.07	1.07
I20-2-1-5	364.89	370.22	364.89	373.59	343.70	6.17	6.17
I20-2-1-6	344.51	344.51	344.51	344.51	344.51	0.00	0.00
I20-2-1-7	379.50	407.70	426.47	479.74	354.59	7.03	20.27
I20-2-1-8	363.34	368.28	366.19	376.44	351.37	3.41	4.22
I20-2-1-9	476.32	476.32	476.32	494.04	476.32	0.00	0.00
Avg						6.51	3.17
O20-2-1-0	240.46	240.46	240.46	240.46	240.46	0.00	0.00
O20-2-1-1	261.02	261.02	278.50	278.56	260.84	0.07	6.77
O20-2-1-2	250.62	250.62	251.75	251.75	250.62	0.00	0.45
O20-2-1-3	254.79	254.79	254.79	254.79	254.79	0.00	0.00
O20-2-1-4	273.98	274.99	275.45	275.56	273.79	0.07	0.61
O20-2-1-5	269.61	269.61	269.61	269.61	269.61	0.00	0.00
O20-2-1-6	260.87	260.92	260.87	261.21	260.31	0.22	0.22
O20-2-1-7	245.95	246.37	246.97	246.97	245.95	0.00	0.41
O20-2-1-8	265.74	265.74	240.28	244.44	240.28	10.60	0.00
O20-2-1-9	247.82	247.97	230.15	235.51	229.92	7.79	0.10
Avg						1.87	0.86
A20-2-1-0	367.97	367.97	367.91	379.79	362.31	1.56	1.55
A20-2-1-1	444.8	444.80	444.80	444.80	444.80	0.00	0.00
A20-2-1-2	364.77	375.31	364.77	404.68	329.67	10.65	10.65
A20-2-1-3	412.44	439.21	423.93	456.66	363.62	13.43	16.59
A20-2-1-4	415.4	415.40	343.77	397.64	343.77	20.84	0.00
A20-2-1-5	295.37	297.82	299.91	305.22	287.74	2.65	4.23
A20-2-1-6	340.74	340.74	338.23	338.74	338.23	0.74	0.00
A20-2-1-7	298.51	304.03	301.26	304.94	290.21	2.86	3.81
A20-2-1-8	314.20	314.20	314.20	314.20	314.20	0.00	0.00
A20-2-1-9	400.40	400.40	323.60	361.33	323.60	23.73	0.00
Avg						7.65	3.68
I40-2-1-0	733.03	769.61	741.58	773.84	706.64	3.73	4.94
I40-2-1-1	617.81	617.81	610.54	675.38	600.90	2.81	1.60
I40-2-1-2	756.99	806.65	755.90	772.53	729.24	3.81	3.66
I40-2-1-3	651.55	681.20	718.16	718.16	651.55	0.00	10.22

3 Shipper collaboration in forward and reverse logistics

Table 3-7(continued)

Instance	GRASP		ILS		GRASP-ILS		
	Zmin	Zavg	Zmin	Zavg	Zmin	Imp _{GRASP}	Imp _{ILS}
I40-2-1-4	699.59	731.00	720.42	720.42	699.59	0.00	2.98
I40-2-1-5	718.38	761.48	672.90	771.28	647.36	10.97	3.95
I40-2-1-6	605.91	639.66	627.27	700.22	590.24	4.35	6.27
I40-2-1-7	653.35	653.35	612.68	686.02	612.68	6.64	0.00
I40-2-1-8	601.37	635.83	582.26	645.55	573.59	4.84	1.51
I40-2-1-9	612.71	654.01	610.28	677.78	598.44	2.38	1.98
Avg						3.95	3.71
O40-2-1-0	573.13	607.63	530.77	613.94	494.73	15.85	7.28
O40-2-1-1	451.96	479.67	476.94	535.79	434.04	4.13	9.88
O40-2-1-2	465.61	486.61	452.72	499.94	445.80	4.44	1.55
O40-2-1-3	523.35	523.35	523.35	523.35	523.35	0.00	0.00
O40-2-1-4	549.35	549.35	549.35	549.35	549.35	0.00	0.00
O40-2-1-5	577.85	601.43	603.35	666.88	573.11	0.83	5.28
O40-2-1-6	492.06	525.27	492.06	492.06	489.14	0.60	0.60
O40-2-1-7	545.21	550.93	545.21	545.21	528.80	3.10	3.10
O40-2-1-8	431.92	455.46	430.07	473.46	427.55	1.02	0.59
O40-2-1-9	579.27	602.79	601.79	668.05	578.85	0.07	3.96
Avg						3.00	3.23
A40-2-1-0	636.15	636.28	551.33	631.55	550.20	15.62	0.21
A40-2-1-1	606.64	644.56	616.86	622.47	597.17	1.59	3.30
A40-2-1-2	587.75	587.75	582.03	583.37	582.03	0.98	0.00
A40-2-1-3	506.85	506.85	508.34	559.68	505.21	0.32	0.62
A40-2-1-4	573.67	573.78	568.42	570.30	567.77	1.04	0.11
A40-2-1-5	683.98	697.73	617.34	703.95	617.34	10.79	0.00
A40-2-1-6	587.71	660.17	569.77	572.96	537.91	9.26	5.92
A40-2-1-7	615.47	645.69	605.92	703.23	542.06	13.54	11.78
A40-2-1-8	624.30	670.44	624.30	702.84	600.61	3.94	3.94
A40-2-1-9	697.84	724.57	697.60	816.89	632.33	10.36	10.32
Avg						6.75	3.62
I60-2-1-0	971.76	930.24	954.90	1040.17	911.77	6.58	4.73
I60-2-1-1	997.55	990.98	997.55	1070.57	987.76	0.99	0.99
I60-2-1-2	893.43	879.02	897.08	1033.44	877.23	1.85	2.26
I60-2-1-3	907.53	902.23	901.81	1008.95	882.44	2.84	2.20
I60-2-1-4	979.14	967.49	975.61	1121.17	896.87	9.17	8.78
I60-2-1-5	1004.53	997.95	1004.53	1065.50	996.95	0.76	0.76
I60-2-1-6	1061.43	1051.96	1056.81	1093.90	1043.88	1.68	1.24
I60-2-1-7	1005.16	981.49	950.37	1110.89	944.32	6.44	0.64
I60-2-1-8	882.39	854.26	854.36	965.17	818.94	7.75	4.33
I60-2-1-9	890.19	877.62	870.52	1028.26	865.24	2.88	0.61
Avg						4.09	2.65
O60-2-1-0	713.15	746.03	703.50	758.65	652.35	9.32	3.73
O60-2-1-1	820.25	872.50	782.50	820.53	746.22	9.92	0.55
O60-2-1-2	782.26	799.70	761.74	868.31	732.49	6.79	0.15

3 Shipper collaboration in forward and reverse logistics

Table 3-7(continued)

Instance	GRASP		ILS		GRASP-ILS		
	Zmin	Zavg	Zmin	Zavg	Zmin	Imp _{GRASP}	Imp _{ILS}
O60-2-1-3	847.18	875.98	820.05	853.67	787.76	7.54	0.52
O60-2-1-4	776.48	845.20	771.15	817.65	727.32	6.76	0.64
O60-2-1-5	820.66	851.19	763.93	844.07	752.74	9.02	0.40
O60-2-1-6	708.48	714.50	680.46	680.46	680.46	4.12	0.00
O60-2-1-7	816.27	830.39	781.70	811.56	752.96	8.41	1.16
O60-2-1-8	723.94	759.78	715.02	806.47	695.58	4.08	0.00
O60-2-1-9	783.28	871.56	747.26	771.70	723.61	8.25	0.18
Avg						7.42	0.73
A60-2-1-0	858.31	858.31	836.63	929.83	836.54	2.60	0.01
A60-2-1-1	956.96	1024.04	952.71	1049.60	911.33	5.01	4.54
A60-2-1-2	719.41	741.14	776.51	778.37	703.79	2.22	10.33
A60-2-1-3	849.45	928.96	802.22	912.04	781.73	8.66	2.62
A60-2-1-4	857.32	880.81	841.54	899.44	793.69	8.02	6.03
A60-2-1-5	808.57	830.08	761.17	803.11	740.28	9.22	2.82
A60-2-1-6	803.29	862.81	803.29	871.89	754.71	6.44	6.44
A60-2-1-7	853.23	853.23	802.72	905.31	780.28	9.35	2.88
A60-2-1-8	780.61	815.35	772.43	843.73	751.38	3.89	2.80
A60-2-1-9	763.12	795.25	762.09	825.88	705.99	8.09	7.95
Avg						6.35	4.64
I100-2-1-0	1638.35	1704.61	1609.09	1890.61	1500.16	9.21	7.26
I100-2-1-1	1475.76	1550.51	1462.03	1720.88	1399.61	5.44	4.46
I100-2-1-2	1549.56	1714.37	1519.43	1792.65	1481.37	4.60	2.57
I100-2-1-3	1541.71	1630.81	1516.8	1799.58	1406.15	9.64	7.87
I100-2-1-4	1586.41	1607.53	1501.97	1774.75	1471.77	7.79	2.05
I100-2-1-5	1547.53	1591.87	1476.42	1763.20	1465.71	5.58	0.73
I100-2-1-6	1594.07	1622.95	1501.05	1791.06	1482.92	7.50	1.22
I100-2-1-7	1568.12	1653.99	1508.18	1741.59	1439.77	8.91	4.75
I100-2-1-8	1340.87	1424.62	1358.42	1513.15	1277.58	4.95	6.33
I100-2-1-9	1393.89	1430.99	1346.03	1604.42	1286.29	8.37	4.64
Avg						7.20	4.19
O100-2-1-0	1279.18	1347.70	1252.87	1352.97	1215.92	5.20	3.04
O100-2-1-1	1169.86	1255.83	1149.36	1236.94	1113.13	5.10	3.25
O100-2-1-2	1123.63	1191.98	1098.08	1156.11	1066.12	5.39	3.00
O100-2-1-3	1272.18	1320.34	1209.93	1297.75	1166.47	9.06	3.73
O100-2-1-4	1278.7	1376.42	1206.94	1273.12	1146.62	11.52	5.26
O100-2-1-5	1282.2	1310.21	1264.78	1444.76	1223.53	4.80	3.37
O100-2-1-6	1112.92	1195.06	1099.75	1266.59	1062.43	4.75	3.51
O100-2-1-7	1271.97	1338.24	1231.68	1310.19	1224.31	3.89	0.60
O100-2-1-8	1071.1	1141.54	1000.51	1190.17	971.56	10.25	2.98
O100-2-1-9	1163.25	1211.45	1197.58	1339.77	1098.25	5.92	9.04
Avg						6.59	3.78
A100-2-1-0	1280.19	1361.66	1265.52	1359.89	1212.68	5.57	4.36
A100-2-1-1	1362.77	1431.84	1362.04	1541.04	1271.73	7.16	7.10

Table 3-7(continued)

Instance	GRASP		ILS		GRASP-ILS		
	Zmin	Zavg	Zmin	Zavg	Zmin	Imp _{GRASP}	Imp _{ILS}
A100-2-1-2	1183.91	1240.90	1159.67	1326.68	1129.63	4.81	2.66
A100-2-1-3	1214.65	1288.61	1198.17	1355.01	1162.85	2.73	3.04
A100-2-1-4	1236.76	1325.19	1243.54	1400.64	1190.23	3.91	4.48
A100-2-1-5	1177.71	1241.31	1144.83	1228.66	1093.48	7.70	4.70
A100-2-1-6	1270.56	1328.54	1256.54	1336.74	1208.76	5.11	3.95
A100-2-1-7	1227.98	1308.64	1221.57	1316.30	1174.24	4.58	4.03
A100-2-1-8	1210.54	1298.73	1192.27	1288.85	1154.51	3.99	3.27
A100-2-1-9	1271.11	1320.95	1253.95	1419.94	1217.18	4.43	3.02
Avg						5.00	4.06

Summarized results for comparison of the three meta-heuristics for each set of instances tested are presented in Table 3-8. In Table 3-8, the three meta-heuristics are compared by the following two performance indicators: $Imp_{GRASP-ILS,GRASP}$, $Imp_{GRASP-ILS,ILS}$. For the instances with 20 requests, GRASP-ILS is more effective than GRASP and ILS with an average improvement of 5.34% and 2.57%, respectively, in terms of cost. When the number of requests increases to 40, GRASP-ILS could obtain better solutions than GRASP and ILS with an average improvement of 4.57% and 3.52%, respectively. For the instances with 60 requests, GRASP-ILS could achieve the largest improvement with 5.95% compared with GRASP, and could obtain better solutions than ILS with an average improvement of 2.67%. When the number of requests increases to 100, GRASP-ILS could obtain better solutions than GRASP and ILS with an average improvement of 6.26% and 4.01%, respectively. In summary, GRASP-ILS significantly outperforms GRASP and ILS for all instances tested with the same computation time.

Table 3-8 Summarized comparison results of GRASP-ILS, GRASP and ILS

Instance set	$Imp_{GRASP-ILS,GRASP}$	$Imp_{GRASP-ILS,ILS}$
I20	6.51	3.17
O20	1.87	0.86
A20	7.65	3.68
Avg	5.34	2.57
I40	3.95	3.71
O40	3.00	3.23
A40	6.75	3.62
Avg	4.57	3.52
I60	4.09	2.65
O60	7.42	0.73
A60	6.35	4.64
Avg	5.95	2.67
I100	7.20	4.19
O100	6.59	3.78
A100	5.00	4.06
Avg	6.26	4.01

All the three meta-heuristic methods contain random factors. In order to analyze the robustness of each method facing its random factors, we also give the statistics of the standard deviation of the costs in 10 runs obtained by each method in Table 3-9.

Table 3-9 Summarized results of deviations among GRASP-ILS, GRASP and ILS

Instance set	GRASP	ILS	GRASP-ILS
	Dev	Dev	Dev
I20	1.93	4.31	0.37
O20	0.26	0.43	0.01
A20	1.21	5.23	0.76
Avg	1.13	3.32	0.38
I40	4.46	7.73	0.42
O40	3.81	7.01	0.44
A40	3.68	8.65	0.89
Avg	3.98	7.80	0.58
I60	6.92	11.58	0.51
O60	4.80	6.72	0.81
A60	4.09	8.66	0.92
Avg	5.27	8.99	0.75
I100	7.04	12.38	0.88
O100	5.25	8.96	1.16
A100	5.40	9.31	1.12
Avg	5.90	10.22	1.05

From this table, GRASP has an average deviation of 1.13% for 20 requests instances, 3.98% for 40 requests instances 5.27% for 60 requests instances and 5.90% for 100 requests instances. It is more robust than ILS with an average deviation of 3.32% for 20 requests instances, 7.80% for 40 requests instances, 8.89% for 60 requests instances and 10.22% for 100 requests. Combing GRASP and ILS makes GRASP-ILS more robust than both GRASP and ILS, with an average deviation of 0.38%, 0.58%, 0.75% and 1.05% for the four sets of instances, respectively. From the results in Table 3-11, we can conclude that GRASP-ILS is robust and can find high quality solutions for instances of different sizes.

3.4.4 Cost savings for shipper collaboration

In this section, we analyse the effect of geographical distributions of customers of the shippers and the number of requests on the cost savings of collaboration. We use the performance indicators N_v and ϕ to denote the number of vehicles used in each case and the cost savings in percentage achieved by the collaboration among the shippers.

We present summarized results of the effect of geographical distributions of customers of the shippers and the number of requests on the collaborative cost savings in Table 3-10 and Table 3-11 respectively. Detailed results for comparison of collaboration and non-collaboration are shown in Table 3-12.

In Table 3-10, the average values of ϕ for the instance sets I , O and A with 20 requests are 22.57%, 17.90%, and 10.76%, respectively, while the change of the average

value of ϕ has the same trend for the instances with 40 requests, the instances with 60 requests and the instances with 100 requests. From the statistical results, we can find that the instances with a higher overlapping of customer regions always lead to a higher collaboration gain than the instances with a lower overlapping of the regions, and the collaboration benefit decreases constantly from instance set *I* to *O* and from instance set *O* to set *A*. In summary, the collaboration among multiple manufacturers and remanufacturers has a higher potential when their customer areas are the same or overlap.

Table 3-10 Summarized results of the impact of customer geographical distributions on cost savings

Geographical distributions of customers	Non-collaboration	Collaboration	ϕ
	<i>N_v</i>	<i>N_v</i>	Dev
I20	4.3	2.3	22.57
O20	4.1	2	17.90
A20	4.2	2.1	10.76
I40	8	6	31.02
O40	7.3	3.5	24.19
A40	7.5	3.9	16.35
I60	11	6.3	33.31
O60	10.1	4.9	28.22
A60	10.1	5.2	24.42
I100	17.8	9.8	41.37
O100	14.1	8.4	33.79
A100	13.8	8.7	30.96

Table 3-11 Summarized results of the impact of the number of requests on cost savings

Customer Requests	Non-collaboration	Collaboration	ϕ
	<i>N_v</i>	<i>N_v</i>	Dev
I20	4.3	2.3	22.57
I40	8	6	31.02
I60	11	6.3	33.31
I100	17.8	9.8	41.37
Avg	4.2	2.1	17.08
O20	4.1	2	17.90
O40	7.3	3.5	24.19
O60	10.1	4.9	28.22
O100	14.1	8.4	33.79
Avg	7.6	4.4	23.85
A20	4.2	2.1	10.76
A40	7.5	3.9	16.35
A60	10.1	5.2	24.42
A100	13.8	8.7	30.96
Avg	10.4	5.5	28.65

Table 3-11 shows the effect of the number of requests on the collaboration gain. We can

observe an increase in percentage cost savings when comparing the costs of the instances with 20 requests and those with 40 requests for the same type of geographical distributions of customers of the shippers. The same observation can be obtained for comparison between the instances with 40 requests, the instances with 60 requests and the instances with 100 requests. For example, for the same type of geographical distributions of customers, the average cost savings in percentage achieved by the collaboration among shippers are: 22.57%, 31.02%, 33.31% and 41.37%, respectively. This implies that, the more requests participated in the collaboration among shippers, the higher their collaboration gain is. The more the customers of the shippers are clustering, the higher their cost savings are.

From Table 3-10 and Table 3-11, we find that with the collaboration, the number of vehicles used by all shippers is almost reduced to half of the total number of vehicles used by them without collaboration on average. This implies that collaborative transportation planning among manufacturers with forward logistics and remanufacturers with reverse logistics can significantly improve the vehicle fill rates and reduce their logistics costs.

Table 3-12 Cost savings for instances of different sizes

Instance	Non-collaboration		Collaboration		ϕ
	Cost	N_v	Cost	N_v	
I20-2-1-0	528.74	5	459.26	3	13.14
I20-2-1-1	477.54	4	366.66	2	23.22
I20-2-1-2	612.48	4	478.19	3	21.93
I20-2-1-3	481.75	4	360.24	2	25.22
I20-2-1-4	491.83	4	383.24	2	22.08
I20-2-1-5	427.16	4	343.7	2	19.54
I20-2-1-6	453.01	5	344.51	2	23.95
I20-2-1-7	476.59	4	354.59	2	25.60
I20-2-1-8	484.62	4	351.37	2	27.50
I20-2-1-9	622.55	5	476.32	3	23.49
Avg		4.3		2.3	22.57
O20-2-1-0	283.63	4	240.46	2	15.22
O20-2-1-1	299.27	4	260.84	2	12.84
O20-2-1-2	336.31	4	250.62	2	25.48
O20-2-1-3	316.26	4	254.79	2	19.44
O20-2-1-4	329.42	5	273.79	2	16.89
O20-2-1-5	323.26	4	269.61	2	16.60
O20-2-1-6	293.28	4	260.31	2	11.24
O20-2-1-7	348.76	4	245.95	2	29.48
O20-2-1-8	296.46	4	240.28	2	18.95
O20-2-1-9	263.93	4	229.92	2	12.89
Avg		4.1		2	17.90
A20-2-1-0	403.54	4	362.31	2	10.22
A20-2-1-1	494.62	4	444.8	3	10.07
A20-2-1-2	383.46	5	329.67	2	14.03
A20-2-1-3	410.31	5	363.62	2	11.38
A20-2-1-4	386.48	4	343.77	2	11.05

3 Shipper collaboration in forward and reverse logistics

Table 3-12(continued)

Instance	Non-collaboration		Collaboration		ϕ
	Cost	N_v	Cost	N_v	
A20-2-1-5	302.36	4	287.74	2	4.83
A20-2-1-6	371.57	4	338.23	2	8.97
A20-2-1-7	333.01	4	290.21	2	12.85
A20-2-1-8	358.15	4	314.2	2	12.27
A20-2-1-9	367.36	4	323.6	2	11.91
Avg		4.2		2.1	10.76
I40-2-1-0	1021.39	8	706.64	6	30.82
I40-2-1-1	861.87	8	600.90	6	30.28
I40-2-1-2	1006.32	8	729.24	6	27.53
I40-2-1-3	943.17	8	651.55	6	30.92
I40-2-1-4	1062.08	8	699.59	6	34.13
I40-2-1-5	930.23	8	647.36	6	30.41
I40-2-1-6	874.73	8	590.24	6	32.52
I40-2-1-7	910.38	8	612.68	6	32.70
I40-2-1-8	841.23	8	573.59	6	31.82
I40-2-1-9	843.80	8	598.44	6	29.08
Avg		8		6	31.02
O40-2-1-0	650.32	7	494.73	3	23.93
O40-2-1-1	574.51	7	434.04	3	24.45
O40-2-1-2	578.02	7	445.80	3	22.87
O40-2-1-3	692.40	8	523.35	4	24.42
O40-2-1-4	749.51	7	549.35	4	26.71
O40-2-1-5	750.72	8	573.11	4	23.66
O40-2-1-6	636.65	7	492.06	4	22.71
O40-2-1-7	734.12	7	528.80	3	27.97
O40-2-1-8	553.40	7	427.55	3	22.74
O40-2-1-9	746.28	8	578.85	4	22.43
Avg		7.3		3.5	24.19
A40-2-1-0	686.52	8	550.2	4	19.86
A40-2-1-1	730.78	7	597.17	4	18.28
A40-2-1-2	708.31	8	582.03	4	17.83
A40-2-1-3	662.45	8	505.21	4	23.74
A40-2-1-4	667.54	8	567.77	4	14.95
A40-2-1-5	714.79	7	617.34	4	13.63
A40-2-1-6	610.43	7	537.91	3	11.88
A40-2-1-7	639.30	7	542.06	4	15.21
A40-2-1-8	695.09	7	600.61	4	13.59
A40-2-1-9	739.69	8	632.33	4	14.51
Avg		7.5		3.9	16.35
I60-2-1-0	1405.67	11	911.77	6	35.14
I60-2-1-1	1466.10	10	987.76	7	32.63
I60-2-1-2	1326.57	12	877.23	6	33.87
I60-2-1-3	1381.98	12	882.44	6	36.15
I60-2-1-4	1341.28	11	896.87	5	33.13

3 Shipper collaboration in forward and reverse logistics

Table 3-12(continued)

Instance	Non-collaboration		Collaboration		ϕ
	Cost	N_v	Cost	N_v	
I60-2-1-5	1438.62	11	996.95	7	30.70
I60-2-1-6	1575.24	13	1043.88	7	33.73
I60-2-1-7	1384.43	10	944.32	6	31.79
I60-2-1-8	1245.97	10	818.94	5	34.27
I60-2-1-9	1266.52	10	865.24	8	31.68
Avg		11		6.3	33.31
O60-2-1-0	920.63	8	652.35	5	29.14
O60-2-1-1	1049.04	11	742.55	4	29.22
O60-2-1-2	1092.15	11	732.49	5	32.93
O60-2-1-3	1083.86	11	787.76	5	27.32
O60-2-1-4	1031.74	11	727.32	5	29.51
O60-2-1-5	981.97	10	752.74	5	23.34
O60-2-1-6	956.39	9	680.46	5	28.85
O60-2-1-7	1052.40	11	752.96	5	28.45
O60-2-1-8	977.50	9	695.58	5	28.84
O60-2-1-9	959.39	10	723.61	5	24.58
Avg		10.1	4.9	4.9	28.22
A60-2-1-0	1133.63	11	836.54	6	26.21
A60-2-1-1	1187.66	10	911.33	6	23.27
A60-2-1-2	956.53	10	703.79	5	26.42
A60-2-1-3	969.58	10	781.73	5	19.37
A60-2-1-4	1074.74	10	793.69	5	26.15
A60-2-1-5	984.88	9	740.28	5	24.84
A60-2-1-6	999.87	10	754.71	5	24.52
A60-2-1-7	1061.10	11	780.28	5	26.46
A60-2-1-8	962.43	11	751.38	5	21.93
A60-2-1-9	941.98	9	705.99	5	25.05
Avg		10.1	5.2	5.2	24.42
A40-2-1-0	686.52	8	550.2	4	19.86
A40-2-1-1	730.78	7	597.17	4	18.28
A40-2-1-2	708.31	8	582.03	4	17.83
A40-2-1-3	662.45	8	505.21	4	23.74
A40-2-1-4	667.54	8	567.77	4	14.95
A40-2-1-5	714.79	7	617.34	4	13.63
A40-2-1-6	610.43	7	537.91	3	11.88
A40-2-1-7	639.30	7	542.06	4	15.21
A40-2-1-8	695.09	7	600.61	4	13.59
A40-2-1-9	739.69	8	632.33	4	14.51
Avg		7.5		3.9	16.35
I100-2-1-0	2741.02	20	1500.16	10	45.27
I100-2-1-1	2308.06	17	1399.61	10	39.36
I100-2-1-2	2634.95	19	1481.37	10	43.78
I100-2-1-3	2517.73	18	1406.15	10	44.15
I100-2-1-4	2275.46	17	1471.77	9	35.32

Table 3-12 (continued)

Instance	Non-collaboration		Collaboration		ϕ
	Cost	N_v	Cost	N_v	
I100-2-1-5	2393.39	17	1465.71	10	38.76
I100-2-1-6	2635.37	19	1482.92	10	43.73
I100-2-1-7	2628.76	19	1439.77	10	45.23
I100-2-1-8	1910.26	15	1277.58	9	33.12
I100-2-1-9	2337.01	17	1286.29	10	44.96
Avg		17.8		9.8	41.37
O100-2-1-0	1791.81	15	1215.92	9	32.14
O100-2-1-1	1692.20	14	1113.13	8	34.22
O100-2-1-2	1690.38	14	1066.12	8	36.93
O100-2-1-3	1803.45	15	1166.47	9	35.32
O100-2-1-4	1641.55	14	1146.62	9	30.15
O100-2-1-5	1924.70	15	1223.53	9	36.43
O100-2-1-6	1606.09	14	1062.43	8	33.85
O100-2-1-7	1786.01	14	1224.31	9	31.45
O100-2-1-8	1538.25	13	971.56	7	36.84
O100-2-1-9	1582.04	13	1098.25	8	30.58
Avg		14.1		8.4	33.79
A100-2-1-0	1760.57	14	1212.68	9	31.12
A100-2-1-1	1809.52	15	1271.73	9	29.72
A100-2-1-2	1717.81	14	1129.63	8	34.24
A100-2-1-3	1497.94	10	1162.85	8	22.37
A100-2-1-4	1611.69	14	1190.23	9	26.15
A100-2-1-5	1613.52	14	1093.48	8	32.23
A100-2-1-6	1895.50	15	1208.76	9	36.23
A100-2-1-7	1764.98	14	1174.24	8	33.47
A100-2-1-8	1764.23	14	1154.51	9	34.56
A100-2-1-9	1727.48	14	1217.18	10	29.54
Avg		13.8		8.7	30.96

3.5 Brief summary

In this chapter, we study shipper collaboration in forward and reverse logistics, in which multiple shippers with forward or/and reverse logistics operations consolidate their transportation requests in order to reduce their empty vehicle repositions and improve their vehicle fill rates. In the forward and reverse logistics, manufacturers deliver new products to their customers, and used products are collected from customers and transported to remanufacturers for repair or reproduction. As there are three types of depots involved in this problem: product depots, vehicle depots and recycle depots, the vehicle routing problem with pickup and delivery requests in forward and reverse logistics (VRPPD-FRL) we have considered is a new variant of pickup and delivery problem. As exact methods cannot solve it in a reasonable time, we propose a meta-heuristic GRASP-ILS to find a near optimal solution for this problem. To evaluate the performance of GRASP-ILS, we compare it with

CPLEX solver, GRASP and ILS. Compared with CPLEX solver, GRASP-ILS can find better solutions in a much shorter computation time. Compared with GRASP and ILS, our hybrid approach GRASP-ILS outperforms both of them in terms of solution quality and the robustness facing random factors in the algorithm. To demonstrate the potential of collaboration, we compare the total transportation cost of the shippers with collaboration and that without collaboration. With the collaboration, the cost savings in percentage can achieve 17.08%, 23.85% and 28.65%, respectively for the instances with different degrees of overlapping of customer areas of the shippers and different problem sizes. Moreover, with the collaboration, the average number of vehicles used by the shippers is almost reduced to half of the number of vehicles used by them without collaboration on average.

4 A multi-round exchange mechanism for carrier collaboration in less than truckload transportation

4.1 Introduction

With the development of e-commerce, shorter cycles of delivery orders and higher customer expectations make small parcel logistic providers seek creative and innovative solutions. One such innovative solution is collaborative transportation in last-mile delivery. Carriers/shippers can achieve the economies of scale by sharing parcel deliveries and transportation resources, in order to reduce transportation costs and capture more business opportunities. For example, the Belgian and Dutch posts have both launched collaborative city logistics projects, in which Fedex, UPS, and USPS consolidate parcels together to provide last-mile service. The Belgian Post, which started its project in 2014, estimates it saves about 30% of the total miles driven (Multichannel Merchant, 2015).

In this chapter, we focus on carrier collaboration, in which an alliance with multiple carriers who provide similar transportation services in a fixed geographic area is formed to exchange self-owned transportation requests to increase profit and optimize the utilization of transportation resources. In this chapter, we propose an iterative request exchange mechanism for carriers to select their requests to offer to other carriers and the requests to acquire from other carriers with limited sharing of transportation cost information. In each iteration, each carrier as a seller first provides multiple bundles of requests to offer and determines their corresponding transfer payments by solving a selective pickup and delivery problem with profits. This decision problem is referred to as outsourcing bundles selection problem. Each carrier as a buyer then determines which bundles of requests to acquire from one or multiple carriers by solving a selective pickup and delivery problem with clusters of requests and profits. This problem is called insourcing bundles selection problem. Here, a carrier outsources a bundle of requests means that it offers this bundle to other carriers and a carrier insources a bundle of requests means that it acquires this bundle from other carriers. Based on the offers and demands submitted by all carriers, the mechanism reassigns (exchanges) some bundles of requests among carriers by solving a winner determination problem. The request exchange process iterates until a certain criterion is reached. In each iteration, each carrier updates its outsourcing bundles of requests based on the feedback information from previous iterations. Numerical experiments on a large set of benchmark instances show that this multi-round exchange mechanism significantly outperforms the auction mechanisms in the literature.

Compared with the auction mechanisms proposed by Berger and Bierwirth (2010), the main contribution of this paper is in three aspects: 1) Each carrier can outsource (offer) multiple bundles of requests to other carriers and each carrier can insource (acquire) more than one bundle of requests from multiple other carriers in each iteration of our exchange mechanism. 2) In our mechanism, each carrier updates the outsourcing price of each request

based on the information from previous iterations, which allows it to select different outsourcing bundles in different iterations. 3) Numerical experiments show that our mechanism significantly outperforms two auction mechanisms proposed by Berger and Bierwirth (2010) and Gansterer, M., & Hartl (2016) with the average improvement of 11.80% in terms of the total profit of all carriers. With possibly insourcing (acquiring) requests from multiple other carriers, our mechanism can bring more profit to the carrier alliance than the mechanisms which insource requests only from one carrier.

The remainder of this chapter is organized in the following structure: Section 4.2 describes the problem studied and notations used and presents an iterative multi-round request exchange mechanism. In Section 4.3, decision problems in the request exchange mechanism are formulated. In Section 4.4, we conduct computational experiments and analyze the results. We end this paper with the conclusion in Section 4.5.

4.2 Problem description and request exchange mechanism

In this chapter, we consider a carrier collaboration problem in LTL transportation, where a set of multiple carriers denoted by M collaborate with each other by exchanging some of their transportation requests. Before collaboration, each carrier $l \in M$ operates a fleet of homogeneous vehicles denoted by K_l with the capacity of each vehicle Q_l to serve its pickup and delivery requests R_l . The set of nodes to be visited by the vehicles of each carrier including its depot node is defined as N_l . Each node $i \in N_l$ has a time window $[a_{l,i}, b_{l,i}]$ to begin servicing its corresponding request (pickup or delivery), while each edge (i, j) has a travel cost c_{ij}^l and a travel time t_{ij}^l . The subset P_l of N_l contains the pickup nodes of all requests for each carrier $l \in M$, while the subset D_l includes the delivery nodes of all requests of carrier $l \in M$. Request $i \in R_l$ is associated with a pickup/delivery quantity $d_{l,i}$ and an amount of revenue $p_{l,i}$. The revenue of a request is the price paid by a shipper to the carrier serving the request.

In the iterative request exchange mechanism to be proposed in Section 4, each carrier solves a request outsourcing problem and a request insourcing problem in each iteration. Both problems are vehicle routing problems. Some parameters of these problems for each carrier are listed below.

Notations:

- M The set of carriers in the alliance
- R_l The set of requests of carrier $l \in M$
- P_l The set of pickup nodes of carrier $l \in M$
- D_l The set of delivery nodes of carrier $l \in M$
- N_l The node set of each carrier $l \in M$
- $d_{l,i}$ The quantity delivered on request $i \in R_l$

- $a_{l,i}$ The earliest time for a vehicle to start service at node $i \in N_l$
 $b_{l,i}$ The latest time for a vehicle to start service at node $i \in N_l$
 K_l The set of vehicles owned by carrier $l \in M$
 c_{ij}^l The transportation cost from node $i \in N_l$ to node $j \in N_l$ for each vehicle
of carrier $l \in M$
 t_{ij}^l The traveling time from node $i \in N_l$ to node $j \in N_l$ for each vehicle of
carrier $l \in M$

We design a multi-round exchange mechanism for LTL carrier collaboration. In this auction, each carrier sequentially decides the requests to outsource (sell) as a seller and the requests to insource (buy) as a buyer. The mechanism then matches the offers and the demands of all carriers and reassigns some bundles of requests among them with limited information sharing. In our exchange mechanism, we allow multiple bundles of requests to be exchanged in each round of the auction, each carrier can outsource multiple requests to multiple carriers and each carrier can insource multiple requests from multiple carriers. Our multi-round exchange mechanism can be outlined in Algorithm 4-1.

Algorithm 4-1: Procedure of the request exchange mechanism

- 1 **Do**
 - 2 Each carrier determines bundles of outsourcing requests
 - 3 Each carrier determines bundles of insourcing requests
 - 4 The auctioneer solves the WDP problem to reassign bundles of requests among carriers
 - 5 **If** the offer matches with the demand for each exchangeable bundle of requests
 - 6 Update the individual profit and request set of each carrier
 - 7 **Else**
 - 8 Update the bundles of outsourcing requests by each carrier, and go to **Step2**
 - 9 **While** (the stopping criterion is not satisfied)
-

The main steps of our multi-round exchange mechanism are described as follows:

Step 1 (Express the willing of request outsourcing). Each carrier provides multiple bundles of requests to offer and their corresponding transfer payments by solving a selective pickup and delivery problem with profits. The transfer payment of each bundle indicates the maximum amount of price the offering carrier is willing to pay to outsource the bundle. The information of the outsourcing bundles of requests of each carrier is transmitted to the auctioneer. After receiving all information about outsourcing bids of requests and their transfer payments submitted by carriers, the auctioneer reveals the information to all carriers in the alliance.

