Applications of Simheuristics and Horizontal Cooperation Concepts in Rich Vehicle Routing Problems

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You know that in a race all the runners run,
but only one runner gets the prize.
So run like that. Run to win!
1 Corinthians 9:24

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Abstract

In a globalized economy, enterprises have to face different challenges related to the complexity of logistics and distribution strategies. Favored by the development of Information and Communication Technologies (ICT), customers and competitors are located everywhere. Customer demands related to shorter response times, higher quality, lower costs and excellent customer service are opposing challenges. Thus, firms need to be more competitive, which implies economic efficiency combined with different sustainability aspects. As a consequence, companies are forced to consider new managerial strategies to optimize their associated processes. One strategy that companies can follow to become more competitive is to cooperate with other firms (Horizontal Cooperation), allowing the use of economies of scale, increased resource utilization levels, and reduced costs. Unfortunately, it is not easy to quantitatively estimate these benefits, which constitutes a serious obstacle for the implementation of HC. Many Logistics & Transportation (L&T) challenges and HC strategies can be tackled by considering different variants of the well-known Vehicle Routing Problem (VRP). Although the VRP has been widely studied during the last 50 years, most published works consider oversimplified versions of real-life situations in which most parameters and constraints are assumed to be known in advance. To fill the existing gap among the academic literature and real-life applications, the concept of Rich VRPs (RVRPs) has emerged in the past few years in order to provide a closer representation of real-life situations. Accordingly, new solving approaches are required to efficiently solve new RVRPs and quantify the benefits generated through the use of HC strategies in real applications. Thus, they can be used to support decision-making processes regarding different implementation degrees of HC.

Particularly, this thesis deals with cooperative strategies in urban distribution under uncertainty, which is represented by the VRP with Multiple Depots and Stochastic Demands. In addition, cooperative initiatives are extended through integrated decisions in facility location and route planning, which is supported by the Capacitated Location Routing Problem (CLRP). Furthermore, city logistics are studied in the context of waste collection and goods distribution in mountainous regions, providing more realistic representations. To cope with this variety of RVRPs, several metaheuristic methods based on biased randomization techniques are proposed. Additionally, these methods are hybridized with simulation (i.e.

simheuristics) to tackle the presence of uncertainty for some of the aforementioned problems, allowing the development of risk/reliability analysis of obtained solutions. The proposed approaches are tested using a large set of theoretical and real-life benchmarks. Several new best known solutions are obtained in relatively short computational times. Noticeable savings of around 55% in economic costs and 52% in CO_2 emissions are generated by the implementation of fully cooperative strategies.

Keywords: Rich Vehicle Routing Problem, Simheuristics, Horizontal Cooperation, Location Routing Problem, Multi-Depot Vehicle Routing Problem, Waste Collection Problem, Reliability Analysis.

Resumen

En una economía globalizada, las compañías se enfrentan a numerosos retos asociados a las complejas tareas de logística y distribución. Gracias al desarrollo de las tecnologías de la información y la comunicación, los clientes pero también los competidores se encuentran en cualquier lugar del mundo. Tiempos de respuesta más cortos, mayor calidad, menores costos y excelente servicio al cliente son retos a los que se enfrentan las organizaciones y que generalmente se oponen entre sí. Por lo tanto, las compañías necesitan ser más competitivas, lo que implica eficiencia económica y sostenibilidad. Como consecuencia, las organizaciones se han visto obligadas a considerar nuevas estrategias gerenciales para optimizar sus procesos asociados. Una estrategia que las firmas pueden seguir para ser más competitivas es la cooperación horizontal, generando así economías de escala, incremento en la utilización de recursos y, reducción de costos. Lamentablemente, la estimación cuantitativa de tales beneficios no es una tarea fácil, lo que constituye un serio obstáculo para la implementación de la cooperación horizontal.