Step 2 (Bid for requests to insource). Each carrier determines which bundles of requests to acquire (insource) from one or multiple carriers by solving a selective pickup and delivery problem with clusters of requests and profits. The information about the insourcing bundles of each carrier is submitted to the auctioneer.

Step 3 (Winner determination). Based on the offers and demands of bundles of requests

submitted by all carriers, the mechanism reassigns (exchanges) some bundles of requests among carriers by solving a winner determination problem.

Step 4 (Verify the stopping condition): Check whether a certain stopping criterion is satisfied. If yes, the request exchange process will stop. Otherwise, go to Step 1 with information from previous iterations.

4.2.1 Adjustment of the parameter for selecting outsourcing requests

To further explore the collaboration potential, the selection of outsourcing requests plays an important role in our multi-round mechanism. To increase the collaboration possibilities by allowing carriers to have more flexibility to select requests to outsource, we adopt a parameter α , the minimum profit margin, to influence whether a request is selected as an outsourcing request. According to Dai and Chen (2011), the minimum profit margin α for a carrier represents its profitability expectation for each request in percentage of the request's price provided by a supplier. For example, for a request i of the carrier, let p_i denotes the price paid by a shipper to the carrier for serving request i . Since the carrier wants to achieve a minimum profit margin α , its least profit to gain by serving the request is $\alpha \cdot p_i$.

Note that each carrier updates its outsourcing bundles of requests based on the feedback information from previous iterations. Each carrier $l \in M$ adjusts the value of α_l based on the matching results of offers and demands determined by the auction mechanism. With different values of α_l , the carrier determines different requests to outsource. Each carrier has a low profitability expectation of his requests with high marginal costs and a high profitability expectation of his requests with low marginal costs. Each carrier prefers to outsource the requests with large self-fulfillment costs whose marginal cost for each request is higher than the price paid by a shipper to the carrier (Berger and Bierwirth, 2010; Li, Rong, and Feng, 2015; Gansterer and Hartl, 2016). In order to make the requests with high marginal costs attractive to other carriers, each carrier $l \in M$ can set the initial value of α , denoted by α_l^0 , to a small value, which represents a low profitability expectation of his requests with high marginal costs. If there is no demands from other carriers for the outsourcing requests of carrier $l \in M$, and carrier l does not acquire any request from other carriers, carrier l increases the value of his parameter α_l with the step size δ to select different bundles of requests to outsource for the next round of the auction. Otherwise, carrier $l \in M$ preserves the same value of α_l as that in the previous iteration.

Formally, the value of parameter α for carrier $l \in M$ is updated in the following way:

$$\alpha_l^{k+1} = \begin{cases} \alpha_l^k + \delta & \text{if } w_l^- = 0 \text{ and } w_l^+ = 0 \\ \alpha_l^k & \text{if } w_l^- = 1 \text{ or } w_l^+ = 1 \end{cases} \quad (4-1)$$

where α_l^k is the value of α in iteration k of the auction.

In (4-1), w_l^-, w_l^+ are two binary variables of WDP, indicating whether carrier $l \in M$ outsources bundles of requests to other carriers and whether it insources bundles of requests

from other carriers, respectively. In each iteration, if a request outsourcing offer from carrier $l \in M$ has a demand of request insourcing from other carriers or a request insourcing demand of carrier $l \in M$ has a request outsourcing offer from other carriers, the value of α_l^{k+1} is the same as α_l^k . Otherwise, the value of α_l^{k+1} is increased with the step size δ .

4.2.2 Transfer payment rule

In this exchange mechanism, the auctioneer collects the transfer payments from the sellers and transfers them to the buyers after a request exchange. The transfer payment of a bundle of requests is the maximum amount of money the bundle's offering carrier is willing to pay to other carriers to serve all requests in the bundle.

In order to make a bundle of requests more attractive to other carriers, we introduce a profit sharing mechanism which allows a carrier to share part of the profit it can gain from outsourcing a bundle of requests with another carrier who insources this bundle, in the determination of the transfer payment of this bundle. Including such side payments can make carriers able to identify more profitable request exchanges (Özener, Ergun, and Savelsbergh, 2011). This makes our determination of transfer payment different from that of Dai and Chen (2010). We use parameter $(1-\beta_l)$ to represent the percentage of the profit generated by outsourcing a bundle of requests that carrier $l \in M$ is willing to share with another carrier. With such side payment and the parameter β , the transfer payment OP_{O_l} for outsourcing a bundle of requests O_l by carrier $l \in M$ is determined by the following rule (equation).

$$OP_{O_l} = \sum_{i \in O_l} p_i (1 - \alpha_l) + B_{O_l}^- \cdot (1 - \beta_l), \alpha_l, \beta_l \in [0,1] \quad (4-2)$$

Where $B_{O_l}^-$ denotes the profit increment of carrier $l \in M$ after outsourcing a bundle of requests O_l .

As a seller, each carrier $l \in M$ tries to outsource a bundle of request O_l with a transfer payment OP_{O_l} . From notations described above, we know that p_i is the price for each request $i \in O_l$. In Equation (4-2), $(1-\alpha_l)$ is the maximum percentage profit gain that carrier $l \in M$ is willing to offer to other carriers and $(1-\beta_l)$ indicates the percentage profit gain that carrier $l \in M$ is willing to share with another carrier.

Sharing the profit gain equally provides a reasonable balance between the risk of rejection by the other carrier and the benefit of a request exchange (Özener, Ergun, and Savelsbergh, 2011). For this reason, we assume $\beta_l = 1/2$ in the multi-round exchange mechanism.

4.3 Decision Problems for Request Exchange

In each round of the exchange mechanism, three decision problems must be solved. The first and the second problem, solved by each carrier, determine non-profitable bundles of requests to offer to other carriers and bundles of requests to acquire from other carriers,

respectively. The third problem, solved by the auctioneer, is a Winner Determination Problem (WDP), which matches the offers and the demands of all carriers and reassigns some bundles of requests among them.

In this section, we present the outsourcing bundles selection problem, the insourcing bundles selection problem, the WDP, and their mathematical models. The notations required to formulate these problems are first given in the following.

Notations

- b_l The set of outsourcing requests for carrier $l \in M$
- B_l The set of bundles of outsourcing requests for carrier $l \in M$
- B The set of outsourcing requests from all carriers, $\sum_{l \in M} B_l$
- OP_{O_l} The transfer payment for the bundle of requests $O_l \in B_l$ provided by carrier $l \in M$
- I_l The set of insourcing multiple bundles of requests for each carrier $l \in M$
- $B_{O_l}^-$ The profit gain of each carrier $l \in M$ after outsourcing its own bundle of requests $O_l \in B_l$
- $B_{I_l}^+$ The profit gain of each carrier $l \in M$ after insourcing the set of multiple bundles of requests I_l from other carriers
- $\theta_{i,R}$ The binary parameter indicating whether request i is included in the set of requests R
- R_l The set of requests currently owned by carrier $l \in M$. It contains the requests from shippers and other carriers.
- n_l The number of requests in the set of requests currently owned by carrier $l \in M$.
- p_i The price paid to serve request $i, i \in R_l$.
- NB_l The maximum number of outsourcing bundles of requests by carrier $l \in M$ for one time
- $G(R_l)$ The revenue obtained from serving the set of requests R_l , this revenue is from shippers and other carriers.
- G_l The profit of carrier $l \in M$ before outsourcing or insourcing requests
- $G_{O_l}^-$ The profit of carrier $l \in M$ after outsourcing each bundle of requests $O_l \in B_l$

$G_{I_l}^+$ The profit of carrier $l \in M$ after insourcing the set of bundles of requests I_l

For simplicity, the carrier index in the notations listed above is omitted. Moreover, for each carrier and each decision problem considered, we use $R = \{1, \dots, n\}$ to denote the set of requests involved, $P = \{1, \dots, n\}$ and $D = \{n+1, \dots, 2n\}$ to denote the set of pickup nodes and the set of delivery nodes of all the requests, where the pick node and the delivery of request i are node i and $n+i$, respectively. For convenience of formulation, nodes 0 and $2n+1$ represent the depot of the carrier considered. It is assumed that each vehicle route begins at node 0 and ends at node $2n+1$.

4.3.1 Outsourcing Bundles Selection

The first decision for each carrier in each round of the exchange mechanism is to select requests to outsource to other carriers from its current request set and then compose multiple outsourcing bundles of requests and determine the transfer payment for each bundle. Our outsourcing requests selection model for each carrier is based on the idea of minimum profit margin as defined in Dai and Chen (2011): the minimum profit margin of a carrier represents its profitability expectation for each request. For each carrier, some of its requests may be not profitable. As each carrier $l \in M$ wants to achieve a minimum profit margin $\alpha_l \in [0,1]$, its least profit gain of each request i is $\alpha_l * p_i, i \in R_l$.

In this stage, each carrier has to solve a selective pickup and delivery problem with time windows and profits in less than truckload transportation (SPDPTWP). The SPDPTWP model for each carrier $l \in M$ is described as follows:

Decision variables

x_{ij}^k Binary variable which equals 1 if and only if vehicle $k \in K$ travels directly through arc (i, j)

y_i Binary variable which equals 1 if and only if request i is outsourced

Q_i^k Load of vehicle $k \in K$ when leaving node i

T_i^k The time at which a vehicle $k \in K$ leaves node i

$$\max \sum_{i \in R_l} p_i \cdot (1 - y_i) + \sum_{i \in R_l} p_i \cdot \alpha \cdot y_i - \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} c_{ij} \cdot x_{ij}^k \quad (4-3)$$

Subject to:

$$\sum_{j \in N, j \neq i} x_{ij}^k = \sum_{j \in N, j \neq i} x_{ji}^k \quad \forall i \in P \cup D, \forall k \in K \quad (4-4)$$

$$\sum_{j \in N, j \neq i} x_{ij}^k = \sum_{j \in N, j \neq n+i} x_{j, n+i}^k \quad \forall i \in P, \forall k \in K \quad (4-5)$$

$$\sum_{j \in P, j \neq 0} x_{0j}^k \leq 1 \quad \forall k \in K \quad (4-6)$$

$$\sum_{i \in D, i \neq 2n+1} x_{i,2n+1}^k \leq 1 \quad \forall k \in K \quad (4-7)$$

$$\sum_{k \in K} \sum_{j \in N, j \neq i} x_{ij}^k + y_i = 1 \quad \forall i \in P, \forall k \in K \quad (4-8)$$

$$Q_j^k \geq Q_i^k + d_j - Q \cdot (1 - x_{ij}^k) \quad \forall i, j \in N, k \in K \quad (4-9)$$

$$\max\{0, d_i\} \leq Q_i^k \leq \min\{Q, Q + d_i\} \quad \forall i \in N, k \in K \quad (4-10)$$

$$T_j^k \geq T_i^k + t_{ij} \cdot x_{ij}^k - T_{ij} \cdot (1 - x_{ij}^k) \quad \forall i, j \in N, k \in K \quad (4-11)$$

$$T_{n+i}^k \geq T_i^k + t_{i,n+i} \quad \forall i \in P, \forall k \in K \quad (4-12)$$

$$a_i \leq T_i^k \leq b_i \quad \forall i \in N, k \in K \quad (4-13)$$

$$x_{ij}^k \in \{0,1\} \quad \forall i, j \in N, k \in K \quad (4-14)$$

$$y_i \in \{0,1\} \quad \forall i \in R_l \quad (4-15)$$

$$Q_i^k \geq 0 \quad \forall i \in N, k \in K \quad (4-16)$$

$$T_i^k \geq 0 \quad \forall i \in N, k \in K \quad (4-17)$$

The objective function (4-3) represents the total profit of the carrier, which equals to the difference between the total payment of serving requests and the total transportation cost. Constraints (4-4) ensure that a vehicle arriving at a pickup or delivery node has to leave it. Constraints (4-5) guarantee that if a vehicle leaves the pickup node of a request, it must arrive at the delivery node of the request later. Constraints (4-6) and (4-7) indicate that each vehicle leaves the depot and returns to it. Constraints (4-8) ensure that a request can be fulfilled by its own carrier or outsourced to other carriers. Constraints (4-9) and (4-10) are vehicle capacity constraints. Time windows and precedence relations for visiting nodes are respected via constraints (4-11)-(4-13). Constraints (4-14)-(4-17) define the variables.

Our outsourcing request selection model is the same as the model considered by Li, Chen and Prins (2016). As the aim of this paper is not to develop a state-of-the-art algorithm that can compete with the best ones in the literature, we adopt the MIP solver of CPLEX to solve the SPDPTWP model for small instances and a meta-heuristic ALNS to solve the model for large instances. ALNS was first successfully applied to the pickup and delivery problem with time windows and later to various vehicle routing problems (Ropke et al., 2006a, 2006b, 2007). Li et al. (2016) proposed an ALNS algorithm to solve the model. The algorithm can find an optimal solution for small to medium instances and generated a high quality feasible solution for large instances with 100 requests. For this reason, we adopt the ALNS algorithm with modifications to solve our SPDPTWP model for large instances.

Offering a bundle of requests instead of offering each request in the bundle individually not only allows expressing synergies among requests, but also guarantees that either all or none of the requests in the bundle are outsourced. Moreover, offering multiple mutually-exclusive bundles of requests can increase the opportunity that one of the bundles

is outsourced. For this reason, each carrier $l \in M$ composes multiple bundles of requests for outsourcing and determines the transfer payment for each bundle. After solving SPDPTWP, set b_l consisting of the requests $i \in R_l$ with $y_i = 0$ can be obtained. That is $b_l := \{i \in R_l : y_i = 0\}$. Different from Berger and Bierwirth (2010), Dai and Chen (2011) and Gansterer and Hartl (2016), we have no limit on the number of outsourcing requests. To increase the collaboration possibilities, we propose multiple bundles of requests to outsource. However, from a practical point of view, offering all possible bundles is not manageable, since the number of outsourcing bundles of requests grows exponentially with the number of outsourcing requests. When the number of outsourcing requests is large, we limit the number of outsourcing bundles of requests to NB_l . Each outsourcing bundle of requests $O_l \in B_l$ is composed by a number of different requests in b_l .

After solving SPDPTWP, carrier $l \in M$ calculates the profit gain $B_{O_l}^-$ for each bundle $O_l \in B_l$ by the formula (4-18).

$$B_{O_l}^- = G_l - G_{O_l}^- \quad (4-18)$$

In formula (4-18), G_l is obtained by solving SPDPTWP with no requests outsourced and $G_{O_l}^-$ is obtained by solving SPDPTWP with the bundle of requests $O_l \in B_l$ outsourced.

To make sure that the individual profit of carrier $l \in M$ will not be decreased after outsourcing a bundle of requests, we select the following set of bundles of requests to outsource:

$$B_l := \{O_l \in B_l : B_{O_l}^- > 0\} \quad (4-19)$$

The transfer payment OP_{O_l} for each outsourcing bundle of requests $O_l \in B_l$ is computed as in formula (4-2) in Section 4.2.

4.3.2 Insourcing Bundles Selection

In the stage of bidding for requests to insource, all information about outsourcing bundles of requests and their transfer payments submitted by carriers is revealed to all carriers (buyers) by the auctioneer. Each carrier can acquire multiple bundles of requests that complement to its existing requests from other carriers. If the carrier insources bundle $O_l \in B_l$ from carrier $l \in M$, the carrier receives a transfer payment of OP_{O_l} .

In this stage, each carrier determines which bundles of requests to acquire (insource) from one or multiple carriers by solving a selective pickup and delivery problem with clusters of requests and profits (SPDP-CRP). In our multi-round exchange mechanism, we assume that once a carrier selects one bundle of requests to insource, it must serve all of the requests in this bundle by its own vehicles. In each round of the auction, the requests in one bundle cannot be assigned to multiple carriers. What's more, each carrier bids for at most one bundle from any other carrier one time. This is because we assume that the outsourcing bundles of requests offered by each carrier have the relationship of XOR, i.e., at most one bundle among them can be outsourced by this carrier. The information about the insourcing

bundles of each carrier is submitted to the auctioneer.

There are two insourcing strategies for each carrier. 1) One buyer to one seller strategy: each carrier bids for only one bundle of requests from only one carrier; 2) One buyer to many sellers strategy: each carrier bids for multiple bundles of requests from multiple other carriers respectively but at most one bundle of requests from each carrier.

Decision variables

x_{ij}^k Binary variable which equals 1 if and only if vehicle $k \in K$ travels directly through arc (i, j)

z_{l,O_m} Binary variable which equals 1 if and only if the bundles of requests $O_m \in B_m, m \in M, m \neq l$ is served by carrier $l \in M$

Q_i^k Load of vehicle $k \in K$ when leaving node i

T_i^k The time at which a vehicle $k \in K$ leaves node i

With the above defined notations, the mixed integer programming model of SPDP-CRP for each carrier $l \in M$ is given as follows:

$$\max G(R_l) + \sum_{m \in M, m \neq l} \sum_{O_m \in B_m} OP_{O_m} \cdot z_{l,O_m} - \sum_{k \in K} \sum_{i \in N} \sum_{j \in N} c_{ij} \cdot x_{ij}^k \quad (4-20)$$

Subject to constraints (4-7), (4-13) and

$$\sum_{k \in K} \sum_{j \in N, j \neq i} x_{ij}^k = 1 \quad \forall i \in R_l \quad (4-21)$$

$$\sum_{k \in K} \sum_{j \in N, j \neq i} x_{ij}^k \geq \theta_{i,O_m} \cdot z_{l,O_m} \quad \forall i \in P, O_m \in B_m, l, m \in M, l \neq m \quad (4-22)$$

$$\sum_{O_m \in B_m} z_{l,O_m} \leq 1 \quad \forall l, m \in M, l \neq m \quad (4-23)$$

$$x_{ij}^k \in \{0,1\} \quad \forall i, j \in N, k \in K \quad (4-24)$$

$$z_{l,O_m} \in \{0,1\} \quad \forall l, m \in M, l \neq m, O_m \in B_m \quad (4-25)$$

$$Q_i^k \geq 0 \quad \forall i \in N, k \in K \quad (4-26)$$

$$T_i^k \geq 0 \quad \forall i \in N, k \in K \quad (4-27)$$

The objective function (4-20) maximizes the profit defined as the difference between the total revenue of serving both own requests and insourced requests and total transportation cost. Constraints (4-21) imply that all requests currently owned by carrier $l \in M$ are served by itself. Constraints (4-22) describe the logical relationship between the routing variables and the bids selection variables: if one bundle of requests is insourced by the carrier, all requests in this bundle are served by this carrier. Constraints (4-23) imply that each carrier insources at most one bundle of requests from any other carrier. Constraints (4-24)-(4-27) indicate the natures of all variables and their upper and lower bounds.

Compared with the model considered by Li, Chen and Prins (2016), the SPDP-CRP is a selective pickup and delivery problem with time windows and clusters of requests, in which all the requests in a bundle of requests must be served by the same carrier once this bundle is selected. Because of the advantages of ALNS mentioned in Section 4.1, we also use ALNS

to solve the SPDP-CRP but with an adaption, that is, an entire bundle of requests is deleted from a solution in the delete operation of ALNS and an entire bundle of requests is inserted in the repair operation of ALNS instead of one request deleted from or inserted into a solution considered each time.

In model SPDP-CRP, each carrier can insource bundles of requests from one or multiple carriers. If we consider the special case that each carrier can insource only one bundle from other carriers, then the following constraint must be added to the model:

$$\sum_{m \in M} \sum_{O_m \in B_m} z_{l, O_m} \leq 1 \quad (4-28)$$

For each carrier $l \in M$, the insourcing set of bundles of requests is $I_l = \bigcup_{m \in M, m \neq l} O_m$ if $z_{l, O_m} = 1$. Therefore the profit gain after insourcing the set of bundles of requests $B_{I_l}^+$ for each carrier $l \in M$ is

$$B_{I_l}^+ = G_{I_l}^+ - G_l \quad (4-29)$$

In formula (4-29), $G_{I_l}^+$ is obtained by solving SPDP-CRP with the set of bundles of requests I_l insourced and G_l is obtained by solving model SPDP-CRP with no bundles of requests insourced. $B_{I_l}^+$ denotes the additional profit that carrier $l \in M$ can gain from insourcing requests.

4.3.3 Winner determination problem

In our request exchange mechanism, each carrier submits bidding information to the auctioneer, then the auctioneer (coordinator) solves a WDP based on the bidding information to reassign (exchange) some bundles of requests among carriers to improve their overall operational efficiency. We consider the WDP in two scenarios of information sharing. In the first scenario, the information submitted by each carrier to the auctioneer includes its offer with the transfer payment and demand of bundles of requests. In the second scenario, each carrier submits the information about its offer with the transfer payment and demand of bundles of requests, the profit gain for each of its bundles of requests to outsource, and the profit gain for its set of multiple bundles of requests to insource to the auctioneer. The difference of information sharing between two scenarios of WDP is whether to submit the profit gained by each carrier to outsource or insource a bundle of requests. Based on the information submitted by all carriers, the mechanism reassigns (exchanges) some bundles of requests among carriers by solving a winner determination problem.

1) Winner determination without profit gain information sharing

As carriers may be competitors, they are not willing to share their confidential information, such as its profit gain or transportation cost. For this reason, the only information submitted by each carrier is its outsourcing bundles of requests with transfer payments and its insourcing bundles of requests. In the scenario of WDP without profit gain information sharing, we solve WDP to reassign some bundles of requests among carriers to maximize the number of bundles of requests to be exchanged among carriers. In WDP, each

carrier $l \in M$ outsources its own bundle of requests $O_l \in B_l$ and insources a set of bundles of requests I_l from other carriers.

Our multi-round exchange mechanism applies the following exchange rules:

(1) In each round of the auction, each carrier plays a role of seller and a role of buyer successively; it can only be a seller or a buyer but not both at any time.

(2) Each carrier can insource one or more than one bundles of requests from one or multiple carriers, but it can only insource at most one bundle of requests from each carrier.

(3) The goal of the auction in each round is to maximize the number of bundles of requests to be exchanged among carriers with respect to the last round.

Decision variables

$w_{O_l}^-$ Binary variable which equals 1 if and only if carrier $l \in M$ is assigned to be a seller and a bundle of requests $O_l \in B_l$ is outsourced by the carrier $l \in M$

$w_{I_l}^+$ Binary variable which equals 1 if and only if carrier $l \in M$ is assigned to be a buyer and a set of bundles of requests I_l is insourced (acquired) by carrier $l \in M$

$$\max(\sum_{l \in M} \sum_{O_l \in B_l} w_{O_l}^- + \sum_{l \in M} w_{I_l}^+) \quad (4-30)$$

Subject to

$$\sum_{l \in M} \sum_{O_l \in B_l} w_{O_l}^- \cdot \theta_{r, O_l} = \sum_{l \in M} \sum_{m \in M, m \neq l} \sum_{O_m \in I_l} w_{I_l}^+ \cdot \theta_{r, O_m} \quad \forall r \in R_o \quad (4-31)$$

$$w_{O_l}^- + w_{I_l}^+ \leq 1 \quad \forall O_l \in B_l, l \in M \quad (4-32)$$

$$w_{O_l}^- \in \{0,1\} \quad \forall O_l \in B_l, l \in M \quad (4-33)$$

$$w_{I_l}^+ \in \{0,1\} \quad \forall l \in M \quad (4-34)$$

The objective function (4-30) maximizes the number of bundles of requests to be exchanged among carriers in each round of the auction. Constraints (4-31) mean that if a request is outsourced, this request must be insourced by other carriers. Constraints (4-32) ensure that each carrier cannot be a seller or a buyer at the same time. Constraints (4-33) and (4-34) define the variables.

2) Winner determination with profit gain information sharing

In the scenario of profit gain information sharing, each carrier submits the profit gain information only to the auctioneer who acts as a virtual coordinator, and this information is not released to other carriers. In WDP, the profit gain of each carrier $l \in M$ after outsourcing (selling) its own bundle of requests $O_l \in B_l$ is denoted by $B_{O_l}^-$. The profit gain of carrier $l \in M$ after insourcing (acquiring) a set of bundles of requests I_l from other carriers is denoted by $B_{I_l}^+$.

In this scenario of WDP, the exchange rules to follow include the first two rules for the first scenario of WDP in Section 4.4.3.1. However, different from WDP without profit gain sharing, the objective of WDP with profit gain sharing is to maximize the total profit increment of all carriers.

The model of WDP with profit gain information sharing is given by (4-35).

$$\max\left(\sum_{l \in M} \sum_{O_i \in B_l} G_{O_i}^- + \sum_{l \in M} G_{I_l}^+\right) \quad (4-35)$$

subject to constraints (4-31) -(4-34).

The objective function (4-35) maximizes the total profit increment in each round of the auction.

4.4 Computational Study

In this section, we evaluate the performance of the proposed request exchange mechanism. Numerical experiments were carried out on a personal computer with an Intel Core i5-3210M CPU and 4.0 GB of RAM under the Microsoft Windows 7 operating system. The commercial optimization software CPLEX 12.6 with default setting was used as the MIP solver. All mixed integer programming models for individual planning of each carrier, centralized planning of all carriers and our multi-round exchange mechanism were solved by calling this solver.

4.4.1 Test instances

We consider carrier collaboration among three carriers. Two sets of instances were first randomly generated. The first instance set contains 15 instances with 3 requests and the second instance set contains 15 instances with 5 requests. The maximum number of vehicles is set to 3 for each carrier and the capacity of each vehicle is set to 20 units. The coordinates of all nodes in the transportation network of each instance are generated in the same way as in Chen (2016). The distance between any two nodes is their Euclidean distance and it is assumed that the traveling time between any two nodes coincides with their distance. The profit of each request is set to two times of the distance from its pickup node to its delivery node (Chen, 2016). We use these two sets of instances to evaluate the performance of our request exchange mechanism by comparing its solution with the optimal solution of each instance obtained by the centralized planning approach.

To further evaluate the performance of our request exchange mechanism, we compare it with a single request auction and a combinatorial auction of Berger and Bierwirth (2010) and Gansterer and Hartl (2016) by testing 90 instances randomly generated by Berger and Bierwirth (2010) and two sets of instances provided by Gansterer and Hartl (2016). The first set of Gansterer and Hartl contains 10 instances with 9 requests and 10 instances with 15 requests. These two subsets of instances are denoted by I9 and I15 respectively. The second set was generated by considering three scenarios about the degree of customer area overlapping. The subsets of instances corresponding to the three scenarios are denoted by O1, O2 and O3 respectively, where each subset contains 10 instances with 10 requests and 10

instances with 15 requests. We compare the solution obtained by our request exchange mechanism with those of Berger and Bierwirth (2010) and Gansterer and Hartl (2016). As CPLEX MIP solver 12.6 cannot solve larger instances optimally within an acceptable time, we adopt a meta-heuristic called adaptive large neighborhood search (ALNS) proposed by Li et al. (2016) to solve the instances generated by Gansterer and Hartl (2016). The ALNS algorithm was used to solve all pickup and delivery problems with profits appeared in our request exchange mechanism.

4.4.2 Comparison of three auction mechanisms on an illustrative instance

We use a simple instance 5 in set O provided by Berger and Bierwirth (2010) to compare our mechanism with their two mechanisms. Table 4-1, Table 4-2, Table 4-3 show the detailed iterative processes of the three mechanisms applied to the instance. For this instance, our mechanism terminates in five iterations, whereas both of their auctions terminate in two iterations.

Table 4-1 shows the outcomes of our mechanism. Table 4-2 shows the outcomes of the first auction in Berger and Bierwirth (2010). In the first three rounds of the auction, as each carrier is not willing to outsource requests with the small values of α , the set of request bundles to outsource and the set of request bundles to insource are both empty. When α increases to 0.3, although carrier 1 outsources a set of requests, no other carrier is willing to insource them, because of the transfer payment for them is less than their service cost. With α increases to 0.4, multiple bundles of requests are exchanged among carriers and an optimal request reassignment solution is obtained.

Table 4-1 The detailed iterative process of the proposed auction

Iteration	α	Outsourcing requests			Insourcing requests			WDP I	WDP II
		Carrier 1	Carrier 2	Carrier 3	Carrier 1	Carrier 2	Carrier 3		
1	0	ϕ	ϕ	ϕ	ϕ	ϕ	ϕ	Profit of Carrier 1: 52 Profit of Carrier 2: 56 Profit of Carrier 3: 59 Total profit: 167	Profit of Carrier 1: 52 Profit of Carrier 2: 56 Profit of Carrier 3: 59 Total profit: 167
2	0.1	ϕ	ϕ	ϕ	ϕ	ϕ	ϕ	Profit of Carrier 1: 52 Profit of Carrier 2: 56 Profit of Carrier 3: 59 Total profit: 167	Profit of Carrier 1: 52 Profit of Carrier 2: 56 Profit of Carrier 3: 59 Total profit: 167
3	0.2	ϕ	ϕ	ϕ	ϕ	ϕ	ϕ	Profit of Carrier 1: 52 Profit of Carrier 2: 56 Profit of Carrier 3: 59 Total profit: 167	Profit of Carrier 1: 52 Profit of Carrier 2: 56 Profit of Carrier 3: 59 Total profit: 167
4	0.3	$\{\{2, 40.46\}\}$	ϕ	ϕ	ϕ	ϕ	ϕ	Profit of Carrier 1: 52 Profit of Carrier 2: 56 Profit of Carrier 3: 59 Total profit: 167 Insource: Carrier 1 Outsource: Carrier 2,3 Profit of Carrier 1: 136	Profit of Carrier 1: 52 Profit of Carrier 2: 56 Profit of Carrier 3: 59 Total profit: 167 Insource: Carrier 1 Outsource: Carrier 2,3 Profit of Carrier 1: 74 Profit of Carrier 2: 74 Total profit: 282
5	0.4	$\{\{1, 2, 3\}, \{104.04\}\}$	$\{\{8, 9, 10\}, \{104.04\}\}$	$\{\{15, 16, 17\}, \{104.04\}\}$	$\{\{8, 9, 10\}, \{15, 16, 17\}\}$	$\{\{1, 2, 3\}, \{15, 16, 17\}\}$	$\{\{1, 2, 3\}, \{8, 9, 10\}\}$	Profit of Carrier 1: 74 Profit of Carrier 2: 74 Profit of Carrier 3: 72 Total profit: 282	Profit of Carrier 1: 136 Profit of Carrier 2: 74 Profit of Carrier 3: 72 Total profit: 282
		$\{\{2\}, \{34.68\}\}$	$\{\{8\}, \{34.68\}\}$	$\{\{1, 2\}, \{69.36\}\}$					

Table 4-2 The detailed iterative process of the first auction proposed by Berger and Bierwirth (2010)

Iteration	Outsourcing requests	Bidding price			WDP	Profit			
		Carrier 1	Carrier 2	Carrier 3		Carrier 1	Carrier 2	Carrier 3	Total
1	{2}	12.78	5.50	37.47	Carrier 3: {2}	27	56	109	192
2	{8}	7.73	45.36	1.67	Carrier 2: {8}	27	109	100	236

In this auction, the requests with the least marginal profit among the three carriers are outsourced in two iterations and only one request is auctioned out (outsourced) in each round. As the outsourcing request in the third iteration is the same as in the second iteration, this auction terminates in the two iterations.

Table 4-3 shows the outcomes of the second auction in Berger and Bierwirth (2010). In this auction, each carrier outsources the request with the least marginal profit and bids for multiple bundles of requests composed of outsourcing requests in two iterations. After the two iterations, as the total profit of all carriers is not improved, this auction terminates.

Table 4-3 Detailed iterative process of the second auction proposed by Berger and Bierwirth (2010)

Iteration	Outsourcing requests			Insourcing requests	WDP	Profit			
	Carrier 1	Carrier 2	Carrier 3			Carrier 1	Carrier 2	Carrier 3	Total
1	{2}	{8}	{15}	{2}, {8}, {15}, {2, 8}, {2, 15}, {8, 15}, {2, 8, 15}	Carrier 2: {8, 15}	39	81	95	215
2	{1}	{8}	{2}	{1}, {8}, {2}, {1, 8}, {2, 8}, {1, 2}, {2, 8, 1}	Carrier 1: {2}	48	81	102	231

Illustrated by this instance, as our auction mechanism allows each carrier to outsource multiple bundles of requests and to insource multiple bundles of requests from multiple other carriers in each iteration, it can achieve better performance than those of the auctions proposed by Berger and Bierwirth (2010).

4.4.3 Sensitivity analysis of auction parameters

The parameters used in our auction mechanism include the initial minimum profit margin (α^0) and the maximum number of outsourcing bundles (NR) for selecting outsourcing bundles, the percentage of profit sharing in the transfer payment rule (β), and the step size (δ). For simplicity, these parameters are set the same for each carrier. We will analyze the impact of each of these parameters on the performance of MRE. We tested MRE with different values of auction parameters on the sets of instances with 3 requests for each carrier, 9 requests for each carrier and 15 requests for each carrier.

In this subsection, we will analyze the impact of the percentage profit gain sharing

parameter β on the performance of MRE. We tested MRE with β ranging from 0 to 1 with a step size of 0.2 on the tested instance sets. The total profit found by MRE as a function of the value of β is given in Figure 4-1.

The total profit in case with $\beta > 0$ is higher than that in case with $\beta = 0$ for all the three instance sets. This implies that transfer payment with profit gain sharing is more effective than that with no profit gain sharing in MRE. When $\beta > 0$, the average relative gap in percentage between the minimum profit and the maximum profit is lower than 5.00% for all positive values of β and the total profit does not change significantly as the value of β increases. From the results in Fig.4-1, we can conclude that MRE is robust with β . As Özener, Ergun, and Savelsbergh (2011) suggested that sharing the profit gain equally provides a reasonable balance between the risk of rejection by the other carrier and the benefit of a request exchange, we assume $\beta_i = 1/2$ in our numerical experiments of the multi-round exchange mechanism.

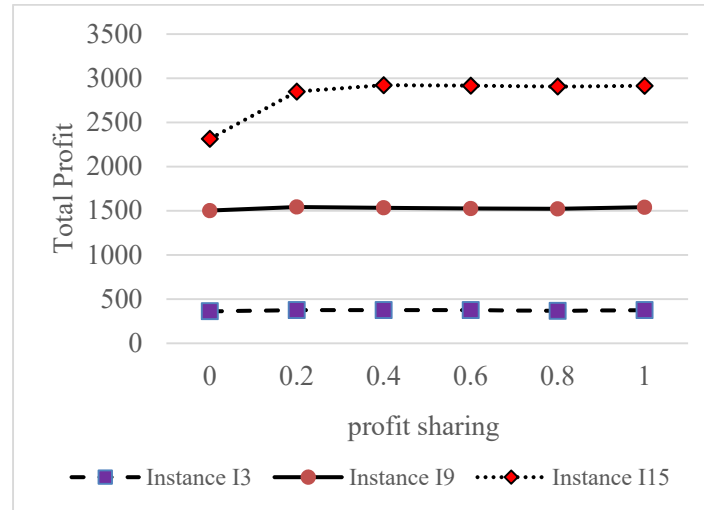


Fig.4-1 The performance of MRE with different values of profit sharing

Next, we will analyze the impact of the profit margin on the performance of MRE, which involves two parts: initial value of profit margin α^0 and the step size δ . We consider $\alpha^0 = 0, 0.2, 0.4, 0.6$ and $\delta = 0.05, 0.1, 0.2$. We present the total profit found by MRE as a function of the value of α^0 and δ in Figure 4-2.

In Fig 4-2, for the instances with 9 requests, MRE with different step size values achieves the same average gap, e.g. (0.2,0.1), (0.2,0.2) and (0.4,0.05), (0.4,0.2). For the instances with 15 requests, MRE with the step size of 0.05 has a lower efficiency than that with 0.1 and 0.2. Based on the results of the sensitivity analysis, MRE is not sensitive to α^0 and δ . In our numerical experiments, we set $\alpha^0 = 0$, and the step size is set to $\delta = 0.1$.

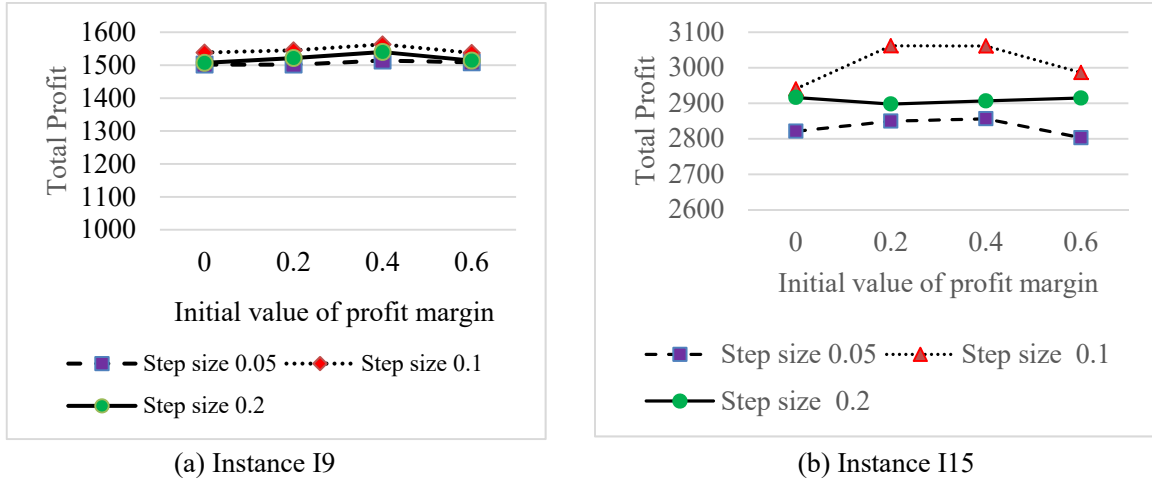


Fig.4-2 The performance of MRE with different combinations of (α^0, δ)

We will analyze the impact of the maximum number of outsourcing bundles of requests on the performance of MRE. We tested MRE with $NR = 50, 100, 150, 200$ on the instances. From Fig.4-3, we can see that the larger the value of NR for each carrier, the more effective MRE. However, as the number of outsourcing bundles of requests increases, our auction mechanism will require more computation time. For the instances of 15 requests, MRE with $NR = 100$ achieves the solution with the average time of 398.80 seconds. Compared to MRE with $NR = 100$ MRE with $NR = 150$ achieves an improvement of 1.58% by consuming more time of 452.07 seconds on average, and MRE with $NR = 200$ achieves an average improvement of 1.97% with the average time of 1164.52 seconds. As MRE consumes much more time to achieve an average improvement of less than 2%, we choose $NR = 100$ in our computational study in the next subsection.

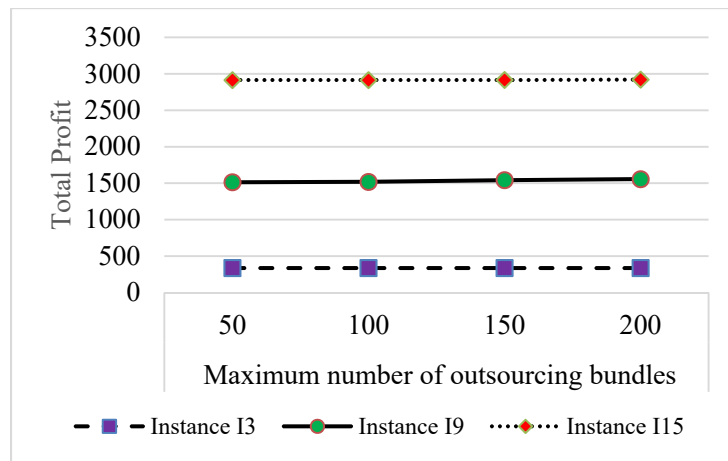


Fig.4-3 The performance of MRE with different values of NR

4.4.4 Evaluation of the request exchange mechanism

In this subsection, we analyze our multi-round request exchange mechanism (MRE) by comparing its solution with the optimal solution of each instance obtained by the centralized planning approach (CP) for the carrier collaboration problem studied.

For this mechanism (auction), we have proposed two strategies for insourcing bundles

of requests from other carriers in each round: one is that each carrier can insource a set of bundles of requests from multiple carriers (MRE-M) and the other is that each carrier can insource only one bundle of requests from one carrier (MRE-O). As insourcing strategy is very important for the mechanism, we first compare MRE with the two insourcing strategies proposed. In this comparison, we assume the complete information scenario for WDP, that is, the objective of WDP is to maximize the total profit increment. Average results are given in Table 4-4. Detailed results for each instance are given in Table 4-5 and Table 4-6 for the 3×3 instance set and the 3×5 instance set, where the first number is the number of carriers and the second number is the number of requests of each carrier. The relative gap between the total profit p_{MRE} obtained by MRE with one of the two insourcing strategies and the total profit p_{CP} obtained by CP is defined as $Gap = (p_{CP} - p_{MRE}) / p_{CP} * 100\%$. Gap is used as the performance indicator of the request exchange mechanism and CPU denotes the computation time in seconds for each approach.

Table 4-4 Comparison of two strategies for insourcing bundles of requests

Instance set	Gap_{MRE-O}	CPU_{MRE-O}	Gap_{MRE-M}	CPU_{MRE-M}
3×3	0.00	56.21	0.00	66.85
3×5	2.12	7586.08	0.34	7984.02

Table 4-5 Results of MRE with two insourcing strategies on 3×3 instance set

Instance	p_{MRE-O}	CPU_{MRE-O}	p_{MRE-M}	CPU_{MRE-M}	p_{CP}	CPU_{CP}	Gap_{MRE-O}	Gap_{MRE-M}
0	271.28	91.18	271.28	142.86	271.28	0.95	0.00	0.00
1	281.62	8.48	281.62	9.63	281.62	0.25	0.00	0.00
2	256.20	16.45	256.20	55.43	256.20	1.64	0.00	0.00
3	350.06	69.65	350.06	85.86	350.06	1.45	0.00	0.00
4	179.71	11.74	179.71	12.75	179.71	0.44	0.00	0.00
5	320.59	121.60	320.59	197.12	320.59	1.89	0.00	0.00
6	274.52	18.18	274.52	18.91	274.52	0.38	0.00	0.00
7	216.28	9.91	216.28	13.41	216.28	0.48	0.00	0.00
8	239.59	12.30	239.59	18.91	239.59	0.97	0.00	0.00
9	427.61	81.34	427.61	132.70	427.61	0.56	0.00	0.00
10	321.55	11.19	321.55	12.62	321.55	1.16	0.00	0.00
11	301.71	105.55	301.71	23.46	301.71	1.34	0.00	0.00
12	384.40	39.81	384.40	15.43	384.40	2.33	0.00	0.00
13	293.75	64.75	293.75	81.94	293.75	1.69	0.00	0.00
14	367.69	181.08	367.69	181.65	367.69	1.48	0.00	0.00
Avg		56.21		66.85		1.13	0.00	0.00

From Table 4-4, we find that no difference exists between the strategy of insourcing only one bundle and the strategy of insourcing multiple bundles for the set of small 3×3 instances. The average computation time for these two strategies is 56.21 seconds and 66.85 seconds respectively. This shows that insourcing requests from multiple carriers have the same effect with insourcing requests from one carrier on this set of small instances. This may be because little collaboration possibility exists among carriers for small size instances. For

the 3×5 instance set, the average relative gap between the solution found by MRE and the optimal solution found by CP is 2.12% and 0.34% for the two strategies respectively. The strategy of insourcing requests from multiple carriers finds an optimal or a near optimal allocation of requests for most instances in this set.

From Table 4-4, we can conclude that the strategy of insourcing requests from multiple carriers is more effective than the strategy of insourcing requests from one carrier for instances of larger size. For this reason, in the rest of comparison, we adopted the first strategy for MRE.

Table 4-6 Results of MRE with two insourcing strategies on 3×5 instance set

Instance	$PMRE-O$	CPU_{MRE-O}	$PMRE-M$	CPU_{MRE-M}	PCP	CPU_{CP}	Gap_{MRE-O}	Gap_{MRE-M}
0	257.27	410.21	274.27	925.85	274.27	294.89	6.20	0.00
1	213.73	1414.18	213.73	1587.20	213.73	213.69	0.00	0.00
2	206.03	592.55	206.03	447.54	206.03	563.33	0.00	0.00
3	244.35	1304.23	256.93	1568.28	256.93	1727.36	4.90	0.00
4	202.09	85.46	211.36	8220.67	211.36	220.09	4.39	0.00
5	523.50	503.25	523.50	7503.28	523.50	3682.44	0.00	0.00
6	226.87	568.22	226.87	4538.65	226.87	340.66	0.00	0.00
7	322.30	113.46	329.82	71225.67	340.28	164.78	5.28	3.07
8	358.77	29962.8	358.77	710.56	366.31	763.91	2.06	2.06
9	232.29	347.63	232.29	914.83	232.29	271.83	0.00	0.00
10	189.67	7047.02	189.67	3260.44	189.67	3541.80	0.00	0.00
11	396.87	521.34	413.51	8902.69	413.51	32811.55	4.02	0.00
12	219.78	586.12	221.36	788.44	221.36	601.92	0.71	0.00
13	277.63	64092	289.76	1266.89	289.76	7418.53	4.19	0.00
14	416.18	6242.73	416.18	7899.32	416.18	4563.17	0.00	0.00
Avg		7586.08		7984.02		3812.00	2.12	0.34

We compare the performance of MRE in the scenario of complete information with that in the scenario of incomplete information for the 3×3 instance set and the 3×5 instance set, respectively. In the complete information scenario (MRE-C), the objective of WDP is to maximize the total profit increment, whereas in the incomplete information scenario (MRE-I), WDP aims to maximize the number of bundles of requests exchanged. The strategy of insourcing requests from multiple carriers was adopted in the comparison. Summarized results are shown in Table 4-7. In Table 4-7, Gap and CPU has the same meaning as in Table 4-4. Detailed results for each instance are given in Table 4-8 and Table 4-9. The strategy of insourcing requests from multiple carriers was adopted in the comparison. For the 3×3 instance set, the average relative gap between the solutions of MRE in the two scenarios is 0. This implies that no significant difference exists in the allocation of requests among carriers in the two scenarios except for the computation time.

Table 4-7 Comparison Results of WDP with complete information and incomplete information

Instance set	Gap_{MRE-I}	CPU_{MRE-I}	Gap_{MRE-C}	CPU_{MRE-C}
3×3	0.00	93.62	0.00	66.85
3×5	0.99	8550.53	0.34	7984.02

Table 4-8 Comparison results of MRE with complete information and incomplete information on 3×3 instance

Instance	p_{MRE-I}	CPU_{MRE-I}	p_{MRE-C}	CPU_{MRE-C}	p_{CP}	CPU_{CP}	Gap_{MRE-I}	Gap_{MRE-C}
0	271.28	118.82	271.28	142.86	271.28	0.95	0.00	0.00
1	281.62	6.08	281.62	9.63	281.62	0.25	0.00	0.00
2	256.20	16.89	256.20	55.43	256.20	1.64	0.00	0.00
3	350.06	84.62	350.06	85.86	350.06	1.45	0.00	0.00
4	179.71	13.39	179.71	12.75	179.71	0.44	0.00	0.00
5	320.59	183.00	320.59	197.12	320.59	1.89	0.00	0.00
6	274.52	21.50	274.52	18.91	274.52	0.38	0.00	0.00
7	216.28	14.48	216.28	13.41	216.28	0.48	0.00	0.00
8	239.59	45.67	239.59	18.91	239.59	0.97	0.00	0.00
9	427.61	123.68	427.61	132.70	427.61	0.56	0.00	0.00
10	321.55	11.32	321.55	12.62	321.55	1.16	0.00	0.00
11	301.71	144.04	301.71	23.46	301.71	1.34	0.00	0.00
12	384.40	384.40	384.40	15.43	384.40	2.33	0.00	0.00
13	293.75	64.72	293.75	81.94	293.75	1.69	0.00	0.00
14	367.69	171.71	367.69	181.65	367.69	1.48	0.00	0.00
Avg		93.62		66.85			0.00	0.00

Table 4-9 Comparison results of MRE with complete information and incomplete information on 3×5 instance

Instance	p_{MRE-I}	CPU_{MRE-I}	p_{MRE-C}	CPU_{MRE-C}	p_{CP}	CPU_{CP}	Gap_{MRE}	Gap_{MRE-C}
0	274.27	1642.09	274.27	925.85	274.27	294.89	0.00	0.00
1	213.73	1543.94	213.73	1587.20	213.73	213.69	0.00	0.00
2	206.03	1063.65	206.03	447.54	206.03	563.33	0.00	0.00
3	254.15	1880.46	256.93	1568.28	256.93	1727.36	1.08	0.00
4	202.09	21560.20	211.36	8220.67	211.36	220.09	4.39	0.00
5	523.50	1399.27	523.50	7503.28	523.50	3682.44	0.00	0.00
6	226.87	1774.31	226.87	4538.65	226.87	340.66	0.00	0.00
7	340.28	17740.20	329.82	71225.67	340.28	164.78	0.00	3.07
8	366.31	12765.40	358.77	710.56	366.31	763.91	0.00	2.06
9	228.04	841.18	232.29	914.83	232.29	271.83	1.83	0.00
10	175.36	6496.37	189.67	3260.44	189.67	3541.80	7.54	0.00
11	413.51	26753.90	413.51	8902.69	413.51	32811.55	0.00	0.00
12	221.36	14886.20	221.36	788.44	221.36	601.92	0.00	0.00
13	289.76	15678.93	289.76	1266.89	289.76	7418.53	0.00	0.00
14	416.18	2231.92	416.18	7899.32	416.18	4563.17	0.00	0.00
Avg		8550.53		7984.02			0.99	0.34

For 3×5 instance set, the average relative gap between the solutions of MRE in the two scenarios is 0.99% and 0.34% respectively. WDP with complete information performs slightly better than WDP with incomplete information on average. This may be because more the number of bundles of requests exchanged among carriers, larger the profit increment for them (Li et al., 2015; Lyu et al., 2018). However, there are exceptions. For instances no.7 and no.8 (in Table 4-9), WDP with incomplete information achieves an

optimal solution, whereas WDP with complete information cannot obtain an optimal request allocation. In terms of implementation, WDP with incomplete information is more practical since it does not require that each carrier reveals its confidential business information, whereas WDP with complete information is required to reveal the profit information of each of its sourcing bundles. From the above comparison, we find that there is no significant difference between WDP with incomplete information and WDP with complete information.

4.4.5 Comparison with other mechanisms

In this subsection, we compare MRE with a single request auction (SRA) and a combinatorial auction (CA) of Berger and Bierwirth (2010) and the auction (GH) proposed by Gansterer and Hartl (2016), by testing the instances provided by them. Summarized results for comparison of MRE, SRA, CA and GH are given in Table 4-10.

Table 4-10 shows the results on the instances of Berger and Bierwirth (2010). We adopt collaboration gain CG as an indicator to evaluate the performance of each method (Berger and Bierwirth, 2010; Gansterer and Hartl, 2016). The percentage collaboration gain CG is defined as the relative gap between the profit of all carriers after collaboration p_C obtained by a method and the profit of the carriers before collaboration p_{NC} , i.e., $CG = (p_C - p_{NC})/p_{NC} * 100\%$. The bigger the value of CG , the better the solution of the method obtained.

Table 4-10 Summarized comparison results for the instances of Berger and Bierwirth (2010)

Scenario	CG_{SRA}	$CPU_{SRA(s)}$	CG_{CA}	$CPU_{CA(s)}$	CG_{GH}	$CPU_{GH(ms)}$	CG_{MRE}	$CPU_{MRE(s)}$	CG_{CP}
A	3.5	0.41	4.7	0.60	3.2	1.43	18.5	19.81	19.1
O	28.7	3.72	30.8	2.59	33.0	3.03	65.9	42.80	67.4
I	76.6	11.61	100.9	4.81	88.2	8.23	155.0	64.86	155.7
Avg	36.3	5.25	45.5	2.67	41.5	4.23	79.8	42.49	80.7

In Table 4-10, SRA achieves the average percentage collaboration gain of 36.3% in 5.25 seconds of average computation time, CG_{CA} reaches 45.5% in 2.67 seconds on average, GH obtains the average percentage collaboration gain of 41.5% in only 4.23 ms, and MRE consumes 42.49 seconds on average to achieve the average percentage collaboration gain of 79.8%. CG_{CP} attains the maximum percentage collaboration gain for each instance set. Compared to Berger and Bierwirth (2010), our auction mechanism could obtain the improvement of more than 34% by consuming around 37 seconds on average. The percentage collaboration gain obtained by MRE is only 0.9% less than the maximum one on average and is significantly higher than those of the other three methods. According to the comparison results, we can conclude that MRE performs much better than SRA, CA, and GH for the instance sets of Berger and Bierwirth (2010). As explained in Li et al. (2015), the iterative request exchange process can be viewed as a searching process in the state space of request allocation among carriers. MRE can generate new states and can jump out of local optima, because each carrier updates its outsourcing bundles of requests based on the feedback information from previous iterations. By contrast, the auction processes proposed

by Berger and Bierwirth (2010) and Gansterer and Hartl (2016) may terminate early and prematurely, because in all iterations the outsourcing requests do not change.

Detailed results for comparison for each instance set are shown in Table 4-11.

Table 4-11 Comparison for the instance set of Berger and Bierwirth (2010)

Instance	P_{NC}	P_{SRA}	P_{CA}	P_{MRE}	P_{CP}	Gap_{SRA}	Gap_{CA}	Gap_{MRE}
A1	21	21	21	25	25	16.00	16.00	0.00
A2	164	164	164	216	207	24.07	24.07	4.17
A3	210	210	210	253	253	17.00	17.00	0.00
A4	187	187	187	187	187	0.00	0.00	0.00
A5	112	149	149	149	149	0.00	0.00	0.00
A6	141	190	190	209	209	9.09	9.09	0.00
A7	237	237	237	300	300	21.00	21.00	0.00
A8	218	218	218	229	229	4.80	4.80	0.00
A9	119	142	142	159	159	10.69	10.69	0.00
A10	230	230	230	289	289	20.42	20.42	0.00
A11	182	182	182	201	201	9.45	9.45	0.00
A12	141	141	141	184	184	23.37	23.37	0.00
A13	156	156	156	172	172	9.30	9.30	0.00
A14	105	105	105	105	105	0.00	0.00	0.00
A15	203	203	203	203	203	0.00	0.00	0.00
A16	208	208	208	243	243	14.40	14.40	0.00
A17	156	156	156	176	176	11.36	11.36	0.00
A18	109	109	109	117	117	6.84	6.84	0.00
A19	171	182	182	202	202	9.90	9.90	0.00
A20	164	164	164	191	191	14.14	14.14	0.00
A21	118	119	119	141	141	15.60	15.60	0.00
A22	167	178	178	209	209	14.83	14.83	0.00
A23	140	140	140	143	143	2.10	2.10	0.00
A24	119	121	121	131	131	7.63	7.63	0.00
A25	182	182	182	220	220	17.27	17.27	0.00
A26	176	176	176	255	237	30.98	30.98	7.06
A27	155	157	157	201	201	21.89	21.89	0.00
A28	203	203	203	225	225	9.78	9.78	0.00
A29	162	162	162	193	193	16.06	16.06	0.00
A30	169	169	169	209	209	19.14	19.14	0.00
Avg						12.57	12.57	0.37
O1	273	273	273	328	328	16.77	16.77	0.00
O2	121	187	187	236	236	20.76	20.76	0.00
O3	107	164	164	231	231	29.00	29.00	0.00
O4	138	247	294	303	278	18.48	2.97	8.25
O5	167	226	231	282	282	19.86	18.09	0.00
O6	198	198	198	280	280	29.29	29.29	0.00
O7	176	176	176	240	230	26.67	26.67	4.17
O8	213	213	213	340	340	37.35	37.35	0.00
O9	66	137	169	183	183	25.14	7.65	0.00
O10	139	184	184	286	286	35.66	35.66	0.00

4 A multi-round exchange mechanism for carrier collaboration in less than truckload transportation

Table 4-11(continued)

Instance	P_{NC}	P_{SRA}	P_{CA}	P_{MRE}	P_{CP}	Gap _{SRA}	Gap _{CA}	Gap _{MRE}
O11	209	211	211	269	269	21.56	21.56	0.00
O12	253	282	282	385	385	26.75	26.75	0.00
O13	201	222	222	236	236	5.93	5.93	0.00
O14	215	257	257	360	360	28.61	28.61	0.00
O15	160	212	212	244	244	13.11	13.11	0.00
O16	186	241	241	325	325	25.85	25.85	0.00
O17	161	228	228	294	294	22.45	22.45	0.00
O18	162	173	199	230	230	24.78	13.48	0.00
O19	123	155	172	211	211	26.54	18.48	0.00
O20	241	241	241	311	311	22.51	22.51	0.00
O21	160	255	212	319	319	20.06	33.54	0.00
O22	219	280	280	300	300	6.67	6.67	0.00
O23	87	114	114	143	143	20.28	20.28	0.00
O24	165	237	237	307	307	22.80	22.80	0.00
O25	158	210	205	286	286	26.57	28.32	0.00
O26	155	229	229	286	286	19.93	19.93	0.00
O27	303	349	349	452	420	22.79	22.79	7.08
O28	232	303	255	385	370	21.30	33.77	3.90
O29	344	344	344	465	465	26.02	26.02	0.00
O30	288	378	378	463	450	18.36	18.36	2.81
Avg						22.73	21.85	0.87
I1	139	268	320	320	320	16.25	0.00	0.00
I2	102	272	187	373	373	27.08	49.87	0.00
I3	142	265	265	367	367	27.79	27.79	0.00
I4	91	158	158	216	227	30.40	30.40	4.85
I5	176	189	189	403	403	53.10	53.10	0.00
I6	141	307	378	439	439	30.07	13.90	0.00
I7	283	283	283	491	491	42.36	42.36	0.00
I8	234	288	417	483	483	40.37	13.66	0.00
I9	170	259	258	355	355	27.04	27.32	0.00
I10	202	314	237	398	398	21.11	40.45	0.00
I11	158	332	382	478	478	30.54	20.08	0.00
I12	84	128	168	346	346	63.01	51.45	0.00
I13	171	228	228	430	430	46.98	46.98	0.00
I14	303	303	327	553	553	45.21	40.87	0.00
I15	163	366	464	464	464	21.12	0.00	0.00
I16	343	458	573	573	573	20.07	0.00	0.00
I17	210	338	338	427	427	20.84	20.84	0.00
I18	224	289	363	440	440	34.32	17.50	0.00
I19	164	307	408	409	413	25.67	1.21	0.97
I20	239	414	418	533	533	22.33	21.58	0.00
I21	61	61	302	302	302	79.80	0.00	0.00
I22	52	185	293	314	314	41.08	6.69	0.00
I23	253	559	582	582	582	3.95	0.00	0.00
I24	203	358	403	453	453	20.97	11.04	0.00

Table 4-11(continued)

Instance	P_{NC}	P_{SRA}	P_{CA}	P_{MRE}	P_{CP}	Gap _{SRA}	Gap _{CA}	Gap _{MRE}
I25	237	492	492	520	520	5.38	5.38	0.00
I26	281	465	465	500	500	7.00	7.00	0.00
I27	185	406	406	478	487	16.63	16.63	1.85
I28	312	331	482	585	585	43.42	17.61	0.00
I29	340	459	459	541	541	15.16	15.16	0.00
I30	256	527	527	527	527	0.00	0.00	0.00
Avg						29.30	19.96	0.26

Summarized results for comparison between MRE and GH for the instances of Gansterer and Hartl (2016) are given in Table 4-12. The performance indicators used for evaluating each method in Table 4-12 are the percentage collaboration gain CG and the percentage improvement of MRE with respect to GH denoted by IMP_{MRE-GH} . IMP_{MRE-GH} is defined as follows:

$$IMP_{MRE-GH} = (p_{MRE} - p_{GH}) / p_{MRE} * 100\% \quad (4-37)$$

Where p_{MRE} and p_{GH} are the profit of all carriers after collaboration obtained by MRE and GH respectively.

From Table 4-12, we can see that compared to non-collaboration, MRE can achieve a collaboration gain of 21.68% with 178.06 seconds of average computation time, whereas GH can only achieve an average collaboration gain of 8.80% with 17.44 seconds on average. In terms of profit gain, the improvement of our auction mechanism over GH is 11.80% on average by consuming 178.06 seconds.

Table 4-12 Comparison results for the instances of Gansterer and Hartl (2016)

Scenario	CG_{GH}	CPU_{GH}	CG_{MRE}	CPU_{MRE}	IMP_{MRE-GH}
I9	19.12	3.27	34.08	48.03	12.57
I15	11.55	49.82	25.18	398.80	12.23
O1_10	3.38	3.86	13.44	50.24	9.76
O1_15	2.03	13.98	11.01	265.24	8.83
O2_10	7.61	4.63	20.72	51.23	12.26
O2_15	5.17	27.93	15.66	274.67	9.97
O3_10	12.69	5.72	30.73	50.89	16.08
O3_15	8.83	30.34	22.61	285.39	12.7
Avg	8.80	17.44	21.68	178.06	11.80

The analysis of comparison results provided by Table 4-10 and Table 4-12 implies that our request exchange mechanism is more effective than the auctions proposed by Berger and Bierwirth (2010) and Gansterer and Hartl (2016). This may be because our request exchange mechanism can search for more states in the state space of request allocation and can jump out of local optima.

Detailed results for comparison between MRE and GH for the instances of Gansterer and Hartl (2016) are given in Table 4-13.

Table 4-13 Detailed results for the instances of Gansterer and Hartl (2016)

Instance	P_{NC}	P_{GH}	P_{MRE}	Imp_{MRE-GH}
I9-0	1023.92	1279.82	1471.99	15.02
I9-1	847.99	1168.93	1295.10	10.79
I9-2	1316.55	1564.37	1752.16	12.00
I9-3	1161.12	1351.15	1482.53	9.72
I9-4	1293.21	1565.48	1776.04	13.45
I9-5	1446.66	1683.87	1885.49	11.97
I9-6	1250.53	1395.90	1541.64	10.44
I9-7	1410.79	1630.06	1888.61	15.86
I9-8	1243.79	1440.74	1620.00	12.44
I9-9	1416.41	1596.38	1819.98	14.01
Avg				12.57
I15-0	2116.52	2409	2853.24	18.44
I15-1	2205.53	2421.94	2800.44	15.63
I15-2	2565.27	2921.09	3104.4	6.28
I15-3	2310.43	2548.8	2826.11	10.88
I15-4	2377.96	2587.08	3017.78	16.65
I15-5	2619.7	2949.41	3259.77	10.52
I15-6	2337.36	2597.65	2853.18	9.84
I15-7	2299.93	2615.69	2893.68	10.63
I15-8	2555.96	2847.48	3224.19	13.23
I15-9	2654.75	2922.15	3219.31	10.17
Avg				12.23
run=0/dist=200/rad=150/n=10	4659.15	4682.32	4823.87	3.02
run=1/dist=200/rad=150/n=10	3498.25	3684.26	3893.01	5.67
run=2/dist=200/rad=150/n=10	4093.55	4291.77	4718.12	9.93
run=3/dist=200/rad=150/n=10	2634.12	2789.90	3218.96	15.38
run=4/dist=200/rad=150/n=10	3464.70	3499.27	4421.89	26.37
run=5/dist=200/rad=150/n=10	3790.59	3955.87	4312.44	9.01
run=6/dist=200/rad=150/n=10	3677.52	3799.64	4347.41	14.42
run=7/dist=200/rad=150/n=10	3118.92	3249.97	3501.48	7.74
run=8/dist=200/rad=150/n=10	3743.75	3866.7	4709.35	21.79
run=9/dist=200/rad=150/n=10	4071.58	4351.96	4469.63	2.70
run=10/dist=200/rad=150/n=10	2975.08	3011.5	3222.27	7.00
run=11/dist=200/rad=150/n=10	3641.07	3923.84	3924.64	0.02
run=12/dist=200/rad=150/n=10	4329.63	4399.67	4576.75	4.02
run=13/dist=200/rad=150/n=10	4104.1	4268.92	4467.78	4.66
run=14/dist=200/rad=150/n=10	4045.86	4140.93	4605.99	11.23
run=15/dist=200/rad=150/n=10	2694.71	2731.93	3076.9	12.63
run=16/dist=200/rad=150/n=10	3574.8	3681.52	4152.07	12.78
run=17/dist=200/rad=150/n=10	3381.22	3512.54	3727.54	6.12
run=18/dist=200/rad=150/n=10	3367.56	3419.61	4081.4	19.35
run=19/dist=200/rad=150/n=10	3161.53	3201.28	3247.26	1.44
Avg				9.76
run=0/dist=200/rad=150/n=15	6252.95	6378.93	6746.95	5.77
run=1/dist=200/rad=150/n=15	3498.25	3684.26	3883.58	5.41

4 A multi-round exchange mechanism for carrier collaboration in less than truckload transportation

Table 4-13(continued)

Instance	P_{NC}	P_{GH}	P_{MRE}	Imp_{MRE-GH}
run=2/dist=200/rad=150/n=15	7145.1	7145.1	7811.58	9.33
run=3/dist=200/rad=150/n=15	6242.11	6421.03	6440.83	0.31
run=4/dist=200/rad=150/n=15	6886.96	6886.96	7456.92	8.28
run=5/dist=200/rad=150/n=15	7667.8	7765.65	8326.87	7.23
run=6/dist=200/rad=150/n=15	5950.05	6105.74	6647.32	8.87
run=7/dist=200/rad=150/n=15	5385.5	5463.27	6216.47	13.79
run=8/dist=200/rad=150/n=15	6713.99	6833.88	8413.88	23.12
run=9/dist=200/rad=150/n=15	6123.2	6332.54	6676.09	5.43
run=10/dist=200/rad=150/n=15	5859.71	5859.71	6695.67	14.27
run=11/dist=200/rad=150/n=15	6535.83	6793.85	7120.37	4.81
run=12/dist=200/rad=150/n=15	6207.73	6454.64	7122.26	10.34
run=13/dist=200/rad=150/n=15	6626.44	6698.71	7337.02	9.53
run=14/dist=200/rad=150/n=15	6694.29	6732.94	7463.87	10.86
run=15/dist=200/rad=150/n=15	5911.69	6129.35	6145.57	0.26
run=16/dist=200/rad=150/n=15	5526.74	5815.06	6373.75	9.61
run=17/dist=200/rad=150/n=15	5659.62	5714.74	6328.62	10.74
run=18/dist=200/rad=150/n=15	5510.94	5510.94	5995.78	8.80
run=19/dist=200/rad=150/n=15	6193.66	6220.76	6833.66	9.85
Avg				8.83
run=0/dist=200/rad=200/n=10	3133.43	3283.55	4391.74	33.75
run=1/dist=200/rad=200/n=10	3899.50	3975.62	4497.81	13.13
run=2/dist=200/rad=200/n=10	3713.20	3930.17	3930.17	0.00
run=3/dist=200/rad=200/n=10	5337.08	5675.77	6128.84	7.98
run=4/dist=200/rad=200/n=10	6596.97	7018.38	7600.48	8.29
run=5/dist=200/rad=200/n=10	5032.71	5252.93	5892.27	12.17
run=6/dist=200/rad=200/n=10	4368.77	5000.68	5052.15	1.03
run=7/dist=200/rad=200/n=10	4525.62	5003.32	6108.56	22.09
run=8/dist=200/rad=200/n=10	4475.09	4665.76	5498.5	17.85
run=9/dist=200/rad=200/n=10	4743.95	5162.3	5290.29	2.48
run=10/dist=200/rad=200/n=10	3824.76	4256.78	5155.7	21.12
run=11/dist=200/rad=200/n=10	5557.14	5950.02	7900.56	32.78
run=12/dist=200/rad=200/n=10	4766.06	5154.44	6164.29	19.59
run=13/dist=200/rad=200/n=10	4928.85	5562.76	5955.36	7.06
run=14/dist=200/rad=200/n=10	5336.17	5690.86	5737.33	0.82
run=15/dist=200/rad=200/n=10	5055.86	5310.14	5978.54	12.59
run=16/dist=200/rad=200/n=10	5399.82	5518.18	6180.19	12.00
run=17/dist=200/rad=200/n=10	4796.37	5518.98	5658.12	2.52
run=18/dist=200/rad=200/n=10	5124.76	5436.21	5678.87	4.46
run=19/dist=200/rad=200/n=10	3455.8	3804.33	4313.74	13.39
Avg				12.26
run=0/dist=200/rad=200/n=15	9697.98	10130.8	10868.05	7.28
run=1/dist=200/rad=200/n=15	7209.27	7499.11	8431.04	12.43
run=2/dist=200/rad=200/n=15	9553.69	9769.71	10398.06	6.43
run=3/dist=200/rad=200/n=15	8591.52	9217.42	9981.28	8.29
run=4/dist=200/rad=200/n=15	6414.36	6871.92	7416.2	7.92

4 A multi-round exchange mechanism for carrier collaboration in less than truckload transportation

Table 4-13(continued)

Instance	P_{NC}	P_{GH}	P_{MRE}	Imp_{MRE-GH}
run=5/dist=200/rad=200/n=15	5804.84	6174.7	7392.63	19.72
run=6/dist=200/rad=200/n=15	8749.85	9400.48	10444.62	11.11
run=7/dist=200/rad=200/n=15	7030.1	7155.14	7882.56	10.17
run=8/dist=200/rad=200/n=15	9474.2	10082.4	10769.34	6.81
run=9/dist=200/rad=200/n=15	7294.23	7649.24	8547.38	11.74
run=10/dist=200/rad=200/n=15	7278.62	7873.02	8494.79	7.90
run=11/dist=200/rad=200/n=15	9176.84	9626.89	10632.74	10.45
run=12/dist=200/rad=200/n=15	9097.15	9334.09	10100.13	8.21
run=13/dist=200/rad=200/n=15	9506.31	10093.6	11110.71	10.08
run=14/dist=200/rad=200/n=15	7886.36	8110.93	8912.21	9.88
run=15/dist=200/rad=200/n=15	6464.4	6958.28	7817.37	12.35
run=16/dist=200/rad=200/n=15	8826.82	9190.23	10216.23	11.16
run=17/dist=200/rad=200/n=15	7885.69	8414.99	8806.84	4.66
run=18/dist=200/rad=200/n=15	9895.55	10349.8	11724.64	13.28
run=19/dist=200/rad=200/n=15	6561.47	6793.93	7445.33	9.59
Avg				9.97
run=0/dist=200/rad=300/n=10	7000.61	7780.62	10459.50	34.43
run=1/dist=200/rad=300/n=10	4880.99	6014.46	6368.83	5.89
run=2/dist=200/rad=300/n=10	7953.54	9088.81	9862.63	8.51
run=3/dist=200/rad=300/n=10	5227.17	6186.97	7422.61	19.97
run=4/dist=200/rad=300/n=10	6811.25	7134.96	8985.86	25.94
run=5/dist=200/rad=300/n=10	8098.27	8683.29	9339.78	7.56
run=6/dist=200/rad=300/n=10	6691.95	7778.42	9074.74	16.67
run=7/dist=200/rad=300/n=10	6741.75	7864.77	8826.16	12.22
run=8/dist=200/rad=300/n=10	5372.69	6241.67	7314.65	17.19
run=9/dist=200/rad=300/n=10	6631.97	7587.31	8748.05	15.30
run=10/dist=200/rad=300/n=10	7454.76	8235.44	9430.56	14.51
run=11/dist=200/rad=300/n=10	6244.76	7431.23	8693.21	16.98
run=12/dist=200/rad=300/n=10	5930.84	6926.72	7963.71	14.97
run=13/dist=200/rad=300/n=10	5793.69	6576.8	7826.56	19.00
run=14/dist=200/rad=300/n=10	6394.26	6937.16	9195.14	32.55
run=15/dist=200/rad=300/n=10	8567.12	8946.65	10039.08	12.21
run=16/dist=200/rad=300/n=10	9374.43	10176.9	11578.41	13.77
run=17/dist=200/rad=300/n=10	7362.79	7932.28	9212.56	16.14
run=18/dist=200/rad=300/n=10	6297.37	6933.56	7822.56	12.82
run=19/dist=200/rad=300/n=10	7818.56	8779.23	9217.18	4.99
Avg				16.08
run=0/dist=200/rad=300/n=15	11697.5	12558.9	14214.5	13.18
run=1/dist=200/rad=300/n=15	12995.8	14146.5	15672.3	10.79
run=2/dist=200/rad=300/n=15	13497.3	14114.9	15696.2	11.20
run=3/dist=200/rad=300/n=15	11077.7	12147.8	13458	10.79
run=4/dist=200/rad=300/n=15	14942.8	15863.2	17825.2	12.37
run=5/dist=200/rad=300/n=15	10401.1	11700	13714.2	17.22
run=6/dist=200/rad=300/n=15	12441.1	13738.5	15822.8	15.17
run=7/dist=200/rad=300/n=15	12575.3	13415.5	15367	14.55

Table 4-13(continued)

Instance	P_{NC}	P_{GH}	P_{MRE}	Imp_{MRE-GH}
run=8/dist=200/rad=300/n=15	11184.9	12659.5	13452.9	6.27
run=9/dist=200/rad=300/n=15	12920.5	14323.5	15115.8	5.53
run=10/dist=200/rad=300/n=15	11212.8	12290.1	14167.5	15.28
run=11/dist=200/rad=300/n=15	10268.4	11490.7	12173.4	5.94
run=12/dist=200/rad=300/n=15	12569.7	13386.9	16158.2	20.70
run=13/dist=200/rad=300/n=15	10550.7	11314.8	13077.4	15.58
run=14/dist=200/rad=300/n=15	11025	11923.6	14072.5	18.02
run=15/dist=200/rad=300/n=15	13021.9	14065.7	16101.7	14.47
run=16/dist=200/rad=300/n=15	10639.5	11950.6	13227.4	10.68
run=17/dist=200/rad=300/n=15	13602.1	14699.8	16201.6	10.22
run=18/dist=200/rad=300/n=15	13800.8	14454.7	16535.5	14.40
run=19/dist=200/rad=300/n=15	13364	14677.8	16383.2	11.62
Avg				12.70

4.5 Brief summary

This chapter proposes a multi-round auction mechanism for carrier collaboration with pickup and delivery requests in less-than truckload transportation. Two mixed integer programming models are formulated to select multiple bundles of requests to outsource and to insource, respectively. The auctioneer solves WDP to match the supplies of requests with the demands and to reassign some bundles of requests among carriers in the collaboration alliance. In our request exchange mechanism, each carrier updates its outsourcing bundles of requests based on the feedback information from previous iterations. Extensive numerical experiments show that insourcing requests from multiple carriers in each iteration of the mechanism is more effective than insourcing requests from only one carrier. Moreover, no significant difference exists between WDP with complete information and incomplete information. The same experiments show that our auction mechanism significantly outperforms the auction mechanisms proposed by Berger and Bierwirth (2010) and Gansterer and Hartl (2016). Based on the preliminary results, we believe that the proposed auction mechanism has the potential to help carriers improve their profitability through effective collaboration among them.