Muchos de estos retos en logística y transporte, así como algunas estrategias de cooperación horizontal pueden ser abordadas mediante diferentes variantes del conocido problema de enrutamiento de vehículos (VRP). Pese a que el VRP ha sido ampliamente estudiado en los últimos 50 años, la mayoría de los trabajos publicados corresponde a versiones demasiado simplificadas de la realidad, en las cuales la mayoría de los parámetros y restricciones se asumen conocidos. Para llenar este vacío entre la teoría y aplicaciones de la vida real, el concepto de problemas "enriquecidos" de enrutamiento de vehículos (RVRPs) ha surgido recientemente, con el objeto de representar situaciones cada vez más realistas. Por lo tanto, se necesitan nuevos métodos de solución para resolver de manera eficiente nuevos RVRPs, así como para cuantificar los beneficios generados mediante la implementación de estrategias de cooperación horizontal en aplicaciones reales, de tal modo que puedan ser usados como apoyo a la toma de decisiones.

Particularmente, esta tesis analiza estrategias de cooperación en distribución urbana en condiciones de incertidumbre, la cual es representada mediante el problema de enrutamiento de vehículos con múltiples depósitos y demanda estocástica. Además, las estrategias de cooperación se extienden hacia decisiones integradas de localización de instalaciones y planeación

de rutas. Para ello, utilizamos el problema de localización y enrutamiento con restricciones de capacidad. Adicionalmente, otros aspectos más realistas de la logística urbana se estudian mediante el problema de recolección de basuras y la distribución de productos en regiones montañosas. Para abordar tal variedad de problemas, se proponen diferentes metaheurísticas basadas en aleatorización sesgada. Estos métodos son combinados con simulación (lo que se conoce como simheurísticas) para resolver situaciones en las cuales la incertidumbre aparece en algunos de los problemas anteriormente mencionados, permitiendo además la realización de análisis de confiabilidad/riesgo de las soluciones obtenidas. Los métodos propuestos han sido evaluados utilizando instancias de prueba tanto teóricas como de la vida real, mejorando, en algunos casos, los mejores resultados conocidos en tiempos computacionales relativamente cortos. Los notables beneficios obtenidos, gracias a la implementación de la cooperación horizontal, alcanzan valores promedios de hasta 55% y 52% en costes económicos y ambientales, respectivamente.

Palabras Clave: Problemas Enriquecidos de Enrutamiento de Vehículos, Simheurísticas, Problema de Localización-Enrutamiento, Cooperación Horizontal, Problema de Enrutamiento de Vehículos con Múltiples Depósitos, Problema de Recolección de Basuras, Análisis de Confiabilidad.

Resum

En una economia globalitzada, les companyies s' enfronten a nombrosos reptes associats a les complexes tasques de logística i distribució. Gràcies al desenvolupament de les tecnologies de la informació i la comunicació, els clients es troben a qualsevol part del mon, però també els competidors. Temps de resposta més curts, millor qualitat, costos menors i excel·lent servei als clients son reptes als quals s'enfronten les organitzacions i generalment son oposats entre ells. Per tant, les companyies necessiten ser més competitives, el que implica eficiència econòmica i sostenibilitat. Com a conseqüencia, les organitzacions s'han vist obligades a considerar noves estratègies gerencials per optimitzar els seus processos associats. Una Estratègia que les firmes poden seguir per ser més competitives es la cooperació horitzontal, generant així economies d'escala, increment en l' utilització de recursos i, reducció de costos. Malauradament, la estimació quantitiva de tals beneficis no es una tasca fàcil, el que constitueix un seri obstacle per la implementació de la cooperació horitzontal.

Molts d'aquests reptes en logística i transport, així com algunes estratègies de cooperació horitzontal poden ser abordades mitjançant diferents variants del conegut problema d'enrutament de vehicles (VRP). Malgrat que el VRP ha estat àmpliament estudiat en els últims 50 anys, la majoria dels treballs publicats corresponen a versions massa simplificades de la realitat, en les quals la majoria dels paràmetres i restriccions s'assumeixen coneguts. Per omplir aquest buit entre la teoria i aplicacions de la vida real, el concepte de problemes "enriquits" d'enrutament de vehicles (RVRPs) ha sorgit recentment, amb l'objectiu de representar situacions cada vegada més realistes. Per tant, es necessiten nous mètodes de solució per a resoldre de manera eficient nous RVRPs, així com per quantificar els beneficis generats per la implementació d'estratègies de cooperació horitzontal en aplicacions reals, de tal manera que puguin ser utilitzats com a suport per a la presa de decisions.