5 A benders decomposition algorithm for bid generation problem in the procurement of multi-echelon transportation services

5.1 Introduction

Effective transportation is playing a critical role in economy as the demand for transporting freight is growing with the development of e-commerce. For instance, Amazon delivered 3.3 billion packages globally in 2019 (CNBC, 2019) and in China over 50 billion packages were delivered across the country in 2018 (National Bureau of Statistics of China, 2019). In modern global competition, the need to control costs and provide high level service make the procurement of transportation services become a key segment for shippers (manufactures). On transportation service market, shippers will seek services from carriers when they have some goods to be transported and they typically put out a request for quotes from a set of carriers. Many service platforms as the third-party exchange service provider allows shippers and carriers to share their needs and capacities and facilitates the trading between shippers and carriers (George and Xu, 2013). Varieties of procurement mechanisms are proposed for solving the transportation service procurement problem, such as combinatorial auctions, double auctions. For more details about auction mechanisms for transportation service procurement, please refer to the review papers of Jothi Basu et al. (2015) and Lafkihi et al. (2019). In a transportation service procurement auction, each carrier needs to solve a bid generation problem (BGP) to select transportation requests for bidding (Lyu et al., 2019). Therefore, we study a BGP for transportation service procurement in less than truckload transportation in this chapter.

There are two main distribution strategies in transportation: direct shipping and multi-echelon distribution. In direct shipping, vehicles starting from a depot transport their freight directly to the customers, while in multi-echelon systems the freight is delivered from the origin to the customers through intermediate depots (Perboli, Tadei and Vigo, 2011). Multi-echelon systems with LTL dispatching policies have been introduced by practitioners in freight transportation. In practice, multi-echelon systems have been usually adopted to satisfy customer demands. E-commerce companies and express delivery companies build logistic centers as intermediate depots to offer inter-city delivery services. For example, in the United States, Amazon redesigned multi-echelon distribution networks with existing retail outlets in close proximity to customers and adopted such multi-echelon distribution networks to provide same-day delivery in 14 U.S. metropolitan areas in May 2015 and ultra-fast one hour delivery service through nationwide Whole Foods outlets (Calero and Zhang, 2019). Although multi-echelon transportation has obtained more attention from practitioners and in the literature, studying BGP for transportation service procurement in a multi-echelon transportation environment was rare. To this end, we study a BGP for transportation service procurement in a three-echelon transportation (3E-BGP).

In this chapter, we consider parcel delivery services in e-commerce, where parcels

ordered by customers are picked up from suppliers in one city and delivered to the customers in another city. To take advantage of transportation scale, the delivery of the parcels passes intermediate facilities called Urban Consolidation Centers (UCC) where parcels are consolidated according to their destinations. In the three-echelon transportation network we consider, parcels are first picked up from suppliers and delivered to an UCC in the city of origin, the parcels are then transported from the UCC to another UCC in the city of destination after consolidation via a long-haul transportation, these parcels are finally delivered to customers from the second UCC. It is assumed that suppliers and customers are located in different zones in each city.

As our problem is more complicated than the capacitated vehicle routing problem in a single echelon transportation, which is NP-hard, we propose a benders decomposition algorithm to find a near-optimal solutions of the problem. In this problem, we assume that the transportation operations for each request in three echelons must be served by the same carrier. Firstly, a path-based formulation is developed, in which the three echelon routes are separated, and the interconnectivity of the first echelon, the second echelon and the third echelon routing is formulated using additional connectivity constraints. For this formulation, a benders decomposition algorithm is proposed to decompose the path-based model into a master problem in the second echelon transportation and two subproblems in the first echelon and the third echelon transportation respectively. Our experimental results demonstrate that the benders decomposition algorithm is effective in terms of solution quality and CPU time.

The remainder of the paper is organized in the following structure: In Section 5.2, one arc-based mathematical model and one path-based model are formulated. Section 5.3 presents the basic benders reformulation, the benders decomposition algorithm and some acceleration strategies. In Section 5.4, we conduct computational experiments and analyze the results. We end this paper with the conclusion in Section 5.5.

5.2 Problem description and mathematical model

We consider a BGP for transportation service procurement in a three-echelon transportation (3E-BGP), in which transportation requests are picked up from clusters of suppliers to the UCC in the first city, then transported via a long-haul between UCCs in the first city and the second city, and in the second city these transportation requests are transported from UCC to the corresponding customers. As some suppliers and customers are close, we assume that these suppliers and customers share the same zone and in the same zone the transportation distance is negligible (Handoko and Lau, 2016). The transportation network is described in the Fig.5-1.

As several suppliers and customers share the same zone, the demand of each zone is large and one vehicle cannot fulfill such large demands. Therefore, we assume that each vehicle serves at most one zone in the two cities. Besides, the distance between the suppliers in one zone is negligible, so there are no routing decisions in this problem. The objective of this problem is to determine the set of profitable transportation requests to bid on to

maximize the carrier's individual profit, while taking into its reserved requests, its vehicle capacity in each echelon and synchronization time windows constraints. select requests and assign these requests to the vehicles to maximize the carrier's individual profit, satisfying the time windows in the three-echelon and capacity constraints in each echelon.

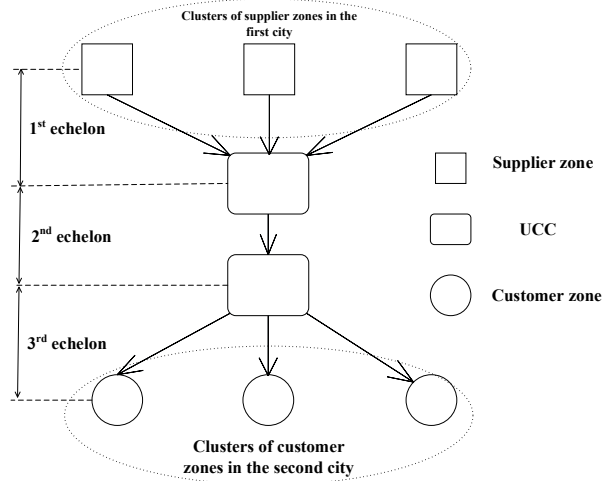


Fig.5-1 The transportation network in a multi-echelon transportation

The assumptions are described as follows:

- 1) In the 1st echelon, each vehicle of the carrier services at most one supplier.
- 2) In the 3rd echelon, each vehicle at most visits one customer zone.
- 3) Each request in the three echelons must be serviced by the same carrier.

5.2.1 Node-based formulation

In our problem, a homogeneous vehicle fleet is used for each echelon. In the city 1, a fleet of vehicles denoted by K^1 with the capacity of each vehicle Q^1 located at the urban center u_1 picks up a transportation request $i \in R$ from the zone $s_i \in Z_1$ and delivers it to u_1 . In the urban centers, the requests from city 1 are consolidated at u_1 and transported between these two urban centers by a fleet of vehicles denoted by K^0 with the capacity of each vehicle Q^0 . In the city 2, a fleet of vehicles denoted by K^2 with the capacity of each vehicle Q^2 is used to deliver a transportation contract $i \in R$ from u_2 to the corresponding zone $d_i \in Z_2$. For the vehicles used in the two cities and urban centers, each vehicle is associated with a fixed cost f^1, f^0 and f^2 . The set of nodes to be visited by the vehicles in the three echelons is defined as N and each edge (i, j) has a travel cost c_{ij} and a travel time t_{ij} . The reserved request set is R_o , the selective request set is R_e , and $R = R_o \cup R_e$. The earliest pickup time for each request $i \in R$ at the corresponding pickup zone s_i is a_i and b_i is the latest delivery time for request $i \in R$ at the corresponding delivery zone. Request $i \in R$ is associated with a pickup/delivery quantity q_i and an amount of revenue p_i . The revenue of a request is the price paid by a shipper to the carrier serving the request.

The notations required to formulate 3E-BGPST are first given in the following.

Notations

Z_1	The set of supplier zones in the first city
Z_2	The set of customer zones in the second city
U	The set of urban centers, $U = \{u_1, u_2\}$
N	The set of nodes in the network, $N = Z_1 \cup Z_2 \cup U$
R_o	The set of reserved customer requests for the carrier
R_e	The set of selective requests
R	The set of customer requests, $R = R_o \cup R_e$
s_i	The supplier zone (pickup location) of request $i \in R$
d_i	The destination zone (delivery location) of request $i \in R$
q_i	The quantity delivered on request $i \in R$
a_i	The earliest pickup time for a vehicle to start service of request $i \in R$
b_i	The latest delivery time for a vehicle to start service of request $i \in R$
p_i	The price the supplier paid to the carrier of request $i \in R$
K^1	The set of vehicles of the carrier in the 1 st echelon
K^0	The set of line-haul vehicles in the 2 nd echelon
K^2	The set of vehicles of the carrier in the 3 rd echelon
Q^1	The capacity of vehicles of the carrier in the 1 st echelon
Q^0	The capacity of vehicles of the carrier in the 2 nd echelon
Q^2	The capacity of vehicles of the carrier in the 3 rd echelon
c_{ij}	The transportation cost by one vehicle on the arc $(i, j), i \in N, j \in N, i \neq j$
t_{ij}	The travel time by one vehicle on the arc $(i, j), i \in N, j \in N, i \neq j$
f^0	The fixed cost of each vehicle in the transfer centers
f^1	The fixed cost of each vehicle in the first city
f^2	The fixed cost of each vehicle in the second city

Decision variables

$v_i^{k,l}$	Binary variable which equals to 1 if and only if request $i \in R$ is served by the vehicle $k \in K^l, l = \{0,1,2\}$
w^k	Binary variable which equals to 1 if and only if the vehicle $k \in K^0$ is used in the transfer urban centers
$y_i^{k,l}$	Binary variable which equals to 1 if and only if the vehicle $k \in K^l$ serves

the node $i \in N$ in the l echelon, $l \in \{1, 2\}$

$T_i^{k,l}$ The service time for each vehicle $k \in K^l, l = \{0, 1, 2\}$ at the node $i \in N$

$$\begin{aligned} \max & \left(\sum_{i \in R} \sum_{k \in K^0} p_i \cdot v_i^{k,0} - \sum_{s \in S} \sum_{k \in K^1} (2 \cdot c_{s,u_1} + f^1) \cdot y_s^{k,1} - \sum_{k \in K^0} (2 \cdot c_{u_1,u_2} + f^0) \cdot w^k \right. \\ & \left. - \sum_{d \in Z_2} \sum_{k \in K^2} (2 \cdot c_{d,u_2} + f^2) \cdot y_d^{k,2} \right) \end{aligned} \quad (5-1)$$

S.t.

$$\sum_{k \in K^l} v_i^{k,l} = 1 \quad \forall i \in R_o, l = \{0, 1, 2\} \quad (5-2)$$

$$\sum_{k \in K^l} v_i^{k,l} \leq 1 \quad \forall i \in R_e, l = \{0, 1, 2\} \quad (5-3)$$

$$\sum_{k \in K^1} v_i^{k,1} = \sum_{k \in K^0} v_i^{k,0} \quad \forall i \in R \quad (5-4)$$

$$\sum_{k \in K^2} v_i^{k,2} = \sum_{k \in K^0} v_i^{k,0} \quad \forall i \in R \quad (5-5)$$

$$\sum_{i \in N} y_i^{k,l} \leq 1 \quad \forall k \in K^l, l = 1, 2 \quad (5-6)$$

$$y_{s_i}^{k,1} \geq v_i^{k,1} \quad \forall i \in R, k \in K^1 \quad (5-7)$$

$$y_{d_i}^{k,2} \geq v_i^{k,2} \quad \forall i \in R, k \in K^2 \quad (5-8)$$

$$w^k \geq v_i^{k,0} \quad \forall i \in R, k \in K^0 \quad (5-9)$$

$$\sum_{i \in R, s_i, d_i = j} v_i^{k,l} \cdot q_i \leq y_j^{k,l} \cdot Q^l \quad \forall j \in Z_l, k \in K^l, l = \{1, 2\} \quad (5-10)$$

$$\sum_{i \in R} v_i^{k,0} \cdot q_i \leq w^k \cdot Q^0 \quad \forall k \in K^0 \quad (5-11)$$

$$T_{s_i}^{k,1} \geq a_i * v_i^{k,1} \quad \forall i \in R, k \in K^1 \quad (5-12)$$

$$T_{d_i}^{k,2} \leq b_i + M * (1 - v_i^{k,2}) \quad \forall i \in R, k \in K^2 \quad (5-13)$$

$$T_{u_1}^{k,0} \geq T_{s_i}^{l,1} + t_{s_i, u_1} - M * (2 - v_i^{l,1} - v_i^{k,2}) \quad \forall k \in K^0, l \in K^1, i \in R \quad (5-14)$$

$$T_{d_i}^{k,2} - t_{u_2, d_i} \geq T_{u_1}^{l,0} + t_{u_1, u_2} - M * (2 - v_i^{l,0} - v_i^{k,2}) \quad \forall k \in K^2, l \in K^0, i \in R \quad (5-15)$$

$$v_i^{k,l} \in \{0, 1\} \quad \forall i \in R, k \in K^l, l = \{0, 1, 2\} \quad (5-16)$$

$$w^k \in \{0, 1\} \quad \forall k \in K^0 \quad (5-17)$$

$$y_i^{k,l} \in \{0, 1\} \quad \forall i \in N, k \in K^l, l = \{1, 2\} \quad (5-18)$$

$$T_i^{k,l} \geq 0 \quad \forall i \in N, k \in K^l, l = \{1, 2\} \quad (5-19)$$

The objective of (5-1) is the maximization of total profit of the three echelons. Constraint (5-2) ensures that in each echelon, each reserved request must be served by the carrier. Constraint (5-3) ensures that each selective request can be served at most once by the carrier. Constraint (5-4)-(5-5) guarantees that each request in the three echelons must be serviced by the same carrier, that is each request cannot be split. Constraint (5-6) ensures that each vehicle can visit at most one zone in two cities. Constraints (5-7)-(5-9) describe the

logical relationship between the request selection variables and the requests assignment variables. Constraints (5-10)-(5-11) is the capacity constraints for each vehicle in the three echelons. Constraint (5-12) is the earliest pickup time for each request in the corresponding supplier zone in the first echelon. Constraint (5-13) is the latest delivery time for each request in the corresponding customer zone in the third echelon. Constraint (5-14) relates the arrival time and departure time of the request at the urban city center in the first city. It denotes that the vehicle in the second echelon serves the request only after it has been delivered to u_1 by the vehicle in the first echelon. Constraint (5-15) relates the arrival time and departure time of the request at the urban city center in the second city. It denotes that the vehicle in the third echelon serves the request only after it has been delivered to u_2 by the vehicle in the second echelon. Constraints (5-18)-(5-21) indicate the natures of all variables and their upper and lower bounds.

5.2.2 Path-based formulation

Inspired from the formulations proposed by Baldacci et al. (2013) for the 2E-VRP and Dellaert et al. (2019) for the 2E-VRPTW, we formulate a path-based mathematical formulation in which the first echelon, the second echelon and the third echelon routes are connected. In the three-echelon transportation, a second echelon tour could be connected with a first echelon tour if they meet at the u_1 to unload freight (from the first echelon vehicle) and load it (to the second echelon vehicle) to serve the demand of a customer and the departure time of the second echelon vehicle tour is after the unloading time of the first echelon tour at the u_1 . A third echelon tour is connected with the second echelon tour in the same condition as a second echelon tour connected with a first echelon tour.

A first echelon vehicle tour and a third echelon vehicle tour are feasible if the associated vehicle capacity and the time windows of all of its transportation requests are respected. The feasible departure time set for each vehicle in the second echelon is T . ϕ_t denotes the set of feasible vehicle routes arrival before $t \in T$ in the first echelon and φ_t denotes the set of feasible vehicle routes departure after $t \in T$ in the third echelon. We indicate with $\phi = \sum_{t \in T} \phi_t, \varphi = \sum_{t \in T} \varphi_t$ the set of all feasible vehicle routes in the first echelon and third echelon respectively. Let α_{il}, β_{il} be a binary coefficient equal to 1 if request $i \in R$ is visited by the vehicle route $l \in \phi$ in the first echelon and the vehicle route $l \in \varphi$ in the third echelon.

Notations

T_i	The feasible departure time set for the request $i \in R$
$nv1$	The number of vehicles in the first echelon
$nv2$	The number of vehicles in the second echelon
$nv3$	The number of vehicles in the third echelon
ϕ_t	The set of feasible vehicle routes arrival before time $t \in T$ in the first echelon
φ_t	The set of feasible vehicle routes departure after time $t \in T$ in the third

	echelon
ϕ	The set of all feasible first echelon vehicle tours, $\phi = \bigcup_{t \in T} \phi_t$
φ	The set of all feasible third echelon vehicle tours, $\varphi = \bigcup_{t \in T} \varphi_t$
α_{il}	The parameter indicates whether request $i \in R$ is included in the vehicle route $l \in \phi$ in the first echelon
β_{ib}	The parameter indicates whether request $i \in R$ is included in the vehicle route $b \in \varphi$ in the third echelon
c_l	The transportation cost associated with the vehicle tour $l \in \phi$ in the first echelon
c_b	The transportation cost associated with the vehicle tour $b \in \varphi$ in the third echelon

Decision variables

x_l	Binary variable which equals to 1 if and only if the vehicle route $l \in \phi$ in the first echelon is served by the carrier
wu_i^{kt}	Binary variable which equals to 1 if and only if request $i \in R$ departs from u_1 at time $t \in T$ in the second echelon by the vehicle $k \in K^0$
yr_{kt}	Binary variable which equals to 1 if and only if the vehicle $k \in K^0$ in the second echelon departs from u_1 at time $t \in T$
z_b	Binary variable which equals to 1 if and only if the vehicle route $b \in \varphi$ in the third echelon is served by each carrier

A path-based formulation for the transportation service procurement in a three-echelon transportation is modeled as follows:

$SP(\lambda, \phi, T, \varphi)$:

$$\max \left(\sum_{i \in R} \sum_{k \in K^2} \sum_{t \in T} p_i \cdot wu_i^{kt} - \sum_{l \in \phi} c_l \cdot x_l - \sum_{k \in K^2} \sum_{t \in T} (2 \cdot c_{u_1, u_2} + f^0) \cdot yr_{kt} - \sum_{b \in \varphi} c_b \cdot z_b \right)$$

(5-22)

S.t.

$$\sum_{k \in K^0} \sum_{t \in T_i} wu_i^{kt} = 1 \quad \forall i \in R_o \quad (5-23)$$

$$\sum_{k \in K^2} \sum_{t \in T_i} wu_i^{kt} \leq 1 \quad \forall i \in R_e \quad (5-24)$$

$$\sum_{i \in R} wu_i^{kt} \cdot d_i \leq Q^0 \quad \forall k \in K^0, t \in T \quad (5-25)$$

$$yr_{kt} \geq wu_i^{kt} \quad \forall i \in R, k \in K^0, t \in T_i \quad (5-26)$$

$$\sum_{t \in T} yr_{kt} \leq 1 \quad \forall k \in K^0 \quad (5-27)$$

$$\sum_{l \in \phi} \alpha_{il} \cdot x_l = \sum_{k \in K^2} \sum_{t \in T_i} wu_i^{kt} \quad \forall i \in R \quad (5-28)$$

$$\sum_{l \in \phi_i} \alpha_{il} \cdot x_l \geq \sum_{k \in K^2} wu_i^{kt} \quad \forall i \in R, t \in T_i \quad (5-29)$$

$$\sum_{b \in \phi} \beta_{ib} \cdot z_b = \sum_{k \in K^2} \sum_{t \in T_i} wu_i^{kt} \quad \forall i \in R \quad (5-30)$$

$$\sum_{b \in \phi_i} \beta_{ib} \cdot z_b \geq \sum_{k \in K^2} wu_i^{kt} \quad \forall i \in R, t \in T_i \quad (5-31)$$

$$\sum_{l \in \phi} x_l \leq nv1 \quad (5-32)$$

$$\sum_{k \in K^2} \sum_{t \in T} y_{kt} \leq nv2 \quad (5-33)$$

$$\sum_{b \in \phi} z_b \leq nv3 \quad (5-34)$$

$$x_l \in \{0,1\} \quad \forall l \in \phi \quad (5-35)$$

$$wu_i^{kt} \in \{0,1\} \quad \forall i \in R, k \in K^2, t \in T_i \quad (5-36)$$

$$y_{kt} \in \{0,1\} \quad \forall k \in K^2, t \in T \quad (5-37)$$

$$z_b \in \{0,1\} \quad \forall b \in \phi \quad (5-38)$$

Objective function (5-22) maximizes the total profit of the three echelons. Constraints (5-23) guarantees that all reserved requests must be served once, whereas in constraints (5-24) selective requests are served at most once. Constraint (5-25) is the capacity constraints for each vehicle in the second echelon. Constraints (5-26) describes the logical relationship between the request assignment variables and the requests selection variables: if one request is serviced by the vehicle, this vehicle is used. Constraint (5-27) ensures that each vehicle can be used at most one time. Constraints (5-28) and (5-30) guarantee that each request in the three echelons must be serviced by the same carrier. Constraints (5-29) and (5-31) denotes the synchronous constraints between the service time in the three echelons. Constraints (5-32) -(5-34) is the maximum number of the used vehicles in the three echelons. Constraints (5-35) -(5-38) define the variables.

5.3 Benders Decomposition (BD) algorithm

In order to solve model 3E-BGP, we develop a Benders decomposition approach. Benders decomposition is a classical solution approach for mixed integer programming problems based on problem decomposition and delayed constraint generation (Benders, 1962). This method partitions the original problem into two smaller and simpler problems: an integer master problem and a linear subproblem. Benders decomposition method is a partitioning algorithm applied to mixed integer programming problems, in which the original problem is decomposed into a master problem consisting of integer variables and corresponding constraints and a subproblem consisting of continuous variables and the remaining constraints. For problems with integrality restrictions in subproblems, the straightforward implementation of Benders decomposition algorithm and the generation of

valid Benders cuts becomes complicated due to the duality gap of integer programming in subproblems (Fakhri et al., 2017). In the current study of Benders decomposition algorithm for integrality restrictions in subproblems, a logic-based benders approach (Hooker and Ottosson, 2003; Hooker 2007; Heching et al., 2019) and a branch and cut method (Fakhri et al., 2017) are proposed. In this section, we first introduce a Benders reformulation of the 3E-BGPST based on the compact formulation (5-22)-(5-38). Then a basic Benders decomposition algorithm is described to solve the reformulation. Because of solving the master problem consumes much time, we thus present acceleration strategies to generate strong cuts for the master problem.

5.3.1 Basic Benders Decomposition Algorithm

The main procedural framework of the benders decomposition algorithm is sketched in Algorithm 5-1. The main loop (lines 3-9) iteratively solves the benders master problem and the sub-problems to get the search process and generate the violated cuts. Let UB and LB denote an upper bound and lower bound on the optimal solution value respectively. In each iteration of the main loop, based on the fixed values of $\bar{w}u_i^{tk}, \bar{y}r_{tk}$ obtained by solving the benders master problem, the benders sub-problems $BSP^1(\phi, \bar{w}u_i^{tk}, \bar{y}r_{tk})$ in the first echelon and $BSP^3(\phi, \bar{w}u_i^{tk}, \bar{y}r_{tk})$ in the third echelon are solved and new cuts are generated and added into the master problem.

Algorithm 5-1 Benders decomposition

- 1 Initialization: $UB = +\infty, LB = -\infty, \varepsilon = 0.01$
 - 2 Generate the initial solution and get values of $\bar{w}u_i^{tk}, \bar{y}r_{tk}$ in the second echelon
 - 3 **Do**
 - 4 Solve the subproblem $BSP^1(\phi, \bar{w}u_i^{tk}, \bar{y}r_{tk})$ in the first echelon, $BSP^3(\phi, \bar{w}u_i^{tk}, \bar{y}r_{tk})$ in the third echelon
 - 5 Get extreme point and Update LB
 - 6 Add cuts to the master problem and
 - 7 Solve the master problem obtaining new values of $\bar{w}u_i^{tk}, \bar{y}r_{tk}$, and update UB
 - 8 **While** ($|UB - LB|/UB > \varepsilon$)
 - 9 **End while**
-

For small size instances, an initial solution is first generated by solving the node-based model with the following constraints:

$$\sum_{k \in K^l} v_i^k = 1, i \in R_o, l = \{0, 1, 2\} \quad (5-57)$$

$$\sum_{k \in K^l} v_i^k = 0, i \in R_e, l = \{0, 1, 2\} \quad (5-58)$$

For medium size and large size instances, we solve the model only with the second

echelon constraints and constraints (5-57)-(5-58). The benders master problem model is solved by CPLEX MIP solver.

In our problem, given that values of $\overline{wu}_i^{tk}, \overline{yr}_{tk}$ in each iteration of Algorithm 5-1, the selective requests, latest departure time at u_1 and earliest arrival time at u_2 are determined in the first echelon and the third echelon. Once these variables are determined, the models of these two subproblems can be simplified to bin-packing models with time constraints. As the optimal solution of the subproblem limits the solution space, the efficiency of the benders cuts added to the master problem becomes lower and the iterations needed to converge the algorithm becomes large. Therefore, we design an approximate benders decomposition algorithm in a heuristic manner.

ϕ, φ is the set of all feasible routes in the first echelon and the third echelon. As we cannot enumerate all routes in ϕ, φ , we construct a limited number of routes $\overline{\phi}, \overline{\varphi}$, which is composed of the optimal routes in the first echelon and the third echelon. As the subproblems can be simplified to bin-packing model with time windows constraints, We solve the models of two subproblems by the CPLEX MIP solver.

Due to the special structure of our problem, using Benders decomposition algorithm leads to slow convergence. In the following sections, we propose some strategies to accelerate the Benders decomposition algorithm.

5.3.2 Benders reformulation

For given the value of $\overline{wu}_i^{tk} (i \in R, t \in T_i, k \in K^0), \overline{yr}_{tk} (k \in K^0, t \in T)$, satisfying constraints (5-23)-(5-27), (5-33) and (5-36)-(5-37), the 3E-BGPST model (5-22)-(5-38) reduces to the following bender sub-problems involving the decision variables in the first echelon and the third echelon, and master problem involving the decision variables in the second echelon.

The bender sub-problem in the first echelon $BSP^1(\phi, \overline{wu}_i^{tk}, \overline{yr}_{tk})$ is modeled as follows:

$$\min(\sum_{l \in \phi} c_l \cdot x_l) \quad (5-39)$$

Subject to (5-32), (5-35) and

$$\sum_{l \in \phi} \alpha_{il} \cdot x_l = \sum_{k \in K^0} \sum_{t \in T_i} \overline{wu}_i^{tk} \quad \forall i \in R \quad (5-40)$$

$$\sum_{l \in \phi} \alpha_{il} \cdot x_l \geq \sum_{k \in K^0} \overline{wu}_i^{tk} \quad \forall i \in R, t \in T_i \quad (5-41)$$

Let $\pi_i, i \in R$ be the dual variable associated with constraint (5-40), $\eta_{it}, i \in R, t \in T_i$ be a variable associated with constraint (5-41), and σ be a dual variable associated with constraint (5-32). The dual problem $BDP^1(\overline{\phi}, \overline{wu}_i^{tk}, \overline{yr}_{tk})$ of a linear relaxation of $BSP^1(\phi, \overline{wu}_i^{tk}, \overline{yr}_{tk})$ can be formulated as:

$$\max(\sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^0} \pi_i \cdot \overline{wu}_i^{tk} + \sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^0} \eta_{it} \cdot \overline{wu}_i^{tk} - \sigma \cdot nv1) \quad (5-42)$$

S.t.

$$\sum_{i \in R} \alpha_{il} \cdot \pi_i + \sum_{i \in R} \sum_{t \in T_i} \alpha_{it} \cdot \eta_{it} - \sigma \leq c_l \quad \forall l \in \overline{\phi} \quad (5-43)$$

$$\pi_i \text{ is free, } i \in R, \eta_{it} \geq 0, \quad \forall i \in R, t \in T_i, \sigma \geq 0 \quad (5-44)$$

In the same way, the bender sub-problem in the third echelon $BSP^3(\overline{\phi}, \overline{wu}_i^{tk}, \overline{yr}_{ik})$ is modeled as follows:

$$\min(\sum_{b \in \overline{\phi}} c_b \cdot z_b) \quad (5-45)$$

Subject to (5-34),(5-38) and

$$\sum_{b \in \overline{\phi}} \beta_{ib} \cdot z_b = \sum_{k \in K^2} \sum_{t \in T_i} \overline{wu}_i^{tk} \quad \forall i \in R \quad (5-46)$$

$$\sum_{b \in \overline{\phi}_i} \beta_{ib} \cdot z_b \geq \sum_{k \in K^2} \overline{wu}_i^{tk} \quad \forall i \in R, t \in T_i \quad (5-47)$$

The dual problem of a linear relaxation of $BSP^3(\overline{\phi}, \overline{wu}_i^{tk}, \overline{yr}_{ik})$ is denoted as $BDP^3(\overline{\phi}, \overline{wu}_i^{tk}, \overline{yr}_{ik})$. Let $\theta_i, i \in R$ be the dual variable associated with constraint (5-46), $\tau_{it}, i \in R, t \in T_i$ be a variable associated with constraint (5-47), and ν be a dual variable associated with constraint (5-34). $BDP^3(\overline{\phi}, \overline{wu}_i^{tk}, \overline{yr}_{ik})$ is formulated as follows:

$$\max(\sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^2} \theta_i \cdot \overline{u}_i^{tk} + \sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^2} \tau_{it} \cdot \overline{u}_i^{tk} - \nu \cdot nv3) \quad (5-48)$$

S.t.

$$\sum_{i \in R} \beta_{ib} \cdot \theta_i + \sum_{i \in R} \sum_{t \in T_i} \beta_{it} \cdot \tau_{it} - \nu \leq c_b \quad \forall b \in \overline{\phi} \quad (5-49)$$

$$\theta_i \text{ is free, } i \in R, \tau_{it} \geq 0, \quad i \in R, t \in T_i, \nu \leq 0 \quad (5-50)$$

Let Δ_1, Δ_3 denote the polyhedron defined by constraints (5-46)-(5-47), and (5-49)-(5-50), and let $P_{\Delta_1}, P_{\Delta_3}$ and $R_{\Delta_1}, R_{\Delta_3}$ be the sets of extreme points and extreme rays of Δ_1, Δ_3 respectively. Introducing the additional free variable Z_1, Z_3 , the 3E-BGP model (22)-(38) can thus be reformulated as the following *Benders master problem*:

$$\max(\sum_{i \in R} \sum_{k \in K^2} \sum_{t \in T} p_i \cdot \overline{u}_i^{tk} - \sum_{k \in K^2} \sum_{t \in T} c_{UCC1, UCC2} \cdot 2 \cdot \overline{yr}_{tk} - Z_1 - Z_3) \quad (5-51)$$

Subject to constraints (5-23)-(5-27), (5-33) and (5-36)-(5-37).

$$\sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^2} \pi_i \cdot \overline{u}_i^{tk} + \sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^2} \eta_{it} \cdot \overline{u}_i^{tk} - \sigma \cdot nv1 \leq Z_1 \quad (\pi, \eta, \sigma) \in P_{\Delta_1} \quad (5-52)$$

$$\sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^2} \pi_i \cdot \bar{u}_i^{tk} + \sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^2} \eta_{it} \cdot \bar{u}_i^{tk} - \sigma \cdot nv1 \leq 0 \quad (\pi, \eta, \sigma) \in R_{\Delta_1} \quad (5-53)$$

$$\sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^2} \theta_i \cdot \bar{u}_i^{tk} + \sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^2} \tau_{it} \cdot \bar{u}_i^{tk} - \nu \cdot nv3 \leq Z_3 \quad (\theta, \tau, \nu) \in P_{\Delta_3} \quad (5-54)$$

$$\sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^2} \theta_i \cdot \bar{u}_i^{tk} + \sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^2} \tau_{it} \cdot \bar{u}_i^{tk} - \nu \cdot nv3 \leq 0 \quad (\theta, \tau, \nu) \in R_{\Delta_3} \quad (5-55)$$

$$Z_1 \geq 0, Z_3 \geq 0 \quad (5-56)$$

To avoid generating feasibility constraints from extreme rays in the case when the primal subproblem is infeasible, this subproblem can be made feasible for any solution of the relaxed master problem. This is accomplished by adding artificial variables with large positive costs in the primal subproblem (Cordeau et al., 2001; Mercier et al., 2005). In this condition, the constraints achieved by extreme rays obtained from the benders sub-problem is unnecessary. The constraints (5-53) and (5-55) can be removed from the benders master problem.

5.3.3 Improved benders decomposition algorithm

Contreras, Cordeau and Laporte (2011) showed that the generation of stronger cuts and the reduction of iterations can reduce the computation effort of the benders decomposition. To accelerate convergence of the Benders decomposition algorithm, in this section, pareto-optimal cuts are proposed and a multi-cut version of the benders reformulation is proposed, which exploits the decomposability of the problem.

1) Pareto-optimal cuts

In order to accelerate our Benders decomposition algorithm, we implement a technique for identifying Pareto-optimal cuts as proposed by Magnanti and Simpson (1978) and Magnanti and Wong (1981). They proposed to generate more than one cut in each iteration of the Benders algorithm, a cut is defined as Pareto-optimal if no other cuts can dominate it.

The search of a Pareto-optimal cut can be achieved by solving a linear programming problem, it is based on the optimality or feasibility cuts found by the classic Benders decomposition algorithm. If the dual subproblem is optimal, the Pareto-optimal cut can be added to the master problem; otherwise the dual subproblem is unbounded, an extreme ray is generated and added to the master problem. The results obtained by Magnanti and Wong (1981) proved that their method significantly improves the convergence of the Benders algorithm. For our problem, a Pareto-optimal cut can be found by solving the following problem.

POC in the first echelon:

$$\max \left(\sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^0} \pi_i \cdot (wu_i^{tk})^0 + \sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^0} \eta_{it} \cdot (wu_i^{tk})^0 - \sigma \cdot nv1 \right) \quad (5-59)$$

Subject to constraints (5-43)-(5-44), and

$$\left(\sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^0} \pi_i \cdot \bar{u}_i^{tk} + \sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^0} \eta_{it} \cdot \bar{u}_i^{tk} - \sigma \cdot nv1 \right) = \overline{ZO}_1 \quad (5-60)$$

POC in the third echelon:

$$\max\left(\sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^2} \theta_i \cdot (u_i^{tk})^0 + \sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^2} \tau_{it} \cdot (u_i^{tk})^0 - \nu \cdot nv3\right) \quad (5-61)$$

Subject to constraints (5-47)-(5-48), and

$$\left(\sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^2} \theta_i \cdot \bar{u}_i^{tk} + \sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^2} \tau_{it} \cdot \bar{u}_i^{tk} - \nu \cdot nv3\right) = \bar{ZO}_3 \quad (5-62)$$

Here, \bar{Z}_1, \bar{Z}_3 is the optimal value of the dual subproblem in the first echelon and the third echelon, $(wu_i^{tk})^0$ is a relative interior point of the polyhedron defined by constraints (5-23)-(5-25). In this paper, we set all $(wu_i^{tk})^0$ to 0.3. After solving the model, a Pareto-optimal cut with form of (5-52) and (5-54) is generated and added to the benders master problem.

2) Multi-cuts

Birge and Louveaux (1988) proposed that the number of cuts required to obtain an optimal solution of the benders reformulation can be reduced given that the subproblem is decomposable into independent subproblems. Camargo et al. (2008) showed that when adding more than one cut per iteration, the number of iterations is reduced. Analysing the subproblems, we can see that the subproblems can be decomposed in smaller problems, one for each supplier zone in the first echelon and for each customer zone in the third echelon.

Instead of adding all cuts in a disaggregated way at each iteration, we can aggregate the information obtained to generate a set of optimality cuts associated with each supplier zone and each customer zone. We can separate the subproblem in the first echelon into $|Z_1|$ independent subproblems in the first echelon and the subproblem in the third echelon into $|Z_2|$ independent subproblems in the third echelon. Hence, we consider the dual polyhedra of these $|Z_1|$ and $|Z_2|$ subproblems and generate cuts from them. We thus obtain the following cuts:

MC in the first echelon:

$$\max \sum_{l \in O_1} \left(\sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^0} \pi_{il} \cdot \bar{wu}_{il}^{tk} + \sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^0} \eta_{itl} \cdot \bar{wu}_{il}^{tk} - \sigma_l \cdot nv1 \right) \quad (5-63)$$

MC in the third echelon:

$$\max \sum_{l \in O_2} \left(\sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^2} \theta_{il} \cdot \bar{wu}_{il}^{tk} + \sum_{i \in R} \sum_{t \in T_i} \sum_{k \in K^2} \tau_{itl} \cdot \bar{wu}_{il}^{tk} - \nu_l \cdot nv3 \right) \quad (5-64)$$

For each supplier zone $i \in Z_1$, we construct $\bar{\phi}_i, \bar{\varphi}_i$ for each independent subproblem and each route $r \in \bar{\phi}_i, r \in \bar{\varphi}_i$ is constructed in the same way as in model.

5.4 Computational experiments

As the problem we study is new, there is no benchmark instance in the literature that can be directly used to evaluate the performance of the proposed benders decomposition

algorithm. To this end, we generate randomly instances for BGPST-TE with different sizes based on the scheme of generating instances in Dellaert et al. (2019). These instances are used to evaluate the performance of our benders decomposition algorithm. The proposed algorithm was coded in C++. Numerical experiments were carried out on a personal computer with Intel Core i5-3210M and 4.0GB of RAM under Microsoft Windows 7 operating system. The commercial optimization software CPLEX 12.7 with default setting was used as the MIP solver.

5.4.1 Test instances

We consider a BGP in a multi-echelon transportation with time windows. The instances of this study were generated based on the instances proposed by Dellaert et al. (2019) for the 2E-VRPTW, available at URL <http://smartlogisticslab.nl>. Three sets of instances were generated. The first instance set contains 30 instances with 15 requests, the second instance set contains 30 instances with 30 requests, and the third instance set contains 30 instances with 50 requests. In each instance set, three types of instances were generated in the same way as Li, Chen and Prins (2016), differing in the number of reserved requests: 10 instances with roughly one-third of reserved requests, 10 instances with 50% of reserved requests, and 10 instances with two-thirds of reserved requests.

The capacity of each vehicle in the first and third echelon is set to 100 units and the capacity of each vehicle in the second echelon is set to 200 units, and the fixed cost of each vehicle in three echelons is 50, 100, and 50 respectively. The demand of each request is set to 10 or 20 and the width of time windows is set to [200,350]. The coordinates of all nodes in the transportation network of each instance are generated in the same way as in Chen (2016), LYU et al. (2019). The distance between any two nodes is their Euclidean distance and it is assumed that the traveling time between any two nodes coincides with their distance. The profit of each request is set to two times of the distance from its pickup node to its delivery node (Chen, 2016, LYU et al. (2019)). We use these three sets of instances to evaluate different improvement strategies of our BD algorithm and the performance of our BD by comparing its solution with the optimal solution of each instance obtained by the centralized planning approach.

5.4.2 Evaluation of different acceleration strategies for BD

The aim of the first part of the computational experiments is to analyse the effectiveness of each of the algorithmic refinements proposed in subsection 5.3.3. We have implemented four different versions of Algorithm 5-1: Basic benders decomposition approach (BD), Pareto-optimal cuts (Pareto), Multiple-cuts (Multi-cuts), the combination of Multiple-cuts with Pareto-optimal cuts (Multi-Pareto). Summarized results of this comparison are given in Table 5-1 for the instance set with 15 requests, 30 requests and 50 requests. The detailed results of the comparison are presented in Table 5-3.

We first focus on analysing the benefits of using the Multiple-cuts Benders reformulation (Multi-cut) over the basic Benders reformulation (BD). Multiple-cuts Benders reformulation uses the stronger reformulation (5-63)-(5-64) in which multiple optimality cuts

are added per iteration. The basic Benders reformulation uses the reformulation (5-39)-(5-56) in which only one optimality cut is added per iteration. In Table 5-1, the first column gives the number of reserved requests and selective requests associated with each group of instances. N_{opt} denotes the number of optimal solutions achieved by BD and Multiple-cuts, *Iters* provides the required number of iterations for BD and Multiple-cuts to converge and *CPU* gives the average CPU time in seconds needed to obtain a solution of the problem by using BD and Multiple-cuts.

The performance indicators used for evaluating the efficiency of each method in Table 5-1 is the percentage improvement of each acceleration of benders decomposition algorithm with respect to the basic benders decomposition algorithm (BD) denoted by *Imp*. *Imp* is defined as follows:

$$IMP = (p - p_{BD}) / p * 100\% \tag{5-65}$$

Where p and p_{BD} are the profit of the carrier obtained by different acceleration strategies of the benders decomposition algorithm and the basic benders decomposition algorithm respectively.

Table 5-1 Comparison results between basic BD algorithm and the BD algorithm with multiple-cuts acceleration strategy

Instance set	BD			Multi-cuts			
	N_{opt}	Iters	CPU	N_{opt}	Iters	Imp	CPU
A15-5-10	10/10	12.5	257.04	10/10	11	0	170.64
B15-7-8	10/10	25.8	165.15	10/10	14.2	0	95.58
C15-10-5	10/10	21.9	164.93	10/10	11.8	0	70.27
Avg		20.1	195.71		12.3	0	112.16
A30-10-20	10/10	523.7	1333.73	10/10	141.9	0	1099.02
B30-15-15	10/10	22.5	676.58	10/10	17.1	0	365.40
C30-20-10	10/10	36.2	884.48	10/10	26.2	0	564.36
Avg		194.1	964.93		61.7	0	676.26
A50-17-33	4/10	470.6	6832.01	8/10	294.8	1.56	4186.15
B50-25-25	10/10	218	3582.51	10/10	129.7	0	1373.58
C50-33-17	10/10	267.3	2950.26	10/10	144.3	0	981.68
Avg		318.6	4454.93		189.6		2180.47

Table 5-1 shows that for the instances with 15 requests and 30 requests, both BD and Multiple-cuts algorithms were able to find an optimal solution for each instance. BD could obtain an optimal solution in 195.71 seconds and 964.93 seconds on average for instances with 15 requests and 30 requests respectively, whereas Multiple-cuts consumed much less CPU time to solve each instance to optimality (in 112.16 seconds and 676.26 seconds on average for instances with 15 requests and 30 requests, respectively). Moreover, compared with BD, the number of required iterations to converge is reduced by 7.8 and 132.4 iterations on average for instances with 15 requests and 30 requests respectively. It can be seen that the convergence of the benders decomposition algorithm is greatly improved by using Multiple-cuts and multiple-cuts requires on average much less computation than BD.

When the number of requests increases to 50, the resolution of the model becomes more

difficult. Among the three instance sets, set A is more difficult to solve than set B and set C. This is because in set A more requests need to be determined whether to serve. As the algorithms cannot solve all the instances in Set A with 50 requests to optimal in a reasonable time, we set the maximum number of iterations to 500 for this instance set. The acceleration strategy of Multiple-cuts was able to solve 28 out of 30 instances to optimal in 2180.47 seconds of average computation time with the convergence of 189.6 iterations on average. In contrast, the BD consumed 4454.93 seconds on average to solve only 24 instances out of 30 instances to optimal with the convergence of 318.6 iterations on average. In contrast, the improvement of the solutions by the acceleration strategy of Multiple-cuts is 1.56% for instance set A.

We next focus on analysing the effectiveness of acceleration strategies of Pareto-optimal cuts. To this end, we compare the acceleration strategies of Pareto-optimal cuts and Multiple-cuts with Pareto-optimal cuts. The results of the comparison between these two strategies are summarized in Table 5-2. To evaluate the efficiency of adding Pareto-optimal cuts, we use the *Imp* indicator to compute the improvements between BD and the acceleration strategies of Pareto-optimal cuts and Multiple-cuts with Pareto-optimal cuts. The notations in Table 5-2 have the same meaning as in Table 5-1.

In Table 5-2, both the two acceleration strategies were able to obtain the optimal solution of all the instances except for the instance set A with 50 requests. As can be seen in the Average time columns, the Multi-Pareto is considerably more efficient than Pareto-optimal.

Table 5-2 Comparison of Pareto-optimal acceleration strategies

Instance set	Pareto				Multi-Pareto			
	N_{opt}	Iters	CPU	Imp	N_{opt}	Iters	CPU	Imp
A15-5-10	10/10	11.6	216.00	0	10/10	11	165.24	0
B15-7-8	10/10	27.2	157.50	0	10/10	7	71.05	0
C15-10-5	10/10	22.8	164.70	0	10/10	7.8	47.39	0
Avg			179.4				94.56	
A30-10-20	10/10	523.7	1333.73	0	10/10	141.9	1099.02	0
B30-15-15	10/10	22.5	676.58	0	10/10	17.1	365.40	0
C30-20-10	10/10	36.2	884.48	0	10/10	26.2	564.36	0
Avg			964.93				676.26	
A50-17-33	5/10	438	5809.67	0.34	7/10	278	3991.90	1.84
B50-25-25	10/10	220.9	2562.85	0	10/10	136.9	1051.33	0
C50-33-17	10/10	217.3	2577.34	0	10/10	126.1	777.26	0
Avg			3649.95				1940.16	

From the summarized results, we can conclude that Multiple-cuts and combination of Multiple-cuts and Pareto-optimal cuts perform best among the different versions of benders decomposition algorithm. The detailed results of the comparison are presented in Table 5-3.

Table 5-3 Comparison of acceleration strategies for benders decomposition method

Instance	Pareto			Multi-cuts			Multi-Pareto		
	Obj	Iters	CPU(s)	Obj	Iters	CPU(s)	Obj	Iters	CPU(s)
A1-15	826.20	11	224.64	826.20	12	203.04	826.20	12	199.80
A2-15	345.35	4	46.44	345.35	4	44.28	345.35	4	38.88
A3-15	606.56	13	281.88	606.56	11	212.76	606.56	11	206.28
A4-15	690.54	26	405.00	690.54	23	317.52	690.54	23	307.80
A5-15	130.68	5	60.48	130.68	6	59.4	130.68	6	60.48
A6-15	723.24	18	420.12	723.24	20	349.92	723.24	20	339.12
A7-15	441.49	5	93.96	441.49	6	100.44	441.49	6	99.36
A8-15	317.85	17	356.40	317.85	14	217.08	317.85	14	200.88
A9-15	789.98	7	131.76	789.98	6	98.28	789.98	6	100.44
A10-15	493.92	10	138.24	493.92	8	100.44	493.92	8	99.36
Avg		11.6	216.00		11	170.64		11	165.24
B1-15	541.79	34	126.23	541.79	18	73.31	541.79	13	89.90
B2-15	771.92	68	600.53	771.92	32	332.51	771.92	5	55.83
B3-15	849.81	5	27.68	849.81	4	28.35	849.81	3	39.15
B4-15	1125.73	20	109.35	1125.73	15	106.92	1125.73	8	72.50
B5-15	128.13	3	10.13	128.13	3	12.15	128.13	3	21.75
B6-15	830.76	10	62.78	830.76	9	63.99	830.76	4	51.48
B7-15	844.98	22	167.40	844.98	13	127.58	844.98	18	243.60
B8-15	303.55	35	178.88	303.55	16	88.70	303.55	3	19.58
B9-15	636.58	29	92.93	636.58	18	42.53	636.58	3	23.93
B10-15	509.23	46	199.80	509.23	14	80.19	509.23	10	95.70
Avg		27.2	157.50		14.2	95.58		7	71.05
C1-15	2036.25	3	12.15	2036.25	3	12.22	2036.25	2	9.95
C2-15	1150.97	52	351.68	1150.97	23	141.00	1150.97	4	19.01
C3-15	1539.48	52	407.25	1539.48	29	202.81	1539.48	27	229.61
C4-15	1987.82	7	119.70	1987.82	6	27.73	1987.82	7	35.69
C5-15	684.97	7	5.63	684.97	2	6.35	684.97	2	7.61
C6-15	922.47	3	10.13	922.47	3	12.93	922.47	2	8.78
C7-15	998.44	12	77.63	998.44	10	58.75	998.44	6	26.91
C8-15	688.42	68	528.53	688.42	27	171.32	688.42	11	66.40
C9-15	1134.42	21	125.33	1134.42	12	59.93	1134.42	14	57.62
C10-15	1038.10	3	10.13	1038.10	3	9.64	1038.10	3	11.70
Avg		22.8	164.70		11.8	70.27		7.8	47.39
A1-30	874.28	232	229.19	874.28	125	100.22	874.28	128	102.42
A2-30	2042.29	96	383.43	2042.29	56	343.41	2042.29	55	302.15
A3-30	1689.53	116	223.70	1689.53	50	150.42	1689.53	50	151.68
A4-30	1024.22	365	360.74	1024.22	99	161.52	1024.22	99	161.43
A5-30	833.79	464	491.00	833.79	120	390.23	833.79	131	399.22
A6-30	1159.31	12	149.63	1159.31	5	120.53	1159.31	5	161.65
A7-30	1136.36	1295	4159.27	1136.36	275	4377.24	1136.36	273	4207.34
A8-30	1298.04	656	874.61	1298.04	183	625.11	1298.04	189	641.11
A9-30	2675.45	514	1745.35	2675.45	212	1462.14	2675.45	223	1506.64
A10-30	684.57	1457	3470.85	684.57	294	3259.42	684.57	333	3017.34

Table 5-3(continued)

Instance	Pareto			Multi-cuts			Multi-Pareto		
	Obj	Iters	CPU(s)	Obj	Iters	CPU(s)	Obj	Iters	CPU(s)
Avg		520.7	1208.78		141.9	1099.02		148.6	1065.10
B1-30	2308.90	13	199.80	2308.90	12	175.05	2308.90	12	180.23
B2-30	3608.94	5	60.98	3608.94	4	51.30	3608.94	4	48.83
B3-30	3655.05	15	456.08	3655.05	14	293.40	3655.05	14	285.53
B4-30	2392.42	13	193.05	2392.42	13	176.18	2392.42	13	175.95
B5-30	3512.09	25	785.93	3512.09	25	550.58	3512.09	29	663.53
B6-30	4226.07	47	1551.60	4226.07	35	851.40	4226.07	34	831.60
B7-30	3126.08	6	97.88	3126.08	6	90.45	3126.08	6	89.78
B8-30	4405.36	4	66.38	4405.36	4	58.05	4405.36	4	58.50
B9-30	4934.40	88	3723.75	4934.40	45	1223.55	4934.40	62	1770.53
B10-30	2611.67	19	274.73	2611.67	13	183.15	2611.67	13	181.80
Avg		23.5	740.93		17.1	365.40		19.1	428.63
C1-30	3011.15	71	2228.85	3011.15	59	1793.93	3011.15	63	1906.88
C2-30	5035.41	21	652.73	5035.41	19	416.93	5035.41	19	437.40
C3-30	3655.05	5	154.58	3655.05	5	101.03	3655.05	5	99.45
C4-30	2387.42	2	66.38	2387.42	2	65.25	2387.42	2	64.69
C5-30	3512.09	22	682.20	3512.09	22	474.53	3512.09	22	467.78
C6-30	4226.07	32	977.18	4226.07	22	485.10	4226.07	26	575.55
C7-30	3732.81	158	1275.03	3732.81	84	1056.93	3732.81	74	966.55
C8-30	4405.36	2	77.06	4405.36	2	69.75	4405.36	2	70.88
C9-30	4934.40	44	1707.08	4934.40	43	1118.70	4934.40	30	748.58
C10-30	2611.67	4	60.30	2611.67	4	61.43	2611.67	4	61.20
Avg		36.1	788.14		26.2	564.36		24.7	539.89
A1-50	4026.27	478	8287.09	4050.74	345	5194.77	4033.74	500	6260.55
A2-50	3896.11	500	5541.88	4084.68	303	4011.86	4084.68	84	3170.10
A3-50	3196.45	500	14230.17	3255.45	268	8593.84	3196.45	500	9616.05
A4-50	2312.41	322	323.99	2312.41	146	155.62	2312.41	125	130.11
A5-50	2988.12	500	9423.12	3043.17	364	7408.34	3043.17	500	8201.44
A6-50	3080.81	500	8469.48	3080.81	500	7152.48	3251.81	236	3664.88
A7-50	2477.49	372	687.25	2477.49	142	206.30	2477.49	242	541.72
A8-50	2938.81	392	895.36	2938.81	240	492.12	2938.81	278	791.03
A9-50	4244.55	500	9503.75	4383.17	500	8520.69	4383.17	212	7393.00
A10-50	2567.14	316	734.57	2567.14	140	125.48	2567.14	103	150.12
Avg		438	5809.67		294.8	4186.15		278	3991.90
B1-50	7800.63	365	4524.91	7800.63	211	2636.69	7800.63	218	2397.34
B2-50	7705.47	728	6945.12	7705.47	409	4532.12	7705.47	382	3793.60
B3-50	5960.88	342	1869.95	5960.88	128	574.00	5960.88	159	585.78
B4-50	4320.39	8	9.52	4320.39	6	6.95	4320.39	130	138.67
B5-50	6061.68	140	821.25	6061.68	102	494.90	6061.68	107	568.82
B6-50	6241.66	63	244.33	6241.66	62	211.35	6241.66	66	250.19
B7-50	5433.52	31	51.88	5433.52	32	48.54	5433.52	33	55.51
B8-50	9490.23	35	103.32	9490.23	38	98.95	9490.23	38	111.15
B9-50	8147.06	384	10528.51	8147.06	240	4878.88	8147.06	165	2310.90

Table 5-3(continued)

Instance	Pareto			Multi-cuts			Multi-Pareto		
	Obj	Iters	CPU(s)	Obj	Iters	CPU(s)	Obj	Iters	CPU(s)
B10-50	7479.49	113	529.73	7479.49	69	253.40	7479.49	71	301.34
Avg		220.9	2562.85		129.7	1373.58		136.9	1051.33
C1-50	7521.25	441	6924.25	7521.25	427	4010.23	7521.25	227	2056.05
C2-50	7665.48	647	5312.23	7665.48	271	1941.25	7665.48	261	1688.00
C3-50	5916.88	185	801.98	5916.88	155	651.20	5916.88	148	555.78
C4-50	6825.64	71	253.32	6825.64	26	70.61	6825.64	46	129.15
C5-50	6032.68	70	309.04	6032.68	60	259.67	6032.68	58	219.62
C6-50	6110.52	73	271.61	6110.52	57	181.43	6110.52	56	184.03
C7-50	7953.91	281	2066.39	7953.91	212	1167.50	7953.91	199	1291.08
C8-50	9490.23	32	94.92	9490.23	35	103.19	9490.23	51	133.78
C9-50	8061.49	352	9658.23	8061.49	174	1338.95	8061.49	152	1321.57
C10-50	7368.49	21	81.44	7368.49	26	92.73	7368.49	63	193.49
Avg		217.3	2577.34		144.3	981.68		126.1	777.26

5.4.3 Evaluation of the BD algorithm

To evaluate the performance of benders decomposition algorithm, we compare the results obtained by the basic benders decomposition algorithm (BD), the best version of the benders decomposition algorithm (BBD) with those of CPLEX MIP solver. Summarizing results for comparison of BD, BBD and CPLEX MIP solver are given in Table 5-4. The detailed results between CPLEX and BD are shown in Table 5-5.

In Table 5-4, the relative gap between the lower bounds LB and the upper bounds UB obtained by CPLEX is defined as follows:

$$Gap = (UB - LB) / LB * 100\% \quad (5-66)$$

The performance indicator used for evaluating each method in Table 5-4 is the percentage improvement of BD and BBD with respect to best solution obtained by CPLEX denoted by Imp . Imp is defined as follows:

$$Imp = (LB - LB_{CPLEX}) / LB_{CPLEX} * 100\% \quad (5-67)$$

Where LB and LB_{CPLEX} are the objective of the best solutions obtained by BD and BBD and CPLEX respectively.

In Table 5-4, we use the indicators Gap_{Avg} , CPU_{Avg} and Imp_{Avg} to indicate the average results for each instance set. The results of Table 5-4 indicate that our benders decomposition method outperforms CPLEX. For the instance set with 15 requests, our algorithm is able to solve all 30 instances within 200 seconds, whereas CPLEX cannot solve all the instances within one hour of CPU time. For the instances with 30 requests, the average gap Gap_{Avg} for CPLEX solver is 19.40%, 0.73% and 0.49% for set A, set B and Set C respectively. Benders decomposition algorithm could find a better solution for all of the 30 instances. We observe that solutions obtained by benders decomposition algorithm are better than CPLEX solver with an average improvement of 12.93%, 0.50%, and 0.26% for Set A30, Set B30 and Set C30 respectively within 1000 seconds.

When the number of requests increases to 50, the resolution of the model becomes more

difficult. The average gap Gap_{Avg} for CPLEX solver increases to 22.92%, 2.19% and 5.06% for set A, set B and set C respectively in 14400 seconds on average. BBD could achieve better solution than CPLEX solver for set A, set B and set C with an average improvement of 8.66%, 0.23% and 1.89% respectively.

Table 5-4 Summarized comparison results between of CPLEX and benders decomposition algorithm

Instance set	CPLEX		BD			BBD		
	Gap	CPU	Gap	CPU	Imp	Gap	CPU	Imp
A-15-5-10	0.99	1056.11	0.57	257.04	0.36	0.57	165.24	0.36
B-15-7-8	0	354.92	0	165.15	0	0	71.05	0
C-15-10-5	0	458.60	0	164.93	0	0	47.39	0
Avg		623.21		195.71			94.56	
A-30-10-20	19.40	6669.49	5.16	1333.73	12.93	5.16	1099.02	12.93
B-30-15-15	0.73	1424.36	0.21	676.58	0.50	0.21	365.40	0.50
C-30-20-10	0.49	2250.16	0.22	884.48	0.26	0.22	539.89	0.26
Avg		3448.00		964.93			668.10	
A-50-15-35	22.92	14400	7.02	6832.01	12.35	11.01	3837.39	8.66
B-50-25-25	2.19	14400	0.23	3582.51	1.80	1.80	1051.33	0.23
C-50-35-15	5.06	14400	1.89	2950.26	2.84	2.84	777.26	1.89
Avg		14400		4454.93			1888.66	

Table 5-5 Comparison of CPLEX and basic benders decomposition method

Instance	CPLEX				BD				
	LB	UB	Gap	CPU(s)	Obj	Iters	CPU(s)	Imp	Gap
A1-15	826.20	826.20	0	443.25	826.20	15	273.26	0	0
A2-15	345.35	345.35	0	1499.85	345.35	6	81.02	0	0
A3-15	585.47	643.43	9.90	3600.00	606.56	14	329.42	3.60	6.08
A4-15	690.54	690.54	0	1869.53	690.54	27	455.76	0	0
A5-15	130.68	130.68	0	10.13	130.68	5	63.74	0	0
A6-15	723.24	723.24	0	44.78	723.24	18	486.00	0	0
A7-15	441.49	441.49	0	32.40	441.49	4	129.60	0	0
A8-15	317.85	317.85	0	949.28	317.85	18	452.54	0	0
A9-15	789.98	789.98	0	2086.20	789.98	7	138.24	0	0
A10-15	493.92	493.92	0	25.65	493.92	11	160.94	0	0
Avg			0.99	1056.11		12.5	257.04	0.36	0.61
B1-15	541.79	541.79	0	5.18	541.79	34	140.85	0	0
B2-15	771.92	771.92	0	26.33	771.92	50	466.65	0	0
B3-15	849.81	849.81	0	90.68	849.81	5	26.33	0	0
B4-15	1125.73	1125.73	0	41.85	1125.73	19	105.75	0	0
B5-15	128.13	128.13	0	567.00	128.13	3	11.70	0	0
B6-15	830.76	830.76	0	216.23	830.76	11	166.05	0	0
B7-15	844.98	844.98	0	1089.30	844.98	23	193.05	0	0
B8-15	303.55	303.55	0	485.10	303.55	39	232.65	0	0
B9-15	636.58	636.58	0	740.03	636.58	26	82.35	0	0
B10-15	509.23	509.23	0	287.55	509.23	48	226.13	0	0
Avg			0	354.92		25.8	165.15	0	0

5 A BD algorithm for BGP in the procurement of multi-echelon transportation services

Table 5-5(continued)

Instance	CPLEX					BD			
	LB	UB	Gap	CPU(s)	Obj	Iters	CPU(s)	Imp	Gap
C1-15	2036.25	2036.25	0	157.05	2036.25	3	12.38	0	0
C2-15	1150.97	1150.97	0	458.55	1150.97	45	327.83	0	0
C3-15	1539.48	1539.48	0	402.53	1539.48	55	465.75	0	0
C4-15	1987.82	1987.82	0	99.90	1987.82	6	27.68	0	0
C5-15	684.97	684.97	0	453.83	684.97	2	6.53	0	0
C6-15	922.47	922.47	0	627.98	922.47	3	9.68	0	0
C7-15	998.44	998.44	0	56.70	998.44	11	72.68	0	0
C8-15	688.42	688.42	0	989.55	688.42	67	535.95	0	0
C9-15	1134.42	1134.42	0	886.95	1134.42	25	184.73	0	0
C10-15	1038.10	1038.10	0	452.93	1038.10	2	6.98	0	0
Avg			0	458.60		21.9	164.93	0	0
A1-30	786.28	940.47	19.61	7200	874.28	230	239.41	0	0
A2-30	2042.29	2172.99	6.40	7200	2042.29	107	396.43	0	0
A3-30	1689.53	1689.53	0.00	1895	1689.53	111	225.42	0	0
A4-30	956.43	1069.48	11.82	7200	1024.22	350	337.46	0	0
A5-30	712.66	852.98	19.69	7200	833.79	412	433.50	0	0
A6-30	1159.31	1236.61	6.67	7200	1159.31	9	106.65	0	0
A7-30	923.17	1275.91	38.21	7200	1136.36	1331	4692.95	0	0
A8-30	1017.37	1329.80	30.71	7200	1298.04	657	949.93	0	0
A9-30	2521.16	2761.93	9.55	7200	2675.45	573	2357.09	3.23	6.12
A10-30	498.92	754.87	51.30	7200	684.57	1457	3598.48	0	0
Avg			19.40	6669.49		523.7	1333.73	0.32	0.61
B1-30	2308.90	2308.90	0	398.03	2308.90	14	218.25	0	0
B2-30	3608.94	3608.94	0	34.20	3608.94	5	59.40	0	0
B3-30	3655.05	3655.05	0	713.70	3655.05	15	496.80	0	0
B4-30	2392.42	2392.42	0	2629.35	2392.42	13	190.58	0	0
B5-30	3512.09	3512.09	0	46.80	3512.09	27	819.23	0	0
B6-30	4023.35	4315.68	7.27	7200.00	4226.07	46	1507.50	2.12	5.04
B7-30	3126.08	3126.08	0	182.03	3126.08	5	81.90	0	0
B8-30	4405.36	4405.36	0	63.90	4405.36	4	62.10	0	0
B9-30	4934.40	4934.40	0	72.00	4934.40	72	2984.18	0	0
B10-30	2611.67	2611.67	0	2903.63	2611.67	24	345.15	0	0
Avg			0.73	1424.36		22.5	676.58	0.21	0.50
C1-30	2934.11	3078.49	4.92	7200.00	3011.15	76	2573.33	2.24	2.63
C2-30	5035.41	5035.41	0	51.98	5035.41	24	733.5	0	0
C3-30	3655.05	3655.05	0	166.95	3655.05	5	144.45	0	0
C4-30	2387.42	2387.42	0	24.53	2387.42	2	69.75	0	0
C5-30	3512.09	3512.09	0	7819.20	3512.09	24	793.35	0	0
C6-30	4226.07	4226.07	0	174.15	4226.07	32	987.53	0	0
C7-30	3732.81	3732.81	0	1031.40	3732.81	152	1758.63	0	0
C8-30	4405.36	4405.36	0	65.03	4405.36	2	78.75	0	0
C9-30	4934.40	4934.40	0	117.00	4934.40	39	1605.83	0	0
C10-30	2611.67	2611.67	0	5851.35	2611.67	6	99.68	0	0
Avg			0.49	2250.16		36.2	884.48	0.22	0.26

Table 5-5(continued)

Instance	CPLEX					BD			
	LB	UB	Gap	CPU(s)	Obj	Iters	CPU(s)	Imp	Gap
A1-50	/	4590.17	/	14400	3968.52	500	10002.59	15.66	/
A2-50	3558.34	4704.13	32.20	14400	3896.11	500	6251.82	20.74	9.49
A3-50	/	3687.64	/	14400	3252.41	500	16538.19	13.38	/
A4-50	2312.41	2632.2	13.83	14400	2312.41	418	521.20	13.83	0
A5-50	2258.76	3519.14	55.80	14400	2988.12	500	11020.69	17.77	32.29
A6-50	/	3416.71	/	14400	3080.81	500	10145.02	10.90	/
A7-50	2477.49	2736.64	10.46	14400	2477.49	422	883.24	10.46	0
A8-50	2938.81	3276.49	11.49	14400	2938.81	463	969.14	11.49	0
A9-50	3945.22	5042.39	27.81	14400	4235.05	500	11108.39	19.06	7.35
A10-50	2567.14	2794.18	8.84	14400	2567.14	403	879.80	8.84	0
Avg			22.92	14400		470.6	6832.01	14.21	7.02
B1-50	7625.25	8662.35	13.60	14400	7800.63	376	10482.00	11.05	2.3
B2-50	7705.47	8053.81	4.52	14400	7705.47	822	8392.62	4.52	0
B3-50	5960.88	6058.33	1.63	14400	5960.88	181	1001.36	1.63	0
B4-50	4320.39	4320.39	0.00	6072.4	4320.39	10	11.70	0.00	0
B5-50	6061.68	6082.12	0.34	14400	6061.68	146	891.07	0.34	0
B6-50	6241.66	6241.66	0.00	2434.34	6241.66	63	252.54	0.00	0
B7-50	5433.52	5433.52	0.00	850.94	5433.52	29	52.19	0.00	0
B8-50	9490.23	9490.23	0.00	1042.23	9490.23	36	113.41	0.00	0
B9-50	8147.06	8290.73	1.76	14400	8147.06	403	14078.70	1.76	0
B10-50	7479.49	7479.49	0.00	3414.19	7479.49	114	549.55	0.00	0
Avg			2.19	8581.41		218	3582.51	1.93	0.23
C1-50	7125.14	8318.38	16.75	14400	7521.25	704	11123.90	10.60	5.56
C2-50	6765.34	8068.34	19.26	14400	7665.48	694	6472.96	5.26	13.31
C3-50	5916.88	6326.33	6.92	14400	5916.88	215	916.82	6.92	0
C4-50	6825.64	7195.59	5.42	14400	6825.64	49	140.22	5.42	0
C5-50	6032.68	6122.67	1.49	14400	6032.68	67	244.94	1.49	0
C6-50	6110.52	6110.52	0.00	7477.67	6110.52	87	296.32	0.00	0
C7-50	7953.91	8014.36	0.76	14400	7953.91	440	66.00	0.76	0
C8-50	9490.23	9490.23	0.00	1860.11	9490.23	30	83.18	0.00	0
C9-50	8061.49	8061.49	0.00	2912.75	8061.49	360	10058.80	0.00	0
C10-50	7368.49	7368.49	0.00	974.06	7368.49	27	99.45	0.00	0
Avg			5.06	9962.46		267.3	2950.26	3.04	1.89

The summarized results for large size instances are shown in Table 5-6. The detailed results are shown in Table 5-7. As we find that Multiple-cuts and Multiple-cuts with Pareto-optimal cuts can achieve better performance, we adopt these two acceleration strategies in this comparison. In Table 5-6, we compare CPLEX solver and benders decomposition method for large size instances. For the instances with 100 requests, the average Gap_{Avg} for CPLEX solver becomes 26.95%. The average improvement of the lower bounds by *Multi-cuts* is 10.70% in 7338.35 seconds, whereas the improvement of the lower bounds by *Multi-Pareto* is 10.67% in 7118.68 seconds of computation time. Therefore, benders decomposition algorithm significantly outperforms CPLEX solver in terms of cost.