Particularment, aquesta tesi analitza estratègies de cooperació en distribució urbana en condicions d'incertesa, la qual és representada mitjançant el problema d'enrutament de vehicles amb múltiples dipòsits i demanda estocàstica. A més, les estratègies de cooperació s'estenen cap a decisions integrades de localització d'instal·lacions i planificació de rutes. Per això, utilitzem el problema de localització i enrutament amb restriccions de capacitat. Addicionalment, altres aspectes més realistes de la logística urbana s'estudien mit-

jançant el problema de recol·lecció d'escombraries i la distribució de productes en regions muntanyoses. Per abordar tal varietat de problemes, es proposen diferents metaheurístiques basades en aleatorització sesgada. Aquests mètodes són combinats amb simulació (el que es coneix com simheurístiques) per resoldre situacions en les quals la incertesa apareix en alguns dels problemes anteriorment esmentats, permetent a més la realització d'anàlisis de fiabilitat/risc de les solucions obtingudes. Els mètodes proposats han estat avaluats utilitzant instàncies de prova tant teòriques com de la vida real, millorant, en alguns casos, els millors resultats coneguts en temps computacionals relativament curts. Els notables beneficis obtinguts, gràcies a la implementació de la cooperació horitzontal, aconsegueixen valors mitjans de fins al 55% i 52% en costos econòmics i ambientals, respectivament.

Paraules Claus: Problemes enriquits de encaminament de vehicles, simheurístiques, problema de localització-encaminament, cooperació horitzontal, problema de encaminament de vehicles amb múltiples dipòsits, problema de recollida d'escombraries, anàlisis de fiabilitat.

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List of Acronyms

ACO Ant Colony Optimization.

ACVRP Asymmetric Capacitated Vehicle Routing Problem.

ARP Arc Routing Problem.

AVRP Asymmetric Vehicle Routing Problem.

BKS Best Known Solution.

CLRP Capacitated Location Routing Problem.

CLRPSD Capacitated Location Routing Problem with Stochastic Demands.

COP Combinatorial Optimization Problem.

CP Constraint Programming.

CVRP Capacitated Vehicle Routing Problem.

CWS Clarke & Wright Savings.

DP Dynamic Programming.

ECR Efficient Customer Response.

FLP Facility Location Problem.

GA Genetic Algorithms.

GAMS General Algebraic Modeling System.

GRASP Greedy Randomized Adaptive Search Procedure.

GVRP Green Vehicle Routing Problem.

HC Horizontal Cooperation.

HSDAVRP Homogeneous Fleet with Site-Dependency Asymmetric Vehicle Routing Problem.

HVRP Vehicle Routing Problem with Heterogeneous Fleet.

ICT Information and Communication Technologies.

ILS Iterated Local Search.

L&T Logistics and Transportation.

LRP Location Routing Problem.

LS Local Search.

MCS Monte Carlo Simulation.

MDVRP Vehicle Routing Problem with Multiple Depots.

MDVRPSD Multi-Depot Vehicle Routing Problem with Stochastic Demands.

MOAMDVRPSD Multi-Objective Asymmetric Vehicle Routing Problem with Multiple Depots and Stochastic Demands.

OR Operations Research.

PVRP Periodic Vehicle Routing Problem.

RVRP Rich Vehicle Routing Problem.

SA Simulated Annealing.

SDVRP Site-Dependent Vehicle Routing Problem.

TS Tabu Search.

VMI Vendor Managed Inventories.

VNS Variable Neighborhood Search.

VRP Vehicle Routing Problem.

VRPB Vehicle Routing Problem with Backhauls.

VRPPD Vehicle Routing Problem with Pickup and Delivery.

VRPSD Vehicle Routing Problem with Split Delivery.

VRPTW Vehicle Routing Problem with Time Windows.

WCP Waste Collection Problem.

WCPSD Waste Collection Problem with Stochastic Demands.