Moreover, benders decomposition algorithm could generate a better solution in a much shorter time compared with CPLEX solver. Moreover, the acceleration strategy of combining Multiple cuts and Pareto-optimal cuts achieve the best performance.

Table 5-6 Comparison results of CPLEX and benders decomposition algorithms for large size instances

Instance set	CPLEX		Multi-cuts			Multi-Pareto		
	Gap	CPU	Gap	CPU	Imp	Gap	CPU	Imp
A-100-30-70	43.75	28800	2.89	8630.71	15.46	1.14	9197.60	15.51
B-100-50-50	16.07	28800	1.36	6260.58	5.40	0.77	5910.81	5.33
C-100-70-30	21.04	28800	1.86	7123.76	11.23	1.05	6247.64	11.18
Avg	26.95	28800	2.04	7338.35	10.70	0.99	7118.68	10.67

From the detailed results for large size instances, *Multi-cuts* and *Multi-Pareto* obtain 3 instances out of 30 instances respectively. For the remaining instances, the gap for *Multi-cuts* is 2.04%, and for *Multi-Pareto* is 0.99.

Table 5-7 Detailed comparison results of CPLEX and the BD algorithms for large size instances

Instance	CPLEX			Multiple-cuts			Multiple cuts with Pareto-optimal				
	LB	UB	CPU	LB	UB	Iters	CPU	LB	UB	Iters	CPU
A1	9622.2	14788.6	28800	11665.8	12133.6	500	7321.5	11691.3	11795.5	345	11909.5
A2	12813.3	16408.30	28800	13118.4	13263.5	500	5598.84	13118.4	13259.6	84	5207.9
A3	13733.2	21304.30	28800	14672.7	14871.9	500	4542.03	14672.7	14855.8	88	6263.5
A4	/	19922.40	28800	13275.9	13474.8	500	12106.00	13275.9	13660.2	125	8071.6
A5	7885.1	11550.60	28800	9949.08	10202.3	500	12886.40	9949.1	10086.2	334	14718.6
A6	/	17872.40	28800	12628	13430.2	500	11009.00	13430.2	13442.7	236	14058.00
A7	/	19217.30	28800	13730.6	13890.3	500	6077.62	13730.6	13854.1	48	3428.25
A8	10388.7	14067.20	28800	12533.6	13530	500	12100.40	12533.6	12716.8	245	15313.00
A9	/	12667.50	28800	12478.7	12667.5	500	7916.00	12478.7	12481.1	212	6347.74
A10	/	23534.50	28800	18884.2	19152.4	500	6749.35	18958.3	19225.8	97	6657.78
Avg			28800			500	8630.71			181.4	9197.60
B1	13687.8	17160.4	28800	14904.2	15130.1	500	5930.2	14904.2	15098.1	500	6173.23
B2	16281	18398.9	28800	16327.4	16327.4	351	4634.22	16306.4	16554.7	500	4674.65
B3	16720	21664.6	28800	18680	18680	220	5098.3	18680	18680	186	4220.55
B4	/	20394.5	28800	16583.3	16829.1	500	6583.51	16529.6	16765.9	500	9612.52
B5	/	13064.2	28800	11884	12252.3	500	5623.19	11884	11884	358	4830.20
B6	16762.5	18203.7	28800	16937.1	17191.4	500	8694.05	16937.1	16993.5	500	1054.87
B7	16036.7	19642	28800	17097.7	17356.8	500	6324.55	17045.5	17214.3	500	10092.70
B8	/	16148.3	28800	15288.3	15508.9	500	4720.16	15368.4	15488.5	500	9081.54
B9	19400.7	20805.7	28800	20423.6	20730.2	500	8462.41	20423.6	20423.6	372	6591.70
B10	22128.8	23498.6	28800	23002.9	23352.2	500	6535.29	23002.9	23322.6	500	2776.10
Avg			28800			174.7	6260.58			441.6	5910.81
C1	13488.8	17954.6	28800	15015.8	15217.3	500	1134.37	15015.8	15232.9	500	2160.3
C2	14454.4	18283.6	28800	16050.3	16293.5	500	9272.77	16050.3	16287.5	500	11964.8
C3	18682.9	21426.7	28800	18765.9	19046.3	500	5117.78	18765.9	19043.6	500	7356.1
C4	16050.9	20744.9	28800	20210.3	20497.3	500	8754.62	20189.9	20319.9	500	4386.7
C5	/	15661.1	28800	12220.1	12588.9	500	6557.28	12220.1	12383.8	500	7860.3
C6	17110.6	18370.4	28800	17110.6	17110.6	336	9655.60	17110.6	17110.6	196	8411.1
C7	/	23134.4	28800	19918.9	21152.3	500	10858.40	19973.9	20170.2	500	4122.4
C8	/	17898.4	28800	17602.7	17700.9	500	9457.90	17668.7	17779.8	500	8101.9
C9	19979.8	20976.7	28800	20667	20879.2	500	6076.45	20667	20805.7	500	6005.4
C10	18297.1	24042.4	28800	23133.2	23608.7	500	4352.44	23101	23531.9	500	2107.4
Avg			28800			483.6	7123.7			469.6	6247.6

5.5 Brief summary

In this chapter, we introduced a new BGP for transportation service procurement in a

multi-echelon transportation. One arc-based formulation and one path-based mathematical models are modeled for this problem. The path-based formulation defines interconnected first-second echelon tours and second-third echelon tours, in which the interconnectivity is satisfied using explicit load constraints and time windows. We designed a benders decomposition algorithm to decompose the path-based model into one master problem in the second echelon and two subproblems in the first echelon and the third echelon by the path interconnectivity between different echelons. Three acceleration strategies are proposed to enhance the performance of basic benders decomposition algorithm, including Multiple-cuts, Pareto-optimal cuts, and combination of Multiple-cuts and Pareto-optimal cuts. Extensive computational experiments on different size instances show that the benders decomposition algorithm can solve all instances with 15 request, 30 requests and two set of instances with 50 requests to optimal within a reasonable time. For the large size instances, the benders decomposition algorithm can achieve average gap of 0.99% within two hours. Among the acceleration strategies, the combination of Multiple-cuts and Pareto-optimal cuts achieves best performance.

6 Conclusions and perspectives

6.1 Summary of research results

We considered three problems in this dissertation: shipper collaboration in forward and reverse logistics, a multi-round exchange mechanism for carrier collaboration in less than truckload transportation, and a benders decomposition algorithm for transportation service procurement in a multi-echelon transportation. With different operations research techniques, these three problems were studied independently. We thus gave the detailed conclusions and discussion on future research directions in each underlying chapter separately. An overview summary on this dissertation work is presented in this chapter.

In the first problem, we study shipper collaboration in forward and reverse logistics, in which multiple shippers with forward or/and reverse logistics operations consolidate their transportation requests. In the forward and reverse logistics, manufacturers deliver new products to their customers and used products are collected from customers and transported to remanufacturers for repair or reproduction. This gives rise to a new vehicle routing problem with pickup and delivery requests and three different types of depots (product depots, vehicle depots and recycle depots). A hybrid approach combining greedy randomized adaptive search procedure (GRASP) and iterated local search (ILS) is proposed to find a near optimal solution of the problem. Numerical experiments on a large set of randomly generated instances with different problem sizes demonstrate that shipper collaboration in forward and reverse logistics can realize significant cost savings compared with the isolated operation of each shipper without cooperation, and the proposed approach is effective in the sense that it can find a high quality solution in a reasonable computation time. The main contributions of this chapter include: (1) Shipper collaboration in forward and reverse logistics is considered for the first time; (2) A new variant of vehicle routing problem with pickup and delivery requests and three types of depots is studied and a mixed integer programming model is formulated for the problem. (3) An effective GRASP-ILS algorithm well adapted to new characteristics of the problem is proposed to solve the NP-hard vehicle routing problem with precedence constraints of each request and split loads at product depots and recycle depots.

In the second problem, a multi-round auction mechanism for carrier collaboration with pickup and delivery requests was proposed in less-than truckload transportation. In each iteration, each carrier first provides multiple bundles of requests to offer and their corresponding transfer payments. Each carrier then determines which bundles of requests to acquire from one or multiple carriers. Multiple bundles of requests can be exchanged among carriers in each iteration. In each round of the auction, each carrier updates its outsourcing bundles of requests based on the feedback information from previous iterations. Numerical experiments show that this multi-round exchange mechanism provides 11.80% more profit compared to other mechanisms. The main contribution of this chapter is in three aspects: (1)

Each carrier can outsource (offer) multiple bundles of requests to other carriers and each carrier can insource (acquire) more than one bundle of requests from multiple other carriers in each iteration of our exchange mechanism. (2) In our mechanism, each carrier updates the outsourcing price of each request based on the information from previous iterations, which allows it to select different outsourcing bundles in different iterations. (3) Numerical experiments show that our mechanism significantly outperforms two auction mechanisms proposed by Berger and Bierwirth (2010) and Gansterer, M., & Hartl (2016) with the average improvement of 11.80% in terms of the total profit of all carriers. With possibly insourcing (acquiring) requests from multiple other carriers, our mechanism can bring more profit to the carrier alliance than the mechanisms which insource requests only from one carrier.

In the third problem, a bid generation problem for transportation service procurement realized by a combinatorial auction in a three-echelon transportation. In transportation service procurement, shippers want to procure transportation services from a set of potential carriers that have reserved transportation requests. The delivery of freight from its origin to its destination is through three echelons. One arc-based mathematical formulation and one path-based formulation for our problem are proposed. A benders decomposition algorithm is developed for the path-based formulation. The basic benders decomposition algorithm is enhanced through the acceleration strategies of multi-cuts and Pareto-optimal cuts. Computational results indicate that the enhanced benders decomposition algorithm outperforms the MILP solver of CPLEX, not only in terms of solution quality but also in terms of CPU time. The main contributions of this paper is in three aspects (1) A new bid generation problem for transportation service procurement in a multi-echelon transportation is considered for the first time and two mixed integer programming models are formulated for this problem; (2) Based on the path-based formulation and the characteristic of the problem, a benders decomposition approach is used to solve the problem. Acceleration strategies including multiple-cuts, Pareto-optimal cuts and Multiple-cuts with Pareto-optimal cuts are used to enhance the performance of the basic benders decomposition algorithm; (3) Numerical experiments show that our benders decomposition algorithm significantly outperforms the CPLEX solver and can solve small and medium size instances to optimal, and large size instances to near-optimal with average gap of 0.99% within a reasonable time.

6.2 Perspectives for future research

Although we have proposed effective algorithms and mechanisms to tackle the shipper collaboration and carrier collaboration in LTL transportation, there are still other works to be done to improve the models and solution approaches in order to make them more applicable in practices.

Firstly, a tight lower bound of the problem studied should be found to well evaluate the performance of the proposed meta-heuristic GRASP-ILS for medium and large sized instances. Another research direction is to take the profit sharing among shippers into

consideration in order to make the centralized collaborative transportation planning approach proposed in this paper more applicable in practice.

Secondly, in the future, we will consider the development of a more efficient and effective algorithm to solve the outsourcing and insourcing requests selection problem, and consider carrier collaboration in less than truckload transportation with new characteristics, such as dynamic arrival of requests in a carrier collaboration network.

Finally, we will try to find some more acceleration strategies for the benders decomposition algorithm to reduce its solution space in order to accelerate its resolution, such as valid constraints and some elimination tests. All of the above mentioned issues will be the topics for future research.

ANNENEX A Extended French abstract

A.1 Introduction Générale

L'importance du transport de marchandises est amplifiée aujourd'hui par l'essor rapide du commerce électronique. Par exemple, Amazon a livré 3,3 milliards de colis dans le monde en 2019 (CNBC, 2019) et en Chine, plus de 50 milliards de colis ont été livrés à travers le pays en 2018 (National Bureau of Statistics of China, 2019). De plus, les détaillants en ligne sont confrontés à des attentes croissantes en matière de niveau de service de la part des consommateurs (Allen et al., 2017). Les détaillants en ligne et les fournisseurs de logistique de commerce électronique sont confrontés à de nombreux défis, notamment des attentes plus élevées des clients concernant des cycles de livraison courts des commandes, des délais de livraison planifiés individuellement et un nombre considérable de tentatives de livraison échouées et de retours de produits (Allen et al., 2017). De plus, en raison des fréquentes activités de commerce électronique, la compétitivité des prestataires de services logistiques s'intensifie progressivement. Dans ce contexte, les transporteurs les détaillants en ligne et les autres parties impliquées dans les chaînes d'achat du commerce électronique ont déployé des efforts adéquats pour exploiter le potentiel interne pour répondre aux attentes des consommateurs et rester compétitifs sur le plan des coûts. Malgré les efforts des entreprises de transport, le facteur de charge moyen des camions est faible et la fréquence de fonctionnement à vide est élevée. Globalement, selon Eurostat (2017), au niveau du transport total, la plupart des camions en Europe se situaient entre 15% et 30% de trajets à vide. La charge moyenne d'un camion est bien inférieure à sa capacité et particulièrement faible dans la distribution urbaine. De plus, le transport de marchandises (dans les pays développés) est responsable de près de 15% des émissions de gaz à effet de serre.

Afin de survivre sous la pression croissante d'opérer plus efficacement et de satisfaire les demandes des clients, l'une des solutions prometteuses est la collaboration entre expéditeurs et transporteurs. Le transport collaboratif est obtenu en partageant les capacités de transport ou les commandes de transport (Verdonck, et al., 2013). Par exemple, DHL, Baxter, Boots (www.boots.com) et UCB (www.ucb.com) envisagent une collaboration horizontale dans le transport et la logistique (Taneja & Kalita, 2014). En Belgique et aux Pays-Bas, le centre de gravité logistique européen, il y a eu au moins cinquante partenariats logistiques horizontaux formellement établis (Cruijssen, Dullaert et Fleuren, 2007). La collaboration entre transporteurs ou expéditeurs peut améliorer les statistiques et générer des avantages économiques pour les transporteurs concernés ainsi que des avantages sociaux et environnementaux. Les résultats de la collaboration logistique horizontale sont impressionnants: des améliorations d'efficacité à deux chiffres pouvant atteindre 30% ont été signalées (Audy, Lehoux, D'Amours et Rönnqvist, 2012; Vanovermeire et al., 2014; Gansterer et Hartl, 2018).

Dans le réseau de collaboration, il est basé sur une plate-forme d'information de commerce électronique similaire à eBay ou Taobao. De nombreuses plateformes de services en tant que fournisseur de services d'échange tiers permettent aux expéditeurs et aux transporteurs de partager leurs informations clés telles que les besoins et les capacités de transport et facilitent les échanges entre les expéditeurs et les transporteurs (George et Xu, 2013). Par exemple, en Europe, Timocom (www.timocom.de) est un fournisseur établi d'un marché électronique pour l'échange de fret. La société agit comme commissaire-priseur et facture des frais aux participants aux enchères. En Chine, Cainiao Network fournit aux vendeurs et acheteurs des informations en temps réel sur les activités logistiques pour améliorer l'efficacité de la livraison. Le partage d'informations joue un rôle important dans le transport collaboratif (Özener et al., 2011; Gansterer, Hartl et Savelsbergh, 2020). En termes de partage d'informations, deux approches de planification ont été proposées pour résoudre le problème du transport collaboratif dans la littérature: la planification centralisée et la planification décentralisée (Dai et al., 2011; Lyu et al., 2020). Dans le cadre centralisé, un décideur disposant d'une information complète sur tous les acteurs détermine la réaffectation optimale des demandes dans le but de minimiser le coût total de transport ou de maximiser le profit total de transport. Dans le cadre décentralisé, plusieurs acteurs intéressés se forment une alliance et échangent leurs demandes de transport avec un partage d'informations limité pour atteindre une efficacité optimale.

Parce que les demandes dans le contexte du commerce électronique sont fragmentaires, nous nous concentrons sur le transport de chargement partiel (LTL). Compte tenu de l'étude actuelle sur le transport collaboratif, dans cette thèse, nous essayons d'aborder les problèmes rencontrés dans le transport collaboratif sous deux aspects: le partage complet d'informations dans une approche de planification centralisée et le partage incomplet d'informations dans une approche de planification décentralisée. Dans une approche de planification centralisée, nous nous concentrons sur l'utilisation d'algorithmes d'optimisation des transports pour réaffecter les demandes entre les acteurs de l'alliance. Alors que dans une approche de planification décentralisée, des mécanismes basés sur les enchères sont développés pour échanger les demandes entre les acteurs afin d'atteindre une efficacité optimale.

Le but de cette thèse est de combler les lacunes de recherche ci-dessus et de fournir des guides pratiques sur la gestion. Notre étude est consacrée à résoudre les trois problèmes suivants:

- 1) Collaboration des expéditeurs en logistique de livraison et de collecte. Ce chapitre étudie la collaboration des expéditeurs en logistique de livraison et de collecte, dans laquelle plusieurs expéditeurs ayant des opérations de logistique livraison ou / et collecte consolident leurs demandes de transport. Dans la logistique de livraison et de collecte, les fabricants livrent de nouveaux produits à leurs clients et les produits usagés sont collectés auprès des clients et transportés chez les remanufactureurs pour réparation ou reproduction. Il en résulte un nouveau problème de tournée de véhicules avec des demandes de livraison et de collecte et trois types de dépôts différents (dépôts de produits, dépôts de véhicules et dépôts de recyclage). Une approche hybride combinant une procédure de recherche adaptative

randomisée gourmande (GRASP) et une recherche locale itérée (ILS) est proposée pour trouver une solution quasi optimale du problème. Des expériences numériques sur un grand nombre d'instances générées aléatoirement avec différentes tailles de problèmes démontrent que la collaboration des expéditeurs dans la logistique birectionnelle de livraison et de collecte peut réaliser des économies de coûts significatives par rapport à l'opération isolée de chaque expéditeur sans coopération, et l'approche proposée est efficace dans le sens où elle peut trouver une solution de haute qualité dans un temps de calcul raisonnable.

2) Un mécanisme d'échange à plusieurs tours pour la collaboration des transporteurs dans le transport de charge partiel. Ce chapitre propose un mécanisme d'échange de demandes itératif pour résoudre la collaboration des transporteurs de chargement partiel. À chaque itération, chaque transporteur fournit d'abord plusieurs ensembles de demandes d'offre et leurs paiements de transfert correspondants. Chaque transporteur détermine ensuite les paquets de demandes à acquérir auprès d'un ou de plusieurs transporteurs. Plusieurs paquets de demandes peuvent être échangés entre les transporteurs à chaque itération. À chaque tour de l'enchère, chaque transporteur met à jour ses ensembles de demandes à sous-traiter en fonction des informations en retour des itérations précédentes. Des expériences numériques montrent que ce mécanisme d'échange multi-tours fournit 11,80% de profit en plus par rapport aux autres mécanismes.

3) Un algorithme de décomposition de benders pour un problème de génération d'enchères dans le transport collaboratif dans plusieurs échelons. Ce recherche traite du problème de génération des offres de transport à plusieurs échelons pour l'achat de services de transport réalisé par une enchère combinatoire. Dans l'achat en services de transport, les expéditeurs veulent se procurer une certaine quantité de services de transport auprès d'un ensemble de transporteurs potentiels qui ont des demandes réservées. Chaque demande est associée à une origine, une destination, une quantité, des fenêtres horaires et un prix de demande payés par son expéditeur de correspondant. La livraison du fret de son origine à sa destination se fait à travers trois échelons. Le premier échelon consiste à transférer le fret des points de collecte vers les dépôts intermédiaires (centres de consolidation urbaine), le deuxième échelon consiste à transférer le fret entre les dépôts intermédiaires de deux villes différentes, tandis qu'au troisième échelon, le fret est transféré de ces dépôts intermédiaires vers les clients finaux dans les fenêtres de temps. Nous proposons un modèle basée sur l'arc et un modèle basée sur le chemin pour notre problème. Un algorithme de décomposition de benders est développé pour le modèle basée sur le chemin. L'algorithme de décomposition de base est amélioré grâce aux accélération stratégies des multi-coupes et des coupes pareto-optimales. Des expériences de calcul extensive ont été effectuées pour évaluer l'efficacité de l'algorithme et les résultats de calcul indiquent que l'algorithme de décomposition de décomposition peut obtenir des solutions optimales pour les instances de petite et moyenne taille et atteindre l'écart moyen de 0,99% pour les grandes instances.

A.2 Revue de Littérature

Il existe deux types de transport collaboratif: la collaboration verticale et la collaboration horizontale. La collaboration verticale est la collaboration lorsque deux ou plusieurs organisations de différents niveaux ou étapes de la chaîne de transport partagent leurs responsabilités, leurs ressources et leurs informations de performance pour servir des clients finaux relativement similaires. La collaboration horizontale fait référence à la collaboration entre plusieurs acteurs au même niveau dans les opérations logistiques telles que la collaboration entre les expéditeurs et la collaboration entre les transporteurs (Cruijssen et al., 2007; Verdonck et al., 2013; Gansterer et Hartl, 2018; Cleophas et al., 2019).

Il existe deux types de collaboration dans le transport collaboratif: la collaboration entre expéditeurs et la collaboration entre transporteurs. La collaboration des expéditeurs prend en compte la situation d'un seul transporteur et de plusieurs expéditeurs. La collaboration entre les transporteurs se concrétise par la consolidation de leurs demandes de transport à proposer aux transporteurs. Dans la collaboration entre transporteurs, plusieurs transporteurs qui fournissent des services de transport similaires ont formé une alliance pour échanger des demandes de transport en propre afin d'augmenter les bénéfices et d'optimiser l'utilisation des ressources de transport.

Il existe deux modes de transport routier: le transport de chargement complète (TL) et le transport de chargement partiel. Dans le transport TL, les marchandises sont transportées d'une origine à une destination par des camions entièrement chargés, tandis que dans le transport LTL, les marchandises sont transportées de plusieurs origines vers plusieurs destinations par des camions partiellement chargés.

Deux approches de planification ont été proposées pour résoudre le problème du transport collaboratif dans la littérature: la planification centralisée et la planification décentralisée. Dans le cadre centralisé, un décideur disposant d'une information complète sur tous les acteurs détermine la réaffectation optimale des demandes entre les transporteurs dans le but de minimiser le coût total du transport ou de maximiser le profit total du transport. Dans le cadre décentralisé, plusieurs acteurs d'intérêt individuel forment une alliance et échangent leurs demandes de transport avec un partage d'informations limité pour atteindre une efficacité optimale.

Dans la prochaine sous-section, nous passerons en revue l'étude actuelle du transport collaboratif sous deux aspects: une approche de planification centralisée et une approche de planification décentralisée.

La plupart des approches de planification centralisée pour le transport collaboratif se concentrent sur des problèmes d'optimisation complexes. Dans la planification centralisée, les demandes des clients de tous les acteurs participants sont combinées et collectées dans un pool central et des schémas d'itinéraire efficaces sont mis en place pour toutes les demandes simultanément en utilisant des techniques de tournée de véhicules appropriées. Il existe deux stratégies principales de distribution dans le transport: le transport direct et la distribution multi-échelons. Dans l'expédition directe, les véhicules partant d'un dépôt transportent leur

fret directement aux clients, tandis que dans les systèmes multi-échelons, le fret est livré de l'origine aux clients via des dépôts intermédiaires / plateformes logistiques (Perboli, Tadei et Vigo, 2011). Dans la sous-section suivante, nous passerons en revue la littérature sur le transport collaboratif dans un transport à un seul échelon et un transport à plusieurs échelons respectivement.

Certaines études sur la collaboration des expéditeurs ont porté sur la collaboration entre les expéditeurs de chargement complet. Ergun et al. (2007a, b) ont introduit un problème de collaboration avec les chargeurs complets et l'ont formulé comme un problème de couverture de voie, qui consiste à identifier un ensemble de tournées qui couvrent tous les ensembles de voies avec le coût de transport minimum sujet à de la longueur ou des contraintes de temps de déplacement total. Deux modèles de programmation linéaire ont été proposés dans un cadre centralisé pour obtenir le coût de transport minimum pour l'alliance des expéditeurs dans le transport forestier: le premier est basé sur les flux directs entre les points d'offre et de demande et le second considère le transport de retour (backhauling) (Frisk et al., 2010). La recherche sur la collaboration entre les expéditeurs et les expéditions LTL est assez limitée. Dai et Chen (2009) ont présenté un modèle mathématique général pour la logistique collaborative dans le transport LTL, qui étend le modèle de couverture de voie à un modèle avec des demandes de collecte et de livraison. Une méthode de relaxation lagrangienne a été proposée pour résoudre le modèle. Yilmaz et Savaseneril (2012) ont étudié un problème de collaboration parmi petits expéditeurs avec des exigences d'expédition stochastiques. Des expériences numériques ont montré que les expéditeurs bénéficient toujours de la collaboration. Audy et al. (2011) ont montré que des économies de coûts significatifs pouvaient être réalisés grâce au transport collaboratif entre les fabricants dans la logistique livraison. Sprenger et Monch (2012) ont proposé une méthode heuristique gourmande pour résoudre un problème de planification de transport coopératif dans la logistique livraison et ont démontré que la stratégie coopérative surpasse celle non coopérative avec des économies de 20% en moyenne. La littérature actuelle sur la collaboration des expéditeurs montre que la planification et la conception conjointes des tournées entre expéditeurs dans un cadre de planification centralisé sont une source majeure d'économies.

Certaines publications se concentrent sur la collaboration des transporteurs. Hernández et Peeta (2011) ont abordé un problème de la collaboration centralisée entre plusieurs transporteurs dépendante du temps. Les auteurs ont formulé le problème sous la forme d'un modèle formulé binaire de coûts minimaux multiservices et ont proposé un algorithme de "branch-and-cut" pour le résoudre. Weng et Xu (2014) ont formulé le problème de tournée de hub optimal des tâches fusionnées dans le transport collaboratif comme un problème de tournée de véhicules sur les arcs et à multi-dépôts et ont proposé deux heuristiques basées sur la relaxation lagrangienne et la décomposition de Benders. Hernández et Peeta (2014) étudient un problème de collaboration à transporteur unique dans le transport LTL, dans laquelle un transporteur cherche à collaborer avec d'autres transporteurs afin d'acquérir une capacité de transport supplémentaire pour répondre à la demande excédentaire. Fernandez et al. (2016) a introduit un nouveau problème de tournée d'arc pour l'optimisation de la

collaboration entre les transporteurs, dans laquelle le modèle mathématique a été formulé comme un problème de tournée d'arc avec plusieurs véhicule dépôts et bénéfices sans contraintes de capacité et un algorithme de "branch-and-cut" a été proposé pour résoudre il. Buijs et al. (2016) ont étudié la planification collaborative du transport pour deux prestataires de services logistiques à travers une planification d'itinéraire conjointe.

Dans un transport à plusieurs échelons, les produits collectés auprès de plusieurs expéditeurs doivent être transbordés et regroupés dans des centres de consolidation urbaine (UCC). La collaboration dans un transport à plusieurs échelons doit livrer conjointement des produits à l'UCC et organiser les livraisons du dernier kilomètre, ce qui contribue à atteindre une efficacité globale plus élevée (Cleophas, et al., 2019). Thompson et Hassall (2012) ont démontré que la collaboration dans un transport à plusieurs échelons peut réaliser des économies de coûts importantes et réduire le nombre de véhicules par rapport à l'opération isolée sans coopération. Wang et al. (2020) ont proposé un problème de tournée collaboratif multicentrique à deux échelons basé sur un réseau état-espace-temps.

Les approches décentralisées pour la collaboration des les transporteurs incluent les mécanismes basés sur les enchères et les mécanismes d'échange non liés aux enchères (Gansterer et Hartl, 2018; Cleophas et al., 2018). Dans la littérature, il existe principalement trois types de mécanismes d'enchères proposés pour la collaboration des transporteurs. Figliozzi et al. (2003, 2004, 2005, 2006) ont mené d'importantes études sur les enchères séquentielles pour le transport TL, où les demandes de transport arrivent sur un marché au hasard et les transporteurs enchérissent pour eux dans une séquence d'enchères. Figliozzi et al. (2003) ont présenté un cadre pour les stratégies d'un transporteur dans un marché du transport basé sur des enchères et ont examiné la complexité des différentes stratégies d'enchères des transporteurs. Dans ce cadre, Figliozzi et al. (2004) ont évalué quatre stratégies de tournée de véhicules différentes sur l'estimation des coûts de service dans diverses conditions de demande. Dans leurs travaux ultérieurs, Figliozzi et al. (2005) ont étudié l'impact des paramètres d'enchères et des mécanismes d'enchères sur la performance du marché des transports. Figliozzi et al. (2006) a fourni une expression pour quantifier les coûts d'opportunité dans les enchères séquentielles. Dans les littérature mentionnés ci-dessus, les enchères séquentielles sont utilisées pour l'achat de services de transport de charement plein dans un environnement dynamique.

Le deuxième type de mécanisme d'enchères est l'enchère combinatoire (CA), dans laquelle les transporteurs sont autorisés à soumettre sur un ensemble de demandes de transport (Pekec & Rothkopf, 2003). Song et Regan (2003) ont conçu un cadre d'échange basé sur CA pour résoudre un problème de collaboration dynamique des transporteurs dans le transport TL. Schonberger (2006) a proposé une approche basée sur l'CA pour résoudre le problème de réaffectation des demandes dans le transport LTL par une procédure en deux étapes. Krajewska et Kopfer (2006) ont étendu la méthode de Schonberger (2006) en considérant la répartition des coûts entre les transporteurs, qui est basée sur l'hypothèse que les coûts de traitement de tout ensemble de demandes peuvent être évalués avec précision. De même, Schwind et al. (2009) ont développé une enchère à un seul rond et une enchère

itérative pour échanger les demandes entre les centres de profit d'une seule entreprise de transport avec un partage complet des informations. Conformément aux études précédentes, Berger et Bierwirth (2010) ont proposé à la fois une vente aux enchères à demande unique et une autorité de certification pour résoudre un problème de collaboration des transporteurs appelé problème du vendeur itinérant collaboratif avec le collecte et les livraisons dans le transport LTL. Gansterer et Hartl (2016) ont adopté la même méthode d'enchères que Berger et Bierwirth (2010) pour la collaboration des transporteurs dans laquelle le BGP a été résolu par une approche heuristique pour les instances plus importantes. Pour réduire la complexité de calcul, Dai et Chen (2011) ont proposé une enchère pour la collaboration des transporteurs dans le transport LTL, dans laquelle chaque transporteur sélectionne une demande à externaliser et chaque transporteur détermine quelle demande de soumettre dans chaque rond de la vente aux enchères. Dai et al. (2014) ont introduit une approche d'enchères combinatoires basée sur la fixation de prix à multi-ronds, dans laquelle chaque transporteur détermine les demandes d'offre et d'enchères en fonction du prix de service de chaque demande à externaliser annoncée par le commissaire-priseur. Wang et Kopfer (2014a) et Wang et al. (2014b) ont présenté une approche d'échange basée sur la route, dans laquelle les transporteurs génèrent et soumettent de nouvelles routes basées sur les valeurs duales d'un problème de relaxation linéaire. Chen (2016) a présenté une méthode d'échange d'horloge-proxy combinatoire pour résoudre la collaboration des transporteurs avec les demandes de réservations dans le transport LTL, dans laquelle des demandes supplémentaires sont générées dans la phase proxy. Pour le transport TL, Lai et al. (2017) ont proposé un mécanisme d'enchères itératives, dans laquelle chaque transporteur externaliser les demandes à de nombreux transporteurs et chaque transporteur n'achète qu'une seule demande auprès des autres dans chaque tour de l'enchère.

Le troisième type de mécanisme d'enchères est la double enchère, dans laquelle les enchères bilatérales sont permises et le marché du transport est effacé par le commissaire-priseur tiers. Comme nous nous concentrons sur les enchères combinatoires, les lecteurs peuvent se référer à Huang et Xu (2013) et Xu et al. (2016) pour une revue de la littérature plus détaillée sur les duales enchères. Certaines études considèrent des mécanismes d'échange de demandes non basées sur des enchères pour la collaboration des transporteurs. Özener, Ergun et Savelsbergh (2011) ont mis au point divers mécanismes efficaces d'échange de voies entre les transporteurs de chargement compétitifs afin de réduire leurs coûts de repositionnement, qui diffèrent en termes de degrés de partage d'informations et d'options de paiement parallèle. Il est facile d'exécuter des méthodes non liées aux enchères sans procédure d'enchères, mais il est moins efficace car aucune information sur les préférences ne peut être obtenue auprès d'autres collaborateurs. Différent de l'échange de demandes, certains mécanismes se concentrent sur l'échange de capacités dans le transport LTL. Agarwal et Ergun (2010), Houghtalen et al. (2011) ont proposé un mécanisme d'échange de capacités pour la collaboration des transporteurs dans le transport maritime de ligne. Hernández et al. (2011) ont examiné le partage des capacités dans un environnement dynamique.

Pour le BGP dans une enchère combinatoire pour la collaboration des transporteurs, chaque transporteur évalue un nombre exponentiel de groupes de demandes potentiels et détermine les groupes de demandes à sousmettre. Park et Rothkopf (2005) ont souligné que le BGP est généralement NP-difficile. Nous nous concentrons sur le BGP en CA. Dans la littérature, deux stratégies d'enchères sont envisagées: enchérir sur une seule demande et enchérir sur certains ensembles de demandes.