Chapter 1

Introduction

1.1 General Overview

Due to globalization and fierce market competition, companies are forced to become more efficient in the planning and execution of their distribution tasks. Favored by the development of Information and Communication Technologies (ICT), customers and competitors are located everywhere. Therefore, challenges related to shorter lead times, quality, costs, after sales services, etc., are nowadays more difficult to deal with, forcing companies to consider new managerial strategies to optimize their processes. On the one hand, most of these challenges which are directly related to Logistics and Transportation (L&T) activities, can be tackled by considering different variants of the well-known Vehicle Routing Problem (VRP). Although the VRP has been widely studied in literature, most published works consider oversimplified versions of real-life situations in which most parameters and constraints are assumed to be known in advance. To fulfill the existing gap among the academic literature and real-life applications, the concept of Rich VRPs (RVRPs) has appeared in the past few years. As the definition of RVRPs is still evolving, this thesis deals with two different ways to obtain richer versions of the VRP: *(i)* by adding different decision layers (i.e., Strategic and Tactical decisions) to the classical VRP; and *(ii)* by including different types of constraints and uncertain data. It is to note that the aim of considering both ways is to provide closer representations of real-life situations. On the other hand, one strategy that companies –especially small and medium-sized ones– can follow to become more competitive is to cooperate with other companies, allowing the use of economies of scale, increased resource utilization levels, and costs reductions.

Cooperation in L&T among companies can occur in many ways and is usually classified according to its structure: vertical, horizontal and lateral (Cruijssen et al., 2007c). Vertical cooperation is well-known in supply chain management and has a long history reaching back to the early nineties with strong influences in strategic firm management (Lambert et al., 1999). Horizontal Cooperation (HC) has been defined by the European Commission (2001) as "concerted practices among companies operating at the same level(s) in the market" and by Bahinipati et al. (2009) as "a business agreement between two or more companies at the same level in the supply chain or network in order to allow ease of work and co-operation towards achieving a common objective". It involves load consolidation centers, conjoint route planning, and purchasing groups, with the purpose of reducing activity costs. Lateral cooperation aims at gaining more flexibility by combining and sharing capabilities in vertical and horizontal channels (Simatupang and Sridharan, 2002). The purpose of lateral cooperation is synchronizing shippers and logistic service providers of multiple companies in an effective logistics network. Due to the fact that the different enterprises in a horizontal cooperation agreement are competitors, one of the key aspect when promoting HC practices among companies is the estimation of the cost reductions associated with such cooperative efforts. Unfortunately, it is not easy to quantitatively estimate these benefits, which constitutes a serious obstacle for the implementation of HC.

Accordingly, new solving methods are needed to efficiently solve new RVRPs and quantify the benefits generated through the use of HC strategies in real applications. Thus, they can be used to support decision-making processes regarding different implementation degrees of HC. In particular, the proposed methods combine the main trends in metaheuristics design. The first one is the use of simple and powerful methodologies (see e.g., Mladenović et al. (2016)), to facilitate their replicability in real-settings. In second place, the use of hybrid methods to benefit from the advantage of the underlying techniques (metaheuristics, computer simulation, parallel computing, etc.). In that sense, this thesis is related to the development of simple and efficient simheuristics (algorithms combining metaheuristics with simulation), as an original way to deal with some of the most difficult problems that arise when implementing HC, especially when dealing with real-life uncertainty and complexity, e.g., random demands, stochastic traveling/processing times, etc. Thus, the main contributions of this thesis are: *(i)* from a theoretical point of view, the development of horizontal cooperation concepts in different L&T activities such as urban distribution and integrated facility location and routing; *(ii)* from a practical perspective, the development and implementation as software of different solving approaches to tackle new RVRPs, especially in the context of urban distribution and city logistics. Some of these approaches belong to the so-called simheuristic framework and have been used to deal with more realistic settings, including uncertainty. The performance of these algorithms is tested using both theoretical and real-life benchmark instances generating, in some cases, new best known solutions.