Pour les stratégies d'enchères sur des demandes individuelles, Dai et Chen (2011) ont formulé le problème de sélection des demandes d'externalisation et le problème de sélection des demandes d'enchères dans coopération du transporteur LTL en tant que problèmes de ramassage et de livraison sélectifs avec des fenêtres de temps. Li et al. (2015) et Lai et al. (2017) ont établi un modèle de sélection de demande à externaliser et un modèle de sélection de demande à insource dans une vente aux enchères dans la collaboration de transporteurs TL basée sur le concept de profit marginal. Les deux problèmes de sélection des demandes ont été formulés comme des problèmes sélectifs de collecte et de livraison avec des fenêtres temporelles dans le transport TL (SPDPTW-TL) et ont été résolus par le solveur CPLEX MIP. Certaines études se concentrent sur les enchères pour plusieurs demandes. Sur la base des prix des demandes de service annoncés par le commissaire-priseur, Dai et Chen (2014) ont formulé le BGP comme un problème sélectif de collecte et de livraison avec des fenêtres temporelles dans le transport LTL. Différent de celui de Dai et Chen (2011), Dai et Chen (2014) ont proposé un modèle SPDPTW-LTL pour déterminer les demandes à soustraire simultanément. Ils ont résolu le modèle SPDPTW-LTL par le solveur CPLEX MIP pour les petites instances. En supposant que chaque transporteur a des demandes réservées, Li et al. (2016) ont modélisé le BGP comme un problème sélectif de collecte et de livraison avec des fenêtres temporelles, des bénéfiques et des demandes réservées (SPDPTWR), et ont proposé une approche adaptative de recherche de grands quartiers (ALNS) pour le résoudre pour les instances de grande taille. Dans un autre courant de recherche, le BGP est également étudié dans la littérature sur l'achat de services de transport dans le transport TL (TSP-TL), où le BGP dans TSP-TL est formulé comme un modèle de réseau de flux à coût minimum. Veuillez vous reporter aux articles de synthèse de Song et Regan (2002, 2005), Caplice et Sheffi (2013), Sheffi (2014), Chen et al. (2009) et Chang (2009) pour plus de détails. Après avoir analysé la littérature sur le BGP dans le transport collaboratif, nous constatons que le BGP dans diverses CA est principalement un problème sélectif de collecte et de livraison avec des fenêtres temporelles. Le solveur CPLEX MIP est généralement utilisé pour résoudre le BGP pour les petites instances et des méta-heuristiques ont été utilisées pour résoudre le BGP pour les grandes instances.

A.3 La collaboration des expéditeurs dans la logistique de livraison et de collecte

Dans ce chapitre, nous étudions la collaboration des expéditeurs en logistique livraison et collecte, dans laquelle les expéditeurs de deux types (fabricants et réusineurs) partagent les clients et ont des demandes de transport complémentaires. En regroupant leurs demandes de transport aller et retour et en proposant un plan de transport globalement optimisé, les expéditeurs peuvent ensemble demander des tarifs plus avantageux lorsqu'ils soustraient le service de ces demandes à un transporteur. Notre objectif est de trouver un plan de transport optimal pour tous les expéditeurs afin que leur coût total de transport soit minimisé. Dans ce problème, les clients peuvent avoir différents types de demandes de transport générées par la logistique de livraison et de collecte. Certains clients peuvent uniquement avoir des demandes de livraison générées par la logistique livraison, où de nouveaux produits sont expédiés aux clients depuis des usines de fabrication (dépôts de produits). Certains clients peuvent fournir des produits d'occasion à des remanufactureurs (dépôts de recyclage) pour réparation et reproduction en logistique de collecte. Les autres clients peuvent avoir à la fois des demandes de livraison et de collecte comme mentionné ci-dessus. De plus, les dépôts de produits, les dépôts de recyclage, les dépôts de véhicules peuvent être dispersés géographiquement à différents endroits. Nous considérons donc trois types de dépôts différents. Cela donne lieu à un nouveau problème de tournée de véhicules avec des demandes de livraison et de collecte et trois types de dépôts différents (dépôts de produits, dépôts de véhicules et dépôts de recyclage) en logistique de livraison et de collecte (VRPPD-FRL).

Comme notre problème VRPPD-FRL est une nouvelle variante du problème de tournée de véhicules avec collecte et livraison et contraintes de capacité, qui est NP-difficile, nous proposons une méta-heuristique qui combine la procédure de recherche adaptative randomisée gourmande (GRASP) et la recherche locale itérative (ILS) pour trouver une solution quasi optimale du problème. Des résultats compétitifs ont été rapportés dans la littérature sur l'utilisation d'algorithmes hybrides GRASP-ILS pour résoudre différentes variantes de problèmes de tournée de véhicule tels que le problème de tournée de véhicule de capacité par Prins (2009) et le problème de tournée de véhicule avec des fenêtres temporelles, des contraintes de synchronisation et de priorité par Haddadene et al. (2016). En adaptant GRASP et ILS aux nouvelles caractéristiques de notre problème, nous proposons une méta-heuristique GRASP-ILS pour résoudre le problème de manière optimale. Nos résultats expérimentaux démontrent que l'algorithme hybride GRASP-ILS est plus efficace et robuste que GRASP et ILS.

Nous considérons la collaboration des expéditeurs dans la logistique de livraison et de collecte, où un ensemble de fabricants désignés par M_1 et un ensemble de fabricants réusinés désignés par M_2 forment une alliance avec $M = M_1 \cup M_2$ en consolidant leurs demandes de collecte et de livraison et en planifiant conjointement les tournées des véhicules pour

répondre à ces demandes ensemble. Soit NC_m l'ensemble des clients du fabricant ou du réusinage $m \in M$, $NC = \bigcup_{m \in M} NC_m$ désigne l'ensemble des clients de l'alliance, s_i et t_i désignent respectivement le dépôt de produits et le dépôt de recyclage de clients $i \in NC$. Chaque fabricant $m \in M_1$ veut livrer de nouveaux produits avec la quantité d_i du dépôt de produits s_i à son client $i \in NC_m$ et chaque remanufacturier $m \in M_2$ veut collecter les produits usagés avec la quantité p_i de son client $i \in NC_m$ pour recycler le dépôt t_i . Pour trouver un plan de transport optimal pour tous les expéditeurs, une nouvelle variante du problème de tournée de véhicules VRPPD-FRL avec l'objectif de minimiser les coûts globaux de transport de l'alliance de collaboration est proposée. VRPPD-FRL vise à planifier une flotte de véhicules homogènes pour répondre aux demandes des clients de tous les expéditeurs afin que chaque client soit visité une seule fois sous les contraintes de capacité du véhicule, les contraintes de longueur de déplacement maximale de chaque véhicule et les contraintes d'appariement et de précédence. Chaque véhicule commence et se termine à le même dépôt de véhicules. Dans notre problème de planification de transport collaboratif, chaque dépôt de produits et chaque centre de recyclage peuvent être visités plusieurs fois par des véhicules, différents clients ayant la demande du même produit sont fournis par le même centre de produits et les mêmes produits usagés recyclés de différents clients sont transportés dans le même dépôt de recyclage.

Hypothèses:

1) Les transbordements ne sont pas permis entre les véhicules et chaque client ne doit être desservi qu'une seule fois par un véhicule.

2) Étant donné que plusieurs expéditeurs peuvent partager le même dépôt de produits et le même dépôt de recyclage, la quantité de nouvelle produits disponible dans un dépôt de produit ou la quantité de utilisée produits dans un dépôt de recyclage peut être supérieure à la capacité du véhicule. Par conséquent, nous permettons à chaque dépôt de produits et dépôt de recyclage d'être visité plusieurs fois par des véhicules, mais peut être visité au plus une fois par chaque véhicule.

3) Chaque demande de livraison n'a qu'un seul dépôt de produit spécifique et chaque demande de collecte n'a qu'un seul dépôt de recyclage désigné.

4) Chaque tournée commence et se termine avec le même dépôt de véhicules.

Variables de décision

x_{ij}^v 1 si $arc(i, j)$ est passé par le véhicule $v \in NV, i, j \in N, i \neq j$; 0 autrement

lp_{ki}^v la charge de nouveaux produits collectés dans le dépôt de produits $k \in NP$ du véhicule $v \in NV$ avant la visite du nœud $i \in N$

lr_{ki}^v la charge de produits usagés livrés au dépôt de recyclage $k \in NR$ du véhicule $v \in NV$ après la visite du nœud $i \in N$

q_i^v la position du nœud $i \in N$ sur la tournée du véhicule $v \in NV$

Avec ces notations, le problème peut être formulé comme suit:

$$\min \sum_{v \in NV} \sum_{i \in N} \sum_{j \in N, j \neq i} c_{ij} x_{ij}^v \quad (\text{A.3-1})$$

Soumis à:

$$\sum_{j \in N, j \neq i} x_{ij}^v \leq 1, \quad \forall i \in O, v \in NV \quad (\text{A.3-2})$$

$$\sum_{v \in NV} \sum_{j \in N, j \neq i} x_{ij}^v = 1, \quad \forall i \in NC \quad (\text{A.3-3})$$

$$\sum_{j \in N, j \neq i} x_{ij}^v = \sum_{j \in N, j \neq i} x_{ji}^v, \quad \forall i \in N, v \in NV \quad (\text{A.3-4})$$

$$\sum_{j \in N, j \neq i} x_{ij}^v \leq \sum_{j \in N, j \neq s_i} x_{s_i, j}^v, \quad \forall i \in NC, v \in NV \quad (\text{A.3-5})$$

$$\sum_{j \in N, j \neq i} x_{ij}^v \leq \sum_{j \in N, j \neq t_i} x_{j, t_i}^v, \quad \forall i \in NC, v \in NV \quad (\text{A.3-6})$$

$$lp_{kj}^v \geq lp_{ki}^v + \sum_{h \in NC, s_h = j} \sum_{i \in N} x_{ih}^v \cdot d_h \cdot \alpha_{jk} - Q \cdot (1 - x_{ij}^v), \quad \forall i \in N, j, k \in NP, i \neq j, v \in NV \quad (\text{A.3-7})$$

$$lp_{kj}^v \geq lp_{ki}^v - d_j \cdot \beta_{jk} - Q \cdot (1 - x_{ij}^v), \quad \forall i \in N, j \in NC, k \in NP, i \neq j, v \in NV \quad (\text{A.3-8})$$

$$lr_{kj}^v \geq lr_{ki}^v - \sum_{h \in NC, t_h = j} \sum_{i \in N} x_{ih}^v \cdot p_h \cdot \alpha_{jk} - Q \cdot (1 - x_{ij}^v), \quad \forall i \in N, j, k \in NR, i \neq j, v \in NV \quad (\text{A.3-9})$$

$$lr_{kj}^v \geq lr_{ki}^v + p_j \cdot \beta_{jk} - Q \cdot (1 - x_{ij}^v), \quad \forall i \in N, j \in NC, k \in NR, i \neq j, v \in NV \quad (\text{A.3-10})$$

$$lp_{ji}^v + lr_{ki}^v = 0, \quad \forall i \in O, j \in NP, k \in NR, v \in NV \quad (\text{A.3-11})$$

$$0 \leq \sum_{k \in NP} lp_{ki}^v + \sum_{k \in NR} lr_{ki}^v \leq Q, \quad \forall i \in N \setminus O, v \in NV \quad (\text{A.3-12})$$

$$q_j^v \geq q_i^v + 1 - N(1 - x_{ij}^v), \quad \forall i \in N, j \in N, j \neq i, v \in NV \quad (\text{A.3-13})$$

$$\sum_{i \in N} \sum_{j \in N, j \neq i} c_{ij} x_{ij}^v \leq L, \quad v \in NV \quad (\text{A.3-14})$$

$$x_{ij}^v \in \{0, 1\}, \quad \forall i, j \in N, v \in NV \quad (\text{A.3-15})$$

$$0 \leq lp_{ki}^v \leq Q, \quad \forall i \in N, k \in NP, v \in NV \quad (\text{A.3-16})$$

$$0 \leq lr_{ki}^v \leq Q, \quad \forall i \in N, k \in NR, v \in NV \quad (\text{A.3-17})$$

$$1 \leq q_i^v \leq N, \quad \forall i \in N, v \in NV \quad (\text{A.3-18})$$

La fonction objectif (A.3-1) minimise les coûts totaux de transport. Les contraintes (A.3-2) garantissent que chaque véhicule commence et se termine au dépôt de véhicules. Les contraintes (A.3-3) indiquent que chaque client peut être visité exactement une seule fois. Les contraintes (A.3-4) garantissent que si un véhicule visite un nœud, il doit quitter ce nœud. Les contraintes (A.3-5) et (A.3-6) garantissent qu'une fois qu'un client est visité par un véhicule, le dépôt de produits et le dépôt de recyclage correspondants doivent également être visités par le même véhicule. Les contraintes (A.3-7) et (A.3-8) sont les flux de poids à chaque nœud de dépôt de produit. Les contraintes (A.3-9) et (A.3-10) sont les flux de charge à chaque nœud de dépôt de recyclage. Les contraintes (A.3-11) garantissent que chaque

véhicule commence et se termine au dépôt de véhicules avec un poids à vide. Les contraintes (A.3-12) sont les contraintes de capacité du véhicule. Les contraintes (A.3-13) garantissent l'élimination du sous-tournée. Les contraintes (A.3-14) - (A.3-17) indiquent la nature de toutes les variables et leurs bornes supérieure et inférieure.

Comme GRASP est une heuristique puissante pour générer des solutions initiales bonnes et diversifiées et ILS est une méthode efficace pour échapper aux optima locaux et explorer plus d'espaces de solutions, nous proposons une approche hybride GRASP-ILS qui combine GRASP et ILS pour trouver des solutions presque optimales pour les étudiés. problème de collaboration des chargeurs. L'hybridation de GRASP-ILS profite à la fois à GRASP et à ILS. Compte tenu des nouvelles caractéristiques de notre problème, nous faisons quelques adaptations de GRASP-ILS pour le résoudre.

Les principales contributions de ce chapitre sont les suivantes: (1) La collaboration des chargeurs en logistiques de livraison et de collecte est considéré pour la première fois; (2) Une nouvelle variante du problème de tournée des véhicules avec des demandes de livraison et de collecte et trois types de dépôts est étudiée et un modèle de programmation d'entiers mixtes est formulé pour le problème. (3) Des expériences numériques sur un grand nombre d'instances générées aléatoirement avec différentes tailles de problèmes démontrent que la collaboration des expéditeurs dans la logistique de livraison et de collecte peut réaliser des économies de coûts significatives par rapport à l'opération isolée de chaque expéditeur sans coopération, et l'approche proposée est efficace dans le sens où elle peut trouver une solution de haute qualité dans un temps de calcul raisonnable.

A.4 Un mécanisme d'échange à plusieurs tours pour la collaboration des transporteurs dans le transport de chargement partiel

Avec le développement du commerce électronique, des cycles de commandes de livraison plus courts et des attentes plus élevées des clients, les prestataires logistiques de petits colis recherchent des solutions créatives et innovantes. L'une de ces solutions innovantes est le transport collaboratif dans la livraison du dernier kilomètre. Les transporteurs / expéditeurs peuvent réaliser des économies d'échelle en partageant les livraisons de colis et les ressources de transport, afin de réduire les coûts de transport et de saisir plus d'opportunités commerciales. Par exemple, les postes belge et néerlandaise ont toutes deux lancé des projets collaboratifs de logistique urbaine, dans lesquels Fedex, UPS et USPS consolident leurs paquets pour fournir un service du dernier kilomètre. La Poste belge, qui a démarré son projet en 2014, estime économiser environ 30% du total de miles parcourus (Multichannel Merchant, 2015).

Dans ce chapitre, nous nous concentrons sur la collaboration des transporteurs, dans laquelle une alliance avec plusieurs transporteurs qui fournissent des services de transport similaires dans une zone géographique fixe est formée pour échanger des demandes de transport en propre afin d'augmenter les bénéfices et d'optimiser l'utilisation des ressources de transport. Dans ce chapitre, nous proposons un mécanisme d'échange de demandes itératif pour aux transporteurs de sélectionner leurs demandes à offrir à d'autres transporteurs et acquérir des demandes auprès d'autres transporteurs avec un partage limité des informations sur les coûts de transport. Dans chaque itération, chaque transporteur en tant que vendeur fournit d'abord plusieurs ensembles de demandes à offrir et détermine leurs paiements de transfert correspondants en résolvant un problème de collecte sélective et de livraison avec bénéfices. Ce problème de décision est appelé problème de sélection des plusieurs lots de demandes à externaliser. Chaque transporteur, en tant qu'acheteur, détermine des plusieurs lots de demandes à acquérir auprès d'un ou plusieurs transporteurs en résolvant un problème de collecte sélective et de livraison avec des clusters (groupes) de demandes et de bénéfices. Ce problème est appelé problème de sélection des plusieurs lots de demandes à Insource. Ici, un transporteur sous-traite un paquet de demandes signifie qu'il offre ce paquet à d'autres transporteurs et un transporteur insources un un ensemble de demandes signifie qu'il acquiert ce paquet auprès d'autres transporteurs. Sur la base des offres et demandes soumises par tous les transporteurs, le mécanisme réaffecte (échange) certains groupes de demandes entre les transporteurs en résolvant le problème de la détermination des gagnants. Le processus d'échange de demande est répété jusqu'à ce qu'un certain critère soit atteint. Dans chaque itération, chaque transporteur met à jour sous-traitance des ensembles de demandes en fonction des informations de retour des itérations précédentes. Des expériences numériques sur un grand nombre d'instances de référence montrent que ce mécanisme d'échange multi-rond surpasse considérablement les mécanismes d'enchères de la littérature.

Par rapport aux mécanismes d'enchères proposés par Berger et Bierwirth (2010), la principale contribution de cet article est sous trois aspects: (1) Chaque transporteur peut externaliser (offrir) plusieurs liasses de demandes à d'autres transporteurs et chaque transporteur peut insource (acquérir) plus d'un ensemble de demandes provenant de plusieurs autres transporteurs dans chaque itération de notre mécanisme d'échange. (2) Dans notre mécanisme, chaque transporteur met à jour le prix de externaliser de chaque demande sur la base des informations des itérations précédentes, ce qui lui permet de sélectionner différents ensembles de demandes à externaliser dans différentes itérations. (3) Des expériences numériques montrent que notre mécanisme surpasse significativement deux mécanismes d'enchères proposés par Berger et Bierwirth (2010) et Gansterer, M., & Hartl (2016) avec une amélioration moyenne de 11,80% en termes de profit total de tous les transporteurs. Avec la possibilité de insource (d'acquérir) les demandes de plusieurs autres transporteurs, notre mécanisme peut apporter plus de bénéfices à l'alliance des transporteurs que les mécanismes qui n'acquièrent que les demandes venant d'un seul transporteur.

Nous concevons un mécanisme d'échange à plusieurs rond pour la collaboration des transporteurs LTL. Dans cette vente aux enchères, chaque transporteur décide séquentiellement les demandes à externaliser en tant que vendeur et les demandes à acquérir en tant qu'acheteur. Le mécanisme fait correspondre les approvisionnements et les demandes de tous les transporteurs et réaffecte certains ensembles de demandes entre eux avec un partage d'informations limité. Dans notre mécanisme d'échange, nous autorisons d'échange quelques paquets de demandes dans chaque rond de l'enchère, chaque transporteur peut externaliser plusieurs demandes à plusieurs transporteurs et chaque transporteur peut insource plusieurs demandes de plusieurs transporteurs.

Les principales étapes de notre mécanisme d'échange multi-ronds sont décrites comme suit:

Étape 1 (Exprimez les demandes à externaliser). Chaque transporteur fournit plusieurs ensembles de demandes d'offre et leurs paiements de transfert correspondants en résolvant un problème sélectif de collecte et de livraison avec des bénéfices. Le paiement de transfert de chaque demandes de paquet indique le montant maximal du prix que le transporteur offrant est prêt à payer pour sous-traiter ce paquet. Les informations des paquets des demandes à externaliser de chaque transporteur sont transmises au commissaire-priseur. Après avoir reçu toutes les informations sur les offres des demandes à externaliser et leurs paiements de transfert soumis par les transporteurs, le commissaire-priseur révèle les informations à tous les transporteurs de l'alliance.

Étape 2 (Sousmettre d'enchères pour acquérir les demandes). Chaque transporteur détermine les paquets de demandes à acquérir auprès d'un ou de plusieurs transporteurs en résolvant un problème sélectif de collecte et de livraison avec des grappes de demandes et de bénéfices. Les informations sur les forfaits d'insource de chaque transporteur sont transmises au commissaire-priseur.

Étape 3 (Détermination des gagnants). Sur la base des offres et des demandes de paquets de demandes soumises par tous les transporteurs, le mécanisme réaffecte (échange)

certains paquets de demandes entre les transporteurs en résolvant un problème de détermination des gagnants.

Étape 4 (Vérifiez la condition d'arrêt): Vérifiez si un critère d'arrêt donné est satisfait. Si oui, le processus d'échange de demande s'arrête. Sinon, passez à l'étape 1 avec les informations des itérations précédentes.

Pour explorer davantage le potentiel de collaboration, la sélection des demandes à sous-traiter joue un rôle important dans notre mécanisme multi-tours. Pour augmenter les possibilités de collaboration en permettant aux transporteurs d'avoir plus de flexibilité pour sélectionner les demandes d'externalisation, nous adoptons un paramètre α , la marge bénéficiaire minimale, pour influencer si une demande est sélectionnée comme demande d'externalisation. Selon Dai et Chen (2011), la marge bénéficiaire minimale α pour un transporteur représente son attente de rentabilité pour chaque demande en pourcentage du prix de la demande fourni par un fournisseur. Par exemple, pour une demande du transporteur i , let p_i désigne le prix payé par un expéditeur au transporteur pour la demande de service i . Étant donné que le transporteur souhaite atteindre une marge bénéficiaire minimale α , son moindre profit à gagner en répondant à la demande est $\alpha \cdot p_i$.

Notez que chaque opérateur met à jour ses ensembles de demandes à sous-traiter en fonction des commentaires des itérations précédentes. Chaque transporteur $l \in M$ ajuste la valeur de α_l sur la base des résultats correspondants des offres et des demandes déterminés par le mécanisme d'enchères. Avec différentes valeurs de α_l , le transporteur détermine différentes demandes d'externalisation. Chaque transporteur a une attente de faible rentabilité de ses demandes à coûts marginaux élevés et une attente de rentabilité élevée de ses demandes à faibles coûts marginaux. Chaque transporteur préfère externaliser les demandes avec des coûts de traitement importants dont le coût marginal pour chaque demande est supérieur au prix payé par un expéditeur au transporteur (Berger et Bierwirth, 2010; Li, Rong et Feng, 2015; Gansterer et Hartl, 2016). Afin de rendre les demandes de coûts marginaux élevés attrayantes pour les autres transporteurs, chaque transporteur $l \in M$ peut définir la valeur initiale de α , notée par α_l^0 , sur une petite valeur, ce qui représente une faible attente de rentabilité de ses demandes de coûts marginaux élevés. S'il n'y a aucune demande d'autres transporteurs $l \in M$ pour les demandes à sous-traiter du transporteur et que le transporteur l n'acquiert aucune demande d'autres transporteurs, le transporteur l augmente la valeur de son paramètre α_l avec la taille de l'étape δ pour sélectionner différents groupes de demandes à externaliser pour le prochain tour de la vente aux enchères. Sinon, le transporteur $l \in M$ conserve la même valeur α_l que celle de l'itération précédente.

Dans ce mécanisme d'échange, le commissaire-priseur recueille les paiements de transfert des vendeurs et les transfère aux acheteurs après une demande d'échange. Le paiement de transfert d'un ensemble de demandes est au montant maximal que le transporteur est prêt à payer à d'autres transporteurs pour servir à toutes les demandes de l'ensemble.

Afin de rendre un ensemble de demandes plus attrayant pour les autres transporteurs, nous introduisons un mécanisme de partage des bénéfices qui permet à un transporteur de partager une partie des bénéfices qu'il peut retirer de à sous-traiter d'un ensemble de demandes avec un autre transporteur qui l'achète, dans la détermination du paiement de transfert de ce forfait. L'inclusion de ces paiements parallèles peut permettre aux transporteurs d'identifier des échanges de demandes plus rentables (Özener, Ergun et Savelsbergh, 2011). Cela rend notre détermination du paiement de transfert différente de celle de Dai et Chen (2010). Nous utilisons le paramètre $(1 - \beta_l)$ pour représenter le pourcentage du profit généré par à sous-traiter d'un ensemble de demandes que le transporteur $l \in M$ est prêt à partager avec un autre transporteur. Avec un tel paiement parallèle et le paramètre β , le paiement de transfert OP_{O_l} pour à sous-traiter d'un ensemble de demandes par le transporteur $l \in M$ est déterminé par la règle suivante (équation).

$$OP_{O_l} = \sum_{i \in O_l} p_i (1 - \alpha_l) + B_{O_l}^- \cdot (1 - \beta_l), \alpha_l, \beta_l \in [0,1] \quad (\text{A.4-1})$$

Où $B_{O_l}^-$ indique l'augmentation de profit du transporteur après à sous-traiter d'un ensemble de demandes O_l .

La principale contribution de ce chapitre est sous trois aspects: (1) Chaque transporteur peut externaliser (offrir) plusieurs ensembles de demandes à d'autres transporteurs et chaque transporteur peut insource (acquérir) plus d'un ensemble de demandes de plusieurs autres transporteurs dans chaque itération de notre mécanisme d'échange. (2) Dans notre mécanisme, chaque transporteur met à jour le prix de l'externalisation pour chaque demande en fonction des informations des itérations précédentes, ce qui lui permet de sélectionner différents paquets à externaliser dans différentes itérations. (3) Des expériences numériques montrent que notre mécanisme surpasses significativement deux mécanismes d'enchères proposés par Berger et Bierwirth (2010) et Gansterer, M., & Hartl (2016) avec une amélioration moyenne de 11,80% en termes de profit total de tous les transporteurs. Avec la possibilité d'insource (d'acquérir) les demandes de plusieurs autres transporteurs, notre mécanisme peut apporter plus d'avantages à l'alliance des transporteurs que les mécanismes qui insources les requêtes d'un seul transporteur.

A.5 Un algorithme de décomposition de Benders pour l'achat de services de transport à plusieurs échelons

Un transport efficace joue un rôle essentiel dans l'économie, car la demande de transport de marchandises augmente avec le développement du commerce électronique. Par exemple, Amazon a livré 3,3 milliards de colis dans le monde en 2019 (CNBC, 2019) et en Chine, plus de 50 milliards de colis ont été livrés à travers le pays en 2018 (National Bureau of Statistics of China, 2019). Dans la concurrence mondiale moderne, la nécessité de maîtriser les coûts et de fournir un service de haut niveau fait de l'achat de services de transport un segment clé pour les expéditeurs (fabricants). Sur le marché des services de transport, les expéditeurs cherchent des services auprès des transporteurs lorsqu'ils ont des marchandises à transporter et ils éteignent généralement une demande de devis auprès d'un ensemble de transporteurs. De nombreuses plateformes de services en tant que fournisseur de services d'échange tiers permettent aux expéditeurs et aux transporteurs de partager leurs besoins et leurs capacités et facilitent les échanges entre expéditeurs et transporteurs (George et Xu, 2013). Divers mécanismes de marché sont proposés pour résoudre le problème de l'achat de services de transport, tels que les enchères combinatoires, les enchères double. Pour plus de détails sur les mécanismes d'enchères dans l'achat de services de transport, veuillez vous reporter aux articles de synthèse de Jothi Basu et al. (2015) et Lafkihi et al. (2019). Dans le mécanisme d'enchères, chaque transporteur doit résoudre le problème de génération d'enchères (BGP) pour sélectionner les demandes d'enchères (Lyu et al., 2019). Par conséquent, nous étudions d'abord le BGP dans l'achat de services de transport de chargement partiel dans ce article.

Il existe deux stratégies principales de distribution dans le transport: le transport direct et la distribution multi-échelons. Dans le transport direct, les véhicules partant d'un dépôt transportent leur fret directement aux clients, tandis que dans les systèmes à plusieurs niveaux, le fret est livré de l'origine aux clients via des dépôts intermédiaires (Perboli, Tadei et Vigo, 2011). En pratique, les transports de marchandises ont introduit des systèmes multi-échelons avec des politiques de répartition LTL. Dans la pratique, les systèmes multi-échelons ont généralement été adoptés pour satisfaire les demandes des clients. Les entreprises de commerce électronique et les sociétés de livraison express construisent des centres logistiques comme des dépôts intermédiaires pour offrir des services de livraison interurbains. Par exemple, aux États-Unis, Amazon a repensé les réseaux de distribution multi-échelons avec des points de vente existants à proximité des clients et a adopté ces réseaux de distribution multi-échelons pour fournir une livraison le jour même dans 14 zones métropolitaines américaines en mai 2015 et un service de livraison ultra-rapide d'une heure dans les points de vente Whole Foods à l'échelle nationale (Calero et Zhang, 2019). Bien que le transport multi-échelons ait attiré plus d'attention de la part des praticiens et de la littérature, il y a peu de littérature sur la résolution du BGP dans un transport multi-échelons. À cette fin, nous résolvons le BGP pour l'achat de services de transport à plusieurs échelons.

Lafkihi et al. (2019) ont souligné que la manière de synchroniser et d'optimiser les

services de transport a une importance dans l'offre d'un service efficace, mais reste un problème dans les services logistiques. Les contraintes de synchronisation dans les services logistiques incluent les aspects spatiaux, temporels et de charge. Mais la plupart de la littérature existante ne prend en compte que les aspects de charge dans l'optimisation du transport multi-échelons, seules quelques-unes considèrent les contraintes de fenêtres temporelles. Par conséquent, dans cet article, nous étudions le BGP avec des fenêtres de temps dans un transport à trois échelons (3E-BGPTW). En pratique, les livraisons de colis sont ramassées auprès des fournisseurs dans une zone spécifique et livrées aux clients dans une zone spécifique. Nous l'appelons respectivement zones fournisseur et zone client et les zones fournisseur et zone client se trouvent dans deux villes différentes. Les dépôts intermédiaires pour partager et consolider les demandes de transport dans chaque ville sont appelées Centres de consolidation urbaine (UCC). Dans le transport à plusieurs échelons, les demandes de transport sont récupérées des grappes de zones de fournisseurs vers l'UCC au premier échelon, puis transportées sur une longue distance entre les UCC entre la première ville et la deuxième ville dans deuxième échelon et au deuxième ville, ces demandes de transport sont transporté de UCC aux clients correspondants dans troisième echelon.

Comme notre problème BGPST-TE est plus compliqué que le problème de tournée de véhicules, qui est NP-difficile, nous proposons un algorithme de décomposition de Benders pour décomposer ce problème afin de trouver une solution quasi optimale de ce problème. Dans ce problème, nous supposons que chaque demande sur trois échelons doit être traitée par le même transporteur. Une fois que les demandes traitées et le temps de service pour chaque demande sont déterminés dans le deuxième échelon, le problème d'optimisation dans le premier échelon et le troisième échelon devient trivial. Sur la base de cette caractéristique, nous appliquons l'algorithme de décomposition des benders pour décomposer le modèle basé sur le chemin en un problème maître et deux sous-problèmes et les tournées dans le problème maître sont liées au temps de service. Nos résultats expérimentaux démontrent que l'algorithme de décomposition de benders est plus efficace en termes de qualité de solution et de temps CPU.

Dans notre problème, un dépôt de véhicules homogène est utilisé pour chaque échelon. Dans la ville 1, une flotte de véhicules notée par K^1 la capacité de chaque véhicule Q^1 situé au centre urbain u_1 récupère une demande de transport $i \in R$ de la zone $s_i \in Z_1$ et la livre à u_1 . Dans les centres urbains, les demandes de la ville 1 sont consolidées u_1 et transportées entre ces deux centres urbains par une flotte de véhicules notée K^0 en fonction de la capacité de chaque véhicule Q^0 . Dans la ville 2, une flotte de véhicules notée K^2 avec la capacité de chaque véhicule Q^2 est utilisée pour livrer un contrat de transport $i \in R$ de la zone correspondante $d_i \in Z_2$. Pour les véhicules utilisés dans les deux villes et centres urbains, chaque véhicule est associé à un coût fixe f^1, f^0 et f^2 . L'ensemble des nœuds à visiter par les véhicules dans les trois échelons est défini comme N et chaque bord (i, j) a un coût de

déplacement c_{ij} et un temps de parcours t_{ij} . Le jeu de demandes réservé est R_o , le jeu de demandes sélectives est R_e , et $R = R_o \cup R_e$. L'heure de collecte la plus ancienne pour chaque demande $i \in R$ dans la zone s_i de collecte correspondante est a_i et est b_i le dernier délai de livraison pour la demande $i \in R$ dans la zone de livraison correspondante. La demande $i \in R$ est associée à une quantité de collecte / livraison et à un montant de revenus. Le revenu d'une demande est p_i le prix payé par un expéditeur au transporteur qui dessert la demande q_i .

Variables de décision

$v_i^{k,l}$ Binary variable which equals to 1 if and only if request $i \in R$ is served by the vehicle $k \in K^l, l = \{0,1,2\}$

w^k Binary variable which equals to 1 if and only if the vehicle $k \in K^0$ is used in the transfer urban centers

$y_i^{k,l}$ Binary variable which equals to 1 if and only if the vehicle $k \in K^l$ serves the node $i \in N$ in the l echelon, $l \in \{1,2\}$

$T_i^{k,l}$ The service time for each vehicle $k \in K^l, l = \{0,1,2\}$ at the node $i \in N$

$$\max \left(\sum_{i \in R} \sum_{k \in K^0} p_i \cdot v_i^{k,0} - \sum_{s \in S} \sum_{k \in K^1} (2 \cdot c_{s,u_1} + f^1) \cdot y_s^{k,1} - \sum_{k \in K^0} (2 \cdot c_{u_1,u_2} + f^0) \cdot w^k - \sum_{d \in Z_2} \sum_{k \in K^2} (2 \cdot c_{d,u_2} + f^2) \cdot y_d^{k,2} \right) \quad (A.5-1)$$

S.t.

$$\sum_{k \in K^l} v_i^{k,l} = 1 \quad \forall i \in R_o, l = \{0,1,2\} \quad (A.5-2)$$

$$\sum_{k \in K^l} v_i^{k,l} \leq 1 \quad \forall i \in R_e, l = \{0,1,2\} \quad (A.5-3)$$

$$\sum_{k \in K^1} v_i^{k,1} = \sum_{k \in K^0} v_i^{k,0} \quad \forall i \in R \quad (A.5-4)$$

$$\sum_{k \in K^2} v_i^{k,2} = \sum_{k \in K^0} v_i^{k,0} \quad \forall i \in R \quad (A.5-5)$$

$$\sum_{i \in N} y_i^{k,l} \leq 1 \quad \forall k \in K^l, l = 1,2 \quad (A.5-6)$$

$$y_{s_i}^{k,1} \geq v_i^{k,1} \quad \forall i \in R, k \in K^1 \quad (A.5-7)$$

$$y_{d_i}^{k,2} \geq v_i^{k,2} \quad \forall i \in R, k \in K^2 \quad (A.5-8)$$

$$w^k \geq v_i^{k,0} \quad \forall i \in R, k \in K^0 \quad (A.5-9)$$

$$\sum_{i \in R, s_i, d_i = j} v_i^{k,l} \cdot q_i \leq y_j^k \cdot Q^l \quad \forall j \in Z_l, k \in K^l, l = \{1,2\} \quad (A.5-10)$$

$$\sum_{i \in R} v_i^{k,0} \cdot q_i \leq w^k \cdot Q^0 \quad \forall k \in K^0 \quad (A.5-11)$$

$$T_{s_i}^{k,1} \geq a_i * v_i^{k,1} \quad \forall k \in K^1, i \in R \quad (A.5-12)$$

$$T_{d_i}^{k,2} \leq b_i + M * (1 - v_i^{k,2}) \quad \forall k \in K^2, i \in R \quad (\text{A.5-13})$$

$$T_{u_1}^{k,0} \geq T_{s_i}^{l,1} + t_{s_i, u_1} - M * (2 - v_i^{l,1} - v_i^{k,2}) \quad \forall k \in K^0, l \in K^1, i \in R \quad (\text{A.5-14})$$

$$T_{d_i}^{k,2} - t_{u_2, d_i} \geq T_{u_1}^{l,0} + t_{u_1, u_2} - M * (2 - v_i^{l,0} - v_i^{k,2}) \quad \forall k \in K^2, l \in K^0, i \in R \quad (\text{A.5-15})$$

$$v_i^{k,l} \in \{0,1\} \quad \forall i \in R, k \in K^l, l = \{0,1,2\} \quad (\text{A.5-16})$$

$$w^k \in \{0,1\} \quad \forall k \in K^0 \quad (\text{A.5-17})$$

$$y_i^{k,l} \in \{0,1\} \quad \forall i \in N, k \in K^l, l = \{1,2\} \quad (\text{A.5-18})$$

$$T_i^{k,l} \geq 0 \quad \forall i \in N, k \in K^l, l = \{0,1,2\} \quad (\text{A.5-19})$$

L'objectif de (A.5-1) est la maximisation du profit total des trois échelons. La contrainte (A.5-2) garantit qu'à chaque échelon, chaque demande réservée doit être servie par le transporteur. La contrainte (A.5-3) garantit que chaque demande sélective peut être servie au plus une fois par le transporteur. La contrainte (A.5-4) - (A.5-5) garantit que chaque demande dans les trois échelons doit être traitée par le même transporteur, c'est-à-dire que chaque demande ne peut pas être divisée. La contrainte (A.5-6) garantit que chaque véhicule peut visiter au plus une zone dans deux villes. Les contraintes (A.5-7) - (A.5-9) décrivent la relation logique entre les variables de sélection de demande et les variables d'affectation des demandes. Contraintes (A.5-10) - (A.5-11) correspond aux contraintes de capacité pour chaque véhicule dans les trois échelons. La contrainte (A.5-12) est le premier délai de collecte pour chaque demande dans la zone fournisseur correspondante du premier échelon. La contrainte (A.5-13) est le dernier délai de livraison pour chaque demande dans la zone client correspondante du troisième échelon. La contrainte (A.5-14) relatere l'heure d'arrivée et l'heure de départ de la demande au centre urbain de la première ville. Il dénote que le véhicule dans deuxième échelon ne servir la demande qu'après avoir été livré à u_1 par le véhicule du premier échelon. La contrainte (A.5-15) relatere l'heure d'arrivée et l'heure de départ de la demande au centre-ville de la deuxième ville. Il dénote que le véhicule du troisième échelon ne servir la demande qu'après avoir été livré à u_2 par le véhicule du deuxième échelon. Les contraintes (A.5-18) - (A.5-21) indiquent la nature de toutes les variables et leurs bornes supérieure et inférieure.