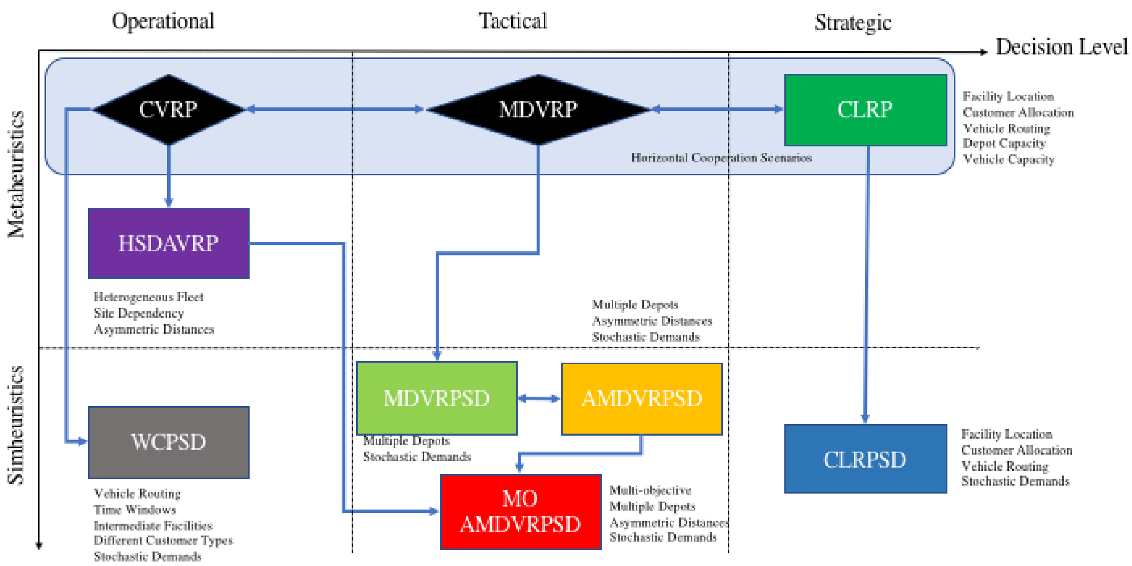


Figure 1.1 Graphical summary of the problems considered in this thesis

Figure 1.1 shows how the aforementioned *"ways to richness"* are used to generate the RVRPs studied in this thesis, which are represented by colored symbols. In the horizontal axis, different decision levels are added to the pure operational CVRP (Upper left) in order to obtain more complex and, at the same time, richer versions such as the Vehicle Routing Problem with Multiple Depots (MDVRP) and the Capacitated Location Routing Problem (CLRP). In the upper right corner, the CLRP appears as a richer version of the well-studied MDVRP, by including facility location decisions. It is to note that the MDVRP is already a RVRP. In addition, all problems at the top level (i.e. CVRP, MDVRP and CLRP) are used to support horizontal cooperation concepts. The vertical axis represents how different characteristics (constraints) are added to the aforementioned problems to generate new RVRP variants. Moving from up to down illustrates how, depending on the presence of uncertain parameters, the recommended solution approach goes from metaheuristics to simheuristics.

From a deterministic perspective, the Site-Dependent Asymmetric VRP with Heterogeneous Fleet (HSDAVRP) appears as a richer version of the CVRP by including asymmetric distances and heterogeneous vehicle fleet to serve customer demands. Moreover, some customers can not be served by all vehicle types (site-dependency). Regarding stochasticity, the Waste Collection Problem with Stochastic Demands (WCPSD), see bottom-left corner of Fig. 1.1, extends the CVRP by including: *(i)* landfills (intermediate facilities) to unload the vehicle when its capacity is exhausted and before returning to the depot, *(ii)* time frames to serve customer demands (time windows), *(iii)* lunch breaks for the vehicle drivers, and *(iv)* stochastic waste levels (demands) for each container. Next, the classical MDVRP is enriched by considering stochastic demands in three different scenarios: *(i)* mono-objective with deterministic demands; *(ii)* mono-objective with stochastic demands; and *(iii)* multi-objective with asymmetric distances and stochastic demands. Finally, the CLRP is extended to its stochastic counterpart by taking into account stochastic demands (see bottom right corner).

1.2 Thesis Framework

This thesis has been developed in the context of the following research projects:

- **ComputerCOOP: Computer-based decision support for Horizontal Cooperation in Transportation and Logistics**. Spanish Ministry of Economy and Competitiveness. TRA2013-48180-C3-3-P.

- **Red de Excelencia en Transporte, Logística, y Producción Inteligente**. Spanish Ministry of Economy and Competitiveness. TRA2015-71883-REDT.

1.3 Objectives

The main goal of this thesis is the development of new hybrid algorithms combining simulation with optimization techniques for solving rich vehicle routing problems under uncertainty. These algorithms can be used to support new managerial strategies such as horizontal cooperation in order to increase economic and environmental benefits while satisfying customer demands. In order to attain this goal, we have proposed the following objectives:

1. To design new and computationally efficient hybrid algorithms by combining metaheuristics with simulation (simheuristics) to solve rich vehicle routing problems, with and without uncertainty.

2. To implement the aforementioned algorithms as software and test them using benchmarks (either from the literature or from real-life data).

3. To determine, how these algorithms can be used to support decision-making processes related to the implementation of horizontal cooperation strategies.

4. To disseminate the outcomes of this thesis in several international indexed journals as well as in international conferences.

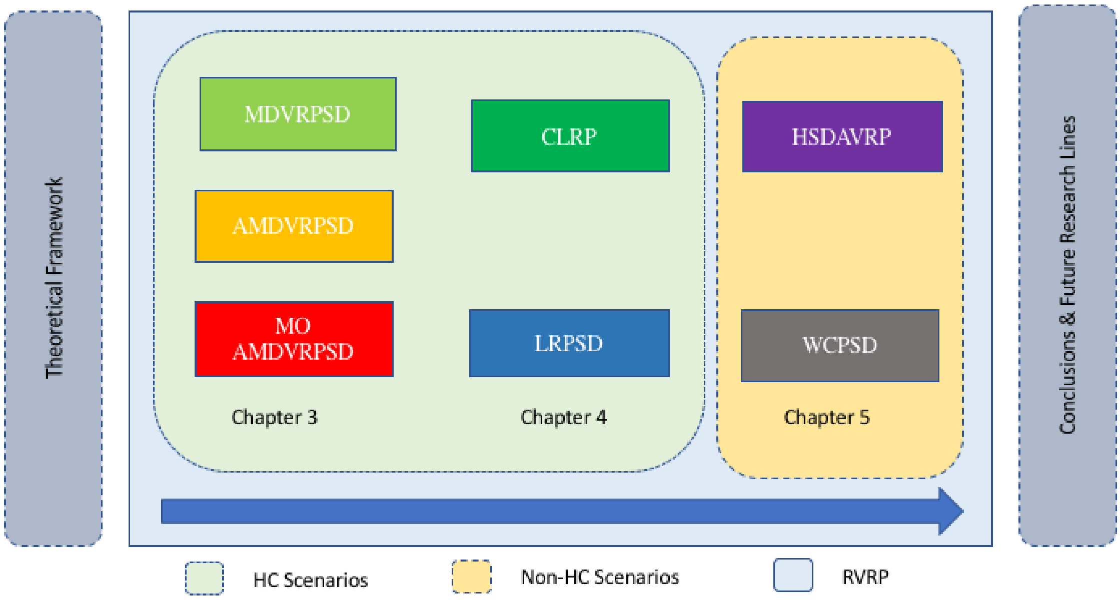


Figure 1.2 General structure of this thesis

1.4 Structure of this Thesis

The general structure of this thesis is depicted in Figure 1.2. The first part (chapter 2), presents *(i)* a theoretical background concerning RVRPs, *(ii)* the different solving methodologies that have been considered and, *(iii)* horizontal cooperation concepts in logistics and transportation. The second part of the thesis (chapters 3–5) analyzes different RVRPs, whereas each chapter is self-contained in terms of notation, methodology, and results. Among them, chapters 3 and 4 are devoted to RVRPs that can be used to support HC agreements between companies. More specifically, chapter 3 deals with horizontal cooperation in urban distribution under uncertainty. A cooperative scenario is represented by the Multi-Depot VRP with stochastic demands considering both short and mid-term planning horizons. In addition, a multi-objective approach is used to determine the vehicle fleet configuration using electric vehicles. Chapter 4, analyses the Capacitated Location Routing Problem in its deterministic and stochastic versions. Competitive metaheuristics are proposed to cope with the deterministic CLRP. In addition, the solving methods are combined with Monte Carlo simulation (MCS) in order to address the stochastic version. This approach allows the completion of risk and reliability analysis on the found solutions. Moreover, this work is extended towards cooperative scenarios in integrated facility location and routing decisions, assessing its benefits in terms of economic and environmental costs. In the following, chapter 5 deals with two RVRPs in city logistics for which HC is not considered: route planning for waste collection and goods distribution in mountainous regions. A mathematical model is proposed for the deterministic version of the WCP. It is also implemented in GAMS®. This model is able to solve instances with up to 24 nodes in reasonable computing time. Next, a simheuristic procedure based on Variable Neighborhood Search (VNS) is proposed to tackle the stochastic version. The results of this approach, when tested in the deterministic version, outperform previously reported ones. Since waste collection is a public service, horizontal cooperation initiatives are referred as inter-municipal cooperation (Bel et al., 2014), belonging to the public administration research field. Thus, HC is not considered for this problem. In addition, the Heterogeneous Fleet with Site-Dependency and Asymmetric Distances Vehicle Routing Problem (HSDAVRP) is solved through a multi-round process and tested using adapted benchmarks. Finally, chapter 6 outlines general conclusions and future research lines. A summary of the outcomes of this thesis is also included in this final chapter.