Les principales contributions de ce travail sont sous trois aspects (1) Un nouveau BGP pour l'achat de services de transport à plusieurs échelons est considéré pour la première fois et deux modèles de programmation d'entiers mixtes sont formulés pour ce problème; (2) Basé sur la formulation basée sur le chemin et de la caractéristique du problème, un algorithme de décomposition de Benders est utilisée pour décomposer le problème en un problème maître et deux sous-problèmes. Des stratégies d'accélération comprenant des coupes multiples, des coupes pareto-optimales et des coupes multiples avec des coupes pareto-optimales sont utilisées pour améliorer les performances de l'algorithme de décomposition de Benders de base; (3) Des expériences numériques montrent que notre algorithme de décomposition de benders peut résoudre des instances d de grande taille avec un écart moyen de 0.99% dans un délai raisonnable.

A.6 Conclusions et perspectives

Nous avons considéré trois problèmes dans cette thèse: la collaboration des chargeurs en logistique de livraison et de collecte, un mécanisme d'échange multi-ronds pour la collaboration des transporteurs de chargement partiel, et un algorithme de décomposition de benders pour pour l'achat de services de transport à plusieurs échelons. Avec différentes techniques de recherche opérationnelle, ces trois problèmes ont été étudiés indépendamment. Nous avons donc donné des conclusions détaillées et une discussion des orientations futures de la recherche séparément dans chaque chapitre sous-jacent. Un résumé de ce travail de thèse est présenté dans ce chapitre.

Dans le premier problème, nous étudions la collaboration des expéditeurs en logistiques de livraison et de collecte, dans laquelle plusieurs expéditeurs avec des opérations de livraison et / ou de collecte consolident leurs demandes de transport. En logistique de livraison et de collecte, les fabricants livrent de nouveaux produits à leurs clients et les produits usagés sont collectés auprès des clients et transportés chez les remanufactureurs pour réparation ou reproduction. Ce résulte un nouveau problème de tournée des véhicules avec des demandes de livraison et de collecte et trois types de dépôts différents (dépôts de produits, dépôts de véhicules et dépôts de recyclage). Une approche hybride combinant une procédure de recherche adaptative randomisée gourmande (GRASP) et une recherche locale itérée (ILS) est proposée pour trouver une solution presque optimal au problème. Des expériences numériques sur un grand nombre d'instances générées aléatoirement avec différentes tailles de problèmes démontrent que la collaboration des expéditeurs dans la logistique de livraison et de collecte peut réaliser des économies de coûts significatives par rapport à l'opération isolée de chaque expéditeur sans coopération et l'approche proposée est efficace dans le sens qu'il peut trouver une solution de haute qualité dans un délai de calcul raisonnable. Les principales contributions de ce chapitre sont les suivantes: (1) La collaboration des expéditeurs dans la logistique de livraison et de collecte est proposé pour la première fois; (2) Une nouvelle variante du problème de tournée des véhicules avec des demandes de livraison et de collecte et trois types de dépôts est étudiée et un modèle de programmation d'entiers mixtes est formulé pour le problème. (3) Des expériences numériques sur un grand nombre d'instances générées aléatoirement avec différentes tailles de problèmes démontrent que la collaboration des expéditeurs dans la logistique de livraison et de collecte peut réaliser des économies de coûts significatives par rapport à l'opération isolée de chaque expéditeur sans coopération, et l'approche proposée est efficace dans le sens où elle peut trouver une solution de haute qualité dans un temps de calcul raisonnable.

Dans le deuxième problème, un mécanisme d'enchères à plusieurs ronds pour la collaboration des transporteurs avec les demandes de collecte et de livraison a été proposé pour transporteurs dans le transport de charge partiel. Dans chaque itération, chaque transporteur fournit d'abord plusieurs ensembles de demandes d'offres et leurs paiements de transfert correspondants. Chaque transporteur détermine ensuite les packages de demande à acquérir auprès d'un ou plusieurs transporteurs. Plusieurs demande paquets peuvent être

échangés entre les transporteurs dans chaque itération. Dans chaque tour de l'enchère, chaque transporteur met à jour ses ensembles de demandes à externaliser en fonction des informations des itérations précédentes. Des expériences numériques montrent que ce mécanisme d'échange multi-ronds fournit 11,80% de profit en plus par rapport aux autres mécanismes. La principale contribution de ce recherche est sous trois aspects: (1) Chaque transporteur peut externaliser (offrir) plusieurs ensembles de demandes à d'autres transporteurs et chaque transporteur peut insource (acquérir) plus d'un ensemble de demandes de plusieurs autres transporteurs dans chaque itération de notre mécanisme d'échange. (2) Dans notre mécanisme, chaque transporteur met à jour l'externaliser prix pour chaque demande en fonction des informations des itérations précédentes, ce qui lui permet de sélectionner différents packages à sous-traiter dans différentes itérations. (3) Des expériences numériques montrent que notre mécanisme dépasse significativement deux mécanismes d'enchères proposés par Berger et Bierwirth (2010) et Gansterer, M., & Hartl (2016) avec une amélioration moyenne de 11,80% en termes de profit total de tous les transporteurs. Avec la possibilité d'insource (d'acquérir) les demandes de plusieurs autres transporteurs, notre mécanisme peut apporter plus d'avantages à l'alliance des transporteurs que les mécanismes qui insources les requêtes d'un seul transporteur.

Dans le troisième problème, un problème de génération d'enchères pour l'achat de services de transport réalisé par une enchère combinatoire dans le transport à plusieurs échelons. Dans le transport collaborative à plusieurs échelons, en services de transport, les expéditeurs veulent se procurer des services de transport auprès d'un ensemble de transporteurs potentiels qui ont des demandes réservés. La livraison du fret de son origine à sa destination se fait à travers trois échelons. Une modèle formulé basée sur l'arc et une modèle formulé basée sur le chemin pour notre problème sont proposées. Un algorithme de décomposition de benders est développé pour le modèle formulé basée sur le chemin. L'algorithme de décomposition de benders est amélioré grâce aux stratégies d'accélération des multi-coups et des coupes pareto-optimales. Les résultats des calculs indiquent que l'algorithme de décomposition améliorée des cintrages surpasse le solveur MILP de CPLEX, non seulement en termes de qualité de la solution mais aussi en termes de temps CPU. Les principales contributions de cet recherche sont sous trois aspects (1) Un nouveau problème de génération d'enchères dans le transport collaboratif dans plusieurs échelons est considéré pour la première fois et deux modèles programmation d'entiers mixtes sont formulés pour ce problème; (2) Sur la base de le modèle formulé basée sur le chemin et des caractéristiques du problème, une approche de décomposition de benders est utilisée pour résoudre le problème. Des stratégies d'accélération comprenant des coupes multiples, des coupes Pareto optimales et des coupes multiples avec des coupes Pareto optimales sont utilisées pour améliorer les performances de l'algorithme de décomposition de benders; (3) Des expériences numériques montrent que notre algorithme de décomposition de benders surpasse considérablement le solveur CPLEX et peut résoudre des instances de petite et moyenne taille à optimales, et des instances de grande taille à quasi optimales avec un écart moyen de 0,99% dans un délai raisonnable.

Bien que nous ayons proposé des algorithmes et des mécanismes efficaces pour tacle contre la collaboration des expéditeurs et des transporteurs dans le transport LTL, il reste du travail à faire pour améliorer les modèles et les approches de solutions afin de les rendre plus applicables dans la pratique.

Premièrement, une lié inférieure serré du problème étudié devrait être trouvée pour évaluer les performances du proposé GRASP-ILS méta-heuristique pour les instances de moyenne et grande taille. Une autre direction de recherche est de considérer partage des profits des expéditeurs afin de rendre plus pratique l'application de l'approche centralisée à la planification collaborative des transports proposée dans cet article.

Deuxièmement, à l'avenir, nous envisagerons le développement d'un algorithme plus efficace et plus efficace pour résoudre le problème de sélection des demandes à externaliser et d'insource, et envisagerons la collaboration des transporteurs le transport de chargement partiel avec de nouvelles caractéristiques, telles que l'arrivée dynamique des demandes dans un transport réseau de collaboration.

Enfin, nous essaierons de trouver des stratégies d'accélération supplémentaires pour l'algorithme de décomposition des benders afin de réduire son espace de solution afin d'accélérer sa résolution, telles que des contraintes valides et des tests d'élimination. Tous les problèmes mentionnés ci-dessus feront l'objet de recherches futures.

References

- Agarwal R, Ergun Ö. Network design and allocation mechanisms for carrier alliances in liner shipping[J]. *Operations research*, 2010, 58(6): 1726-1742.
- Andres Figliozzi M, Mahmassani H S, Jaillet P. Framework for study of carrier strategies in auction-based transportation marketplace[J]. *Transportation Research Record*, 2003, 1854(1): 162-170.
- Archetti C, Speranza M G. Vehicle routing problems with split deliveries[J]. *International transactions in operational research*, 2012, 19(1-2): 3-22.
- Audy J F, D'Amours S, Rousseau L M. Cost allocation in the establishment of a collaborative transportation agreement—an application in the furniture industry[J]. *Journal of the Operational Research Society*, 2011, 62(6): 960-970.
- Baldacci R, Mingozzi A, Roberti R, et al. An exact algorithm for the two-echelon capacitated vehicle routing problem[J]. *Operations research*, 2013, 61(2): 298-314.
- Battarra M, Cordeau J F, Iori M. Chapter 6: pickup-and-delivery problems for goods transportation[M]//*Vehicle Routing: Problems, Methods, and Applications*, Second Edition. Society for Industrial and Applied Mathematics, 2014: 161-191.
- Bent R, Van Hentenryck P. A two-stage hybrid algorithm for pickup and delivery vehicle routing problems with time windows[J]. *Computers & Operations Research*, 2006, 33(4): 875-893.
- Berbeglia G, Cordeau J F, Gribkovskaia I, et al. Static pickup and delivery problems: a classification scheme and survey[J]. *Top*, 2007, 15(1): 1-31.
- Berger S, Bierwirth C. Solutions to the request reassignment problem in collaborative carrier networks[J]. *Transportation Research Part E: Logistics and Transportation Review*, 2010, 46(5): 627-638.
- Bianchessi N, Righini G. Heuristic algorithms for the vehicle routing problem with simultaneous pick-up and delivery[J]. *Computers & Operations Research*, 2007, 34(2): 578-594.
- Birge J R, Louveaux F V. A multicut algorithm for two-stage stochastic linear programs[J]. 1988.
- Bolduc M C, Renaud J, Boctor F, et al. A perturbation metaheuristic for the vehicle routing problem with private fleet and common carriers[J]. *Journal of the Operational Research Society*, 2008, 59(6): 776-787.
- Breunig U, Schmid V, Hartl R F, et al. A large neighbourhood based heuristic for two-echelon routing problems[J]. *Computers & Operations Research*, 2016, 76: 208-225.
- Calero N, Zhang Y. Modeling Large Scale e-commerce Distribution Networks[J]. 2019.
- Caplice C, Sheffi Y. Optimization-based procurement for transportation services[J]. *Journal of Business Logistics*, 2003, 24(2): 109-128.
- Caputo A C, Fratocchi L, Pelagagge P M. A genetic approach for freight transportation planning[J]. *Industrial Management & Data Systems*, 2006.

- Çetinkaya C, Karaoglan I, Gökçen H. Two-stage vehicle routing problem with arc time windows: A mixed integer programming formulation and a heuristic approach[J]. *European Journal of Operational Research*, 2013, 230(3): 539-550.
- Chang T S. Decision support for truckload carriers in one-shot combinatorial auctions[J]. *Transportation Research Part B: Methodological*, 2009, 43(5): 522-541.
- Chen H. Combinatorial clock-proxy exchange for carrier collaboration in less than truck load transportation[J]. *Transportation Research Part E: Logistics and Transportation Review*, 2016, 91: 152-172.
- Chen R L Y, AhmadBeygi S, Cohn A, et al. Solving truckload procurement auctions over an exponential number of bundles[J]. *Transportation Science*, 2009, 43(4): 493-510.
- Cleophas C, Cottrill C, Ehmke J F, et al. Collaborative urban transportation: Recent advances in theory and practice[J]. *European Journal of Operational Research*, 2019, 273(3): 801-816.
- CNBC, Amazon to deliver 3.5 billion packages through own network in 2019. <https://www.cnbc.com/2019/12/20/amazon-to-deliver-3point5-billion-packages-through-own-network-in-2019.html>
- Contreras I, Cordeau J F, Laporte G. Benders decomposition for large-scale uncapacitated hub location[J]. *Operations research*, 2011, 59(6): 1477-1490.
- Crainic T G, Mancini S, Perboli G, et al. Multi-start heuristics for the two-echelon vehicle routing problem[C]//*European Conference on Evolutionary Computation in Combinatorial Optimization*. Springer, Berlin, Heidelberg, 2011: 179-190.
- Crispim J, Brandão J. Metaheuristics applied to mixed and simultaneous extensions of vehicle routing problems with backhauls[J]. *Journal of the Operational Research Society*, 2005, 56(11): 1296-1302.
- Cuda R, Guastaroba G, Speranza M G. A survey on two-echelon routing problems[J]. *Computers & Operations Research*, 2015, 55: 185-199.
- Dai B, Chen H. Mathematical model and solution approach for collaborative logistics in less than truckload (LTL) transportation[C]//*2009 International Conference on Computers & Industrial Engineering*. IEEE, 2009: 767-772.
- Dai B, Chen H. A multi-agent and auction-based framework and approach for carrier collaboration[J]. *Logistics Research*, 2011, 3(2-3): 101-120.
- Dai B, Chen H, Yang G. Price-setting based combinatorial auction approach for carrier collaboration with pickup and delivery requests[J]. *Operational Research*, 2014, 14(3): 361-386.
- de Camargo R S, Miranda Jr G, Luna H P. Benders decomposition for the uncapacitated multiple allocation hub location problem[J]. *Computers & Operations Research*, 2008, 35(4): 1047-1064.
- Dellaert N, Dashty Saridarq F, Van Woensel T, et al. Branch-and-Price-Based Algorithms for the Two-Echelon Vehicle Routing Problem with Time Windows[J]. *Transportation Science*, 2019, 53(2): 463-479

- Dethloff J. Vehicle routing and reverse logistics: the vehicle routing problem with simultaneous delivery and pick-up[J]. *OR-Spektrum*, 2001, 23(1): 79-96.
- Dror M, Trudeau P. Savings by split delivery routing[J]. *Transportation Science*, 1989, 23(2): 141-145.
- Ergun Ö, Kuyzu G, Savelsbergh M. Shipper collaboration[J]. *Computers & Operations Research*, 2007, 34(6): 1551-1560.
- Ergun O, Kuyzu G, Savelsbergh M. Reducing truckload transportation costs through collaboration[J]. *Transportation science*, 2007, 41(2): 206-221.
- Fakhri A, Ghatee M, Fragkogios A, et al. Benders decomposition with integer subproblem[J]. *Expert Systems with Applications*, 2017, 89: 20-30.
- Feo T A, Bard J F. Flight scheduling and maintenance base planning[J]. *Management Science*, 1989, 35(12): 1415-1432.
- Figliozzi M A, Mahmassani H S, Jaillet P. Competitive performance assessment of dynamic vehicle routing technologies using sequential auctions[J]. *Transportation Research Record*, 2004, 1882(1): 10-18.
- Figliozzi M A, Mahmassani H, Jaillet P. Auction settings and performance of electronic marketplaces for truckload transportation services[J]. *Transportation Research Record*, 2005, 1906: 89-97.
- Figliozzi M A, Mahmassani H S, Jaillet P. Quantifying opportunity costs in sequential transportation auctions for truckload acquisition[J]. *Transportation Research Record*, 2006, 1964(1): 247-252.
- Frisk M, Göthe-Lundgren M, Jörnsten K, et al. Cost allocation in collaborative forest transportation[J]. *European Journal of Operational Research*, 2010, 205(2): 448-458.
- Gajpal Y, Abad P. An ant colony system (ACS) for vehicle routing problem with simultaneous delivery and pickup[J]. *Computers & Operations Research*, 2009, 36(12): 3215-3223.
- Gansterer M, Hartl R F. Request evaluation strategies for carriers in auction-based collaborations[J]. *OR spectrum*, 2016, 38(1): 3-23.
- Gansterer M, Hartl R F. Collaborative vehicle routing: a survey[J]. *European Journal of Operational Research*, 2018, 268(1): 1-12.
- Goksal F P, Karaoglan I, Altiparmak F. A hybrid discrete particle swarm optimization for vehicle routing problem with simultaneous pickup and delivery[J]. *Computers & Industrial Engineering*, 2013, 65(1): 39-53.
- Gonzalez-Feliu J, Perboli G, Tadei R, et al. The two-echelon capacitated vehicle routing problem[J]. 2008.
- Gonzalez-Feliu J. Models and methods for the city logistics: The two-echelon capacitated vehicle routing problem[D]., 2008.
- Grangier P, Gendreau M, Lehuédé F, et al. An adaptive large neighborhood search for the two-echelon multiple-trip vehicle routing problem with satellite synchronization[J]. *European Journal of Operational Research*, 2016, 254(1): 80-91.

- Handoko S D, Lau H C, Cheng S F. Achieving economic and environmental sustainabilities in urban consolidation center with bicriteria auction[J]. *IEEE Transactions on Automation Science and Engineering*, 2016, 13(4): 1471-1479.
- Heching A, Hooker J N, Kimura R. A logic-based Benders approach to home healthcare delivery[J]. *Transportation Science*, 2019, 53(2): 510-522.
- Hemmelmayr V C, Cordeau J F, Crainic T G. An adaptive large neighborhood search heuristic for two-echelon vehicle routing problems arising in city logistics[J]. *Computers & operations research*, 2012, 39(12): 3215-3228.
- Hernández S, Peeta S, Kalafatas G. A less-than-truckload carrier collaboration planning problem under dynamic capacities[J]. *Transportation Research Part E: Logistics and Transportation Review*, 2011, 47(6): 933-946.
- Hernández S, Peeta S. Centralized time-dependent multiple-carrier collaboration problem for less-than-truckload carriers[J]. *Transportation research record*, 2011, 2263(1): 26-34.
- Hooker J N, Ottosson G. Logic-based Benders decomposition[J]. *Mathematical Programming*, 2003, 96(1): 33-60.
- Hooker J N. Planning and scheduling by logic-based Benders decomposition[J]. *Operations research*, 2007, 55(3): 588-602.
- Houghtalen L, Ergun Ö, Sokol J. Designing mechanisms for the management of carrier alliances[J]. *Transportation Science*, 2011, 45(4): 465-482.
- Huang G Q, Xu S X. Truthful multi-unit transportation procurement auctions for logistics e-marketplaces[J]. *Transportation Research Part B: Methodological*, 2013, 47: 127-148.
- Jepsen M, Spoorendonk S, Ropke S. A branch-and-cut algorithm for the symmetric two-echelon capacitated vehicle routing problem[J]. *Transportation Science*, 2013, 47(1): 23-37.
- Jothi Basu R, Subramanian N, Cheikhrouhou N. Review of full truckload transportation service procurement[J]. *Transport reviews*, 2015, 35(5): 599-621.
- Kergosien Y, Lenté C, Billaut J C, et al. Metaheuristic algorithms for solving two interconnected vehicle routing problems in a hospital complex[J]. *Computers & Operations Research*, 2013, 40(10): 2508-2518.
- Krajewska M A, Kopfer H. Collaborating freight forwarding enterprises[J]. *OR spectrum*, 2006, 28(3): 301-317.
- Krajewska M A, Kopfer H. Transportation planning in freight forwarding companies: Tabu search algorithm for the integrated operational transportation planning problem[J]. *European Journal of Operational Research*, 2009, 197(2): 741-751.
- Lai M, Cai X, Hu Q. An iterative auction for carrier collaboration in truckload pickup and delivery[J]. *Transportation Research Part E: Logistics and Transportation Review*, 2017, 107: 60-80.
- Lai M Y, Liu C S, Tong X J. A two-stage hybrid meta-heuristic for pickup and delivery vehicle routing problem with time windows[J]. *Journal of Industrial & Management Optimization*, 2010, 6(2): 435.

- Lafkihi M, Pan S, Ballot E. Freight transportation service procurement: A literature review and future research opportunities in omnichannel E-commerce[J]. *Transportation Research Part E: Logistics and Transportation Review*, 2019, 125: 348-365.
- Lee C G, Kwon R H, Ma Z. A carrier's optimal bid generation problem in combinatorial auctions for transportation procurement[J]. *Transportation Research Part E: Logistics and Transportation Review*, 2007, 43(2): 173-191.
- Li H, Lim A. A metaheuristic for the pickup and delivery problem with time windows[J]. *International Journal on Artificial Intelligence Tools*, 2003, 12(02): 173-186.
- Li H, Zhang L, Lv T, et al. The two-echelon time-constrained vehicle routing problem in linehaul-delivery systems[J]. *Transportation Research Part B: Methodological*, 2016, 94: 169-188.
- Li J, Pardalos P M, Sun H, et al. Iterated local search embedded adaptive neighborhood selection approach for the multi-depot vehicle routing problem with simultaneous deliveries and pickups[J]. *Expert Systems with Applications*, 2015, 42(7): 3551-3561.
- Li J, Rong G, Feng Y. Request selection and exchange approach for carrier collaboration based on auction of a single request[J]. *Transportation Research Part E: Logistics and Transportation Review*, 2015, 84: 23-39.
- Li Y, Chen H, Prins C. Adaptive large neighborhood search for the pickup and delivery problem with time windows, profits, and reserved requests[J]. *European Journal of Operational Research*, 2016, 252(1): 27-38.
- Liu R, Jiang Z, Fung R Y K, et al. Two-phase heuristic algorithms for full truckloads multi-depot capacitated vehicle routing problem in carrier collaboration[J]. *Computers & Operations Research*, 2010a, 37(5): 950-959.
- Liu R, Jiang Z, Liu X, et al. Task selection and routing problems in collaborative truckload transportation[J]. *Transportation Research Part E: Logistics and Transportation Review*, 2010b, 46(6): 1071-1085.
- Liu R, Xie X, Augusto V, et al. Heuristic algorithms for a vehicle routing problem with simultaneous delivery and pickup and time windows in home health care[J]. *European Journal of Operational Research*, 2013, 230(3): 475-486.
- Lourenço H R, Martin O C, Stützle T. Iterated local search[M]//*Handbook of metaheuristics*. Springer, Boston, MA, 2003: 320-353.
- Lu Q, Dessouky M M. A new insertion-based construction heuristic for solving the pickup and delivery problem with time windows[J]. *European Journal of Operational Research*, 2006, 175(2): 672-687.
- Lyu X, Wang N, Yang Z, et al. Shipper collaboration in forward and reverse logistics[J]. *Journal of Industrial & Management Optimization*, 2018, 13(5): 1.
- Lyu X, Chen H, Wang N, et al. A multi-round exchange mechanism for carrier collaboration in less than truckload transportation[J]. *Transportation Research Part E: Logistics and Transportation Review*, 2019, 129: 38-59.

- Magnanti T L, Simpson R W. Transportation network analysis and decomposition methods[R]. United States. Dept. of Transportation. Research and Special Programs Directorate, 1978.
- Magnanti T L, Wong R T. Accelerating Benders decomposition: Algorithmic enhancement and model selection criteria[J]. *Operations research*, 1981, 29(3): 464-484.
- Min H. The multiple vehicle routing problem with simultaneous delivery and pick-up points[J]. *Transportation Research Part A: General*, 1989, 23(5): 377-386.
- Mitra S. An algorithm for the generalized vehicle routing problem with backhauling[J]. *Asia-Pacific Journal of Operational Research*, 2005, 22(02): 153-169.
- Mitra S. A parallel clustering technique for the vehicle routing problem with split deliveries and pickups[J]. *Journal of the operational Research Society*, 2008, 59(11): 1532-1546.
- Multichannel Merchant (2015), The internet of (postal) things is coming. <https://multichannelmerchant.com/news/internet-postal-things-coming/>
- Nagy G, Salhi S. Heuristic algorithms for single and multiple depot vehicle routing problems with pickups and deliveries[J]. *European journal of operational research*, 2005, 162(1): 126-141.
- Nanry W P, Barnes J W. Solving the pickup and delivery problem with time windows using reactive tabu search[J]. *Transportation Research Part B: Methodological*, 2000, 34(2): 107-121.
- National Bureau of Statistics, 2019. <http://www.stats.gov.cn/>
- Nowak M, Ergun Ö, White III C C. Pickup and delivery with split loads[J]. *Transportation science*, 2008, 42(1): 32-43.
- Nowak M, Ergun O, White III C C. An empirical study on the benefit of split loads with the pickup and delivery problem[J]. *European Journal of Operational Research*, 2009, 198(3): 734-740.
- Özener O Ö, Ergun Ö, Savelsbergh M. Lane-exchange mechanisms for truckload carrier collaboration[J]. *Transportation Science*, 2011, 45(1): 1-17.
- Pankratz G. A grouping genetic algorithm for the pickup and delivery problem with time windows[J]. *Or Spectrum*, 2005, 27(1): 21-41.
- Park S, Rothkopf M H. Auctions with bidder-determined allowable combinations[J]. *European Journal of Operational Research*, 2005, 161(2): 399-415.
- Parkes D C, Ungar L H. Iterative combinatorial auctions: Theory and practice[J]. *AAAI/IAAI*, 2000, 7481.
- Pekeč A, Rothkopf M H. Combinatorial auction design[J]. *Management Science*, 2003, 49(11): 1485-1503.
- Perboli G, Tadei R. New families of valid inequalities for the two-echelon vehicle routing problem[J]. *Electronic notes in discrete mathematics*, 2010, 36: 639-646.
- Perboli G, Tadei R, Vigo D. The two-echelon capacitated vehicle routing problem: models and math-based heuristics[J]. *Transportation Science*, 2011, 45(3): 364-380.
- Pisinger D, Ropke S. A general heuristic for vehicle routing problems[J]. *Computers &*

- operations research, 2007, 34(8): 2403-2435.
- Prins C, Labadi N, Reghioui M. Tour splitting algorithms for vehicle routing problems[J]. *International Journal of Production Research*, 2009, 47(2): 507-535.
- Reghioui M, Prins C, Labadi N. GRASP with path relinking for the capacitated arc routing problem with time windows[C]//*Workshops on Applications of Evolutionary Computation*. Springer, Berlin, Heidelberg, 2007: 722-731.
- Renaud J, Boctor F F, Laporte G. Perturbation heuristics for the pickup and delivery traveling salesman problem[J]. *Computers & Operations Research*, 2002, 29(9): 1129-1141.
- Ropke S, Pisinger D. An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows[J]. *Transportation science*, 2006a, 40(4): 455-472.
- Ropke S, Pisinger D. A unified heuristic for a large class of vehicle routing problems with backhauls[J]. *European Journal of Operational Research*, 2006b, 171(3): 750-775.
- Salhi S, Nagy G. A cluster insertion heuristic for single and multiple depot vehicle routing problems with backhauling[J]. *Journal of the operational Research Society*, 1999, 50(10): 1034-1042.
- Schönberger J. *Operational freight carrier planning: basic concepts, optimization models and advanced memetic algorithms[M]*. Springer Science & Business Media, 2006.
- Schopka K, Kopfer H. Pre-selection strategies for the collaborative vehicle routing problem with time windows[M]//*Dynamics in Logistics*. Springer, Cham, 2017: 231-242.
- Schwind M, Gujo O, Vykoukal J. A combinatorial intra-enterprise exchange for logistics services[J]. *Information systems and e-business management*, 2009, 7(4): 447-471.
- Sheffi Y. Combinatorial auctions in the procurement of transportation services[J]. *Interfaces*, 2004, 34(4): 245-252.
- Sitek P, Wikarek J. A novel integrated approach to the modelling and solving of the Two-Echelon Capacitated Vehicle Routing Problem[J]. *Production & Manufacturing Research*, 2014, 2(1): 326-340.
- Song J, Regan A. Combinatorial auctions for transportation service procurement: The carrier perspective[J]. *Transportation Research Record*, 2003, 1833(1): 40-46.
- Song J, Regan A C. An auction based collaborative carrier network[J]. 2003.
- Song J, Regan A. Approximation algorithms for the bid construction problem in combinatorial auctions for the procurement of freight transportation contracts[J]. *Transportation Research Part B: Methodological*, 2005, 39(10): 914-933.
- Soysal M, Bloemhof-Ruwaard J M, Bektaş T. The time-dependent two-echelon capacitated vehicle routing problem with environmental considerations[J]. *International Journal of Production Economics*, 2015, 164: 366-378.
- Sprenger R, Mönch L. A methodology to solve large-scale cooperative transportation planning problems[J]. *European Journal of Operational Research*, 2012, 223(3): 626-636.
- Subramanian A, Drummond L M A, Bentes C, et al. A parallel heuristic for the vehicle routing problem with simultaneous pickup and delivery[J]. *Computers & Operations Research*, 2010, 37(11): 1899-1911.

-
- Subramanian A, Uchoa E, Ochi L S. A hybrid algorithm for a class of vehicle routing problems[J]. *Computers & Operations Research*, 2013, 40(10): 2519-2531.
- Tasan A S, Gen M. A genetic algorithm based approach to vehicle routing problem with simultaneous pick-up and deliveries[J]. *Computers & Industrial Engineering*, 2012, 62(3): 755-761.
- Usberti F L, França P M, França A L M. GRASP with evolutionary path-relinking for the capacitated arc routing problem[J]. *Computers & Operations Research*, 2013, 40(12): 3206-3217.
- Wang X, Kopfer H. Collaborative transportation planning of less-than-truckload freight[J]. *OR spectrum*, 2014, 36(2): 357-380.
- Wang X, Kopfer H, Gendreau M. Operational transportation planning of freight forwarding companies in horizontal coalitions[J]. *European Journal of Operational Research*, 2014, 237(3): 1133-1141.
- Wassan N A, Wassan A H, Nagy G. A reactive tabu search algorithm for the vehicle routing problem with simultaneous pickups and deliveries[J]. *Journal of combinatorial optimization*, 2008, 15(4): 368-386.
- Xu S X, Huang G Q, Cheng M. Truthful, budget-balanced bundle double auctions for carrier collaboration[J]. *Transportation science*, 2017, 51(4): 1365-1386.
- Yilmaz O, Savaseneril S. Collaboration among small shippers in a transportation market[J]. *European journal of operational research*, 2012, 218(2): 408-415.
- Zeng Z, Xu W, Xu Z, et al. A hybrid GRASP+ vnd heuristic for the two-echelon vehicle routing problem arising in city logistics[J]. *Mathematical Problems in Engineering*, 2014.
- Zhang T, Chaovalitwongse W A, Zhang Y. Integrated ant colony and tabu search approach for time dependent vehicle routing problems with simultaneous pickup and delivery[J]. *Journal of Combinatorial Optimization*, 2014, 28(1): 288-309.

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Doctorat : Optimisation et Sûreté des Systèmes

Année 2020

Études sur le transport collaboratif dans le transport de chargement partiel

La planification efficace des opérations de transport est primordiale pour les chargeurs et les transporteurs de réduire leurs coûts logistiques en raison des prix élevés de carburants et de la concurrence accrue sur le marché de transport. La collaboration entre chargeurs ou transporteurs peut améliorer leur rentabilité en réduisant les repositionnements de véhicules vides et en augmentant les taux de remplissage de leurs véhicules. Cette thèse étudie trois problèmes posés par la logistique collaborative dans le transport de chargement partiel. Tout d'abord, un mécanisme itératif d'échange de demandes de transport est proposé pour la collaboration entre transporteurs dans le transport à un seul échelon. Des expériences numériques montrent que ce mécanisme d'échange à plusieurs tours surpasse de manière significative les autres mécanismes d'enchère dans la littérature. Ensuite, un algorithme de décomposition Benders est développé pour résoudre un problème d'achat de prestations de transport dans le transport à plusieurs échelons. Enfin, un problème de collaboration entre chargeurs dans la logistique de distribution et de retour est étudié. L'algorithme proposé est efficace à la fois en termes de qualité de solution et de temps de calcul. Tous ces mécanismes d'enchère et algorithmes proposés peuvent aider les transporteurs et les chargeurs à améliorer leur rentabilité grâce à une collaboration efficace entre eux.

Mots clés : logistique collaborative – problème de tournées de véhicules – algorithmes – transport, planification – vente aux enchères – programmation (mathématiques).

Studies on Collaborative Transportation in Less than Truckload Transportation

Effective transportation planning is important for shippers and carriers to reduce their logistics costs because of high fuel prices and an increasing competition in the transportation market. Collaboration among shippers or carriers can improve their profitability by reducing empty vehicle repositions and increasing vehicle fill rates. This thesis studies three problems raised in collaborative logistics in less than truckload transportation. Firstly, an iterative request exchange mechanism is proposed for carrier collaboration in a single echelon transportation. Numerical experiments show that this multi-round exchange mechanism significantly outperforms other auction mechanisms in the literature. Then, a Benders decomposition algorithm is developed to solve a transportation service procurement problem in a multi-echelon transportation. Finally, a problem of collaboration among shippers in forward and reverse logistics is investigated and an algorithm is proposed, which is effective in terms of both solution quality and computation time. Numerical experiments demonstrate that this shipper collaboration can realize significant cost savings compared with the isolated operation of each shipper without cooperation. The proposed auction mechanisms and algorithms have the potential to help carriers and shippers improve their profitability through effective collaboration among them.

Keywords: collaborative logistics – vehicle routing problem – algorithms – transportation, planning – auctions – programming (mathematics).

Thèse réalisée en partenariat entre :