Chapter 2

Theoretical Framework

2.1 Rich Vehicle Routing Problems

The Vehicle Routing Problem (VRP) is one of the most studied problems in the Operations Research (OR) literature. The classical version of the VRP is to determine a set of routes to serve customer demands while respecting problem-specific constraints, at minimal cost. These constraints are related to the number of visits to customers, vehicle capacity, demand satisfaction, etc. Even in its simplest version, the VRP is known to be NP-Hard (Non-Deterministic Polinomyal-time Hard) (Lenstra and Rinnooy Kan, 1981), which means that there are not exact methods providing optimal solutions in a polynomial time for any size of the problem. There are different variants of the VRP, depending on the considered parameters and constrains, among the most populars we can find:

- Asymmetric VRP (AVRP): the cost of going from node i to node j may be different from the cost of going from node j to i.
- VRP with Heterogeneous Fleet (HVRP): the fleet is composed of vehicles with different capacities. Therefore, the total demand of the customers served by a given vehicle must respect the capacity of the corresponding vehicle.
- VRP with Multiple Depots (MDVRP): different depots are available to serve customer demands. In this version, customers need to be assigned to a depot from which they are served.
- VRP with PickUp and Delivery (VRPPD): customers can demand (from the depot) and return goods (to the depot). The capacity of the vehicle must be respected at any point of the route. Within this variant, there are different possibilities like simultaneous pick-up and delivery, transferable demands, etc.

- VRP with Time Windows (VRPTW): each customer has a time interval in which it can be served. Early arrivals generate waiting time while tardy arrivals are not allowed (hard time windows) or penalized (soft time windows).
- VRP with Split Deliveries (VRPSD): customers can be served by different vehicles, if this reduces overall costs.
- VRP with Backhauls (VRPB): customers can request for or return goods. All linehaul customers have to be visited before the backhaul customers in a route.

More recently, thanks to the development of new optimization algorithms and also to the growth in computational power, the interest of the scientific community has turned towards more realistic VRP variants, which are known as Rich VRPs (RVRPs). However, the definition of RVRPs is still in construction, as can be seen in the following. According to Caceres-Cruz et al. (2014), a RVRP "deals with realistic (and sometimes multi-objective) optimization functions, uncertainty (i.e., stochastic or fuzzy behaviors), and dynamism, along with a wide variety of real-life constraints related to time and distance factors, use of heterogeneous fleets, linkage with inventory and scheduling problems, integration with ICT, environmental and energy issues, and more". Pellegrini et al. (2007) proposed that "the problems grouped under this denomination have in common the characteristics of including additional constraints, aiming at a closer representation of real cases". More recently, Lahyani et al. (2015) proposed a taxonomy for RVRPs based on the strategic, tactical and operational characteristics involved in the VRP variants analyzed by them. This taxonomy can be appreciated in Table 2.1. Furthermore, Lahyani et al. (2015) propose the following definition: " When a VRP is mainly defined through strategic and tactical aspects, at least five of them are present in a RVRP. When a VRP is mainly defined through physical characteristics, at least nine of them are present in a RVRP".

In the following subsections, we introduce the RVRPs addressed in this thesis.

2.1.1 The Vehicle Routing Problem with Multiple Depots (MDVRP)

One of the more realistic variants of the VRP is the MDVRP in which the final delivery of products (services) is done from several depots to a set of customers. The MDVRP consists in finding a set of routes that minimize total distribution costs in such a way that: *(i)* each vehicle starts and finishes its route at the same depot, *(ii)* each customer is served once and, *(iii)* the total demand served by a vehicle must respect its capacity. The MDVRP is more challenging than the VRP since it involves customer allocation decisions, in addition to routing. Probably, the first authors to address the MDVRP were Carpaneto et al. (1989);

1.Strategic & Tactical Characteristics	**2. Operational Characteristics**
1.1 Input Data	*2.1 Vehicles*
1.1.1 Static	2.1.1 Type
1.1.2 Dynamic	2.1.1.1 Homogeneous
1.1.3 Deterministic	2.1.1.2 Heterogeneous
1.1.4 Stochastic	2.1.2 Number
1.2 Decision Management Components	2.1.2.1 Fixed
1.2.1 Routing	2.1.2.2 Unlimited
1.2.2 Inventory and Routing	2.1.3 Structure
1.2.3 Location and Routing	2. 1.3.1 Compartmentalized
1.2.4 Routing and Driver Scheduling	2.1.3.2 Not Compartmentalized
1.2.5 Production and Distribution Planning	2.1.4 Capacity Constraints
1.3 Number of Depots	2.1.5 Loading Policy
1.3.1 Single	2.1.5.1 Chronological Order
1.3.2 Multiple	2.1.5.2 No Policy
1.4 Operation Type	2.1.6 Drivers Regulations
1.4.1 Pickup or Delivery	*2.2 Time Constraints*
1.4.2 Pickup and Delivery	2.2.1 Restriction on customer
1.4.3 Backhauls	2.2.2 Restriction on Road Access
1.4.4 Dial-a-ride	2.2.3 Restriction on Depot
1.5 Load Splitting Constraints	2.2.4 Service Time
1.5.1 Splitting Allowed	2.2.5 Waiting Time
1.5.2 Splitting not Allowed	*2.3 Time Window Structure*
1.6 Planning Period	2.3.1 Single Time Window
1.6.1 Single Period	2.3.2 Multiple Time Windows
1.6.2 Multiple Period	*2.4 Incompatibility Constraints*
1.7 Multiple Use of Vehicles	*2.5 Specific Constraints*
1.7.1 Single Trip	*2.6 Objective Function*
1.7.2 Multi-Trip	2.6.1 Single Objective
	2.6.1 Multiple Objectives

Table 2.1 Taxonomy of RVRPs proposed by Lahyani et al. (2015)

Kulkarni and Bhave (1985); Laporte et al. (1988); Tillman (1969). The work of Tillman (1969) introduced an extended version of the Clarke & Wright Heuristic (CWS), while the works of Carpaneto et al. (1989); Kulkarni and Bhave (1985); Laporte et al. (1988) were the pioneers on exact methods to address the MDVRP. Regarding heuristic methods, the work of Salhi and Sari (1997) proposed a multi-level heuristic which solves in a first stage a VRP and then modifies the solution to make it feasible for the MDVRP. Lim and Wang (2005) proposed two solving methodologies to tackle the MDVRP. A two-stage heuristic which solves the customer allocation and the routing independently. The other heuristic deals with both sub-problems in an integrated way. This second method outperformed the first one. Some of the most efficient solving approaches for the multi-depot VRP are based on metaheuristic algorithms, as the ones proposed by Pisinger and Ropke (2007), Vidal et al. (2012), De Oliveira et al. (2016), Mancini (2016), Karakatič and Podgorelec (2015) and Li et al. (2015). In the work of Juan et al. (2015b), customers are first allocated to one of the available depots before each customers-depot assignment is solved as a VRP, this multi-start process is then improved through an ILS algorithm. An updated review on the multi-depot VRP can be found in Montoya-Torres et al. (2015).

The most common appearance of uncertainty in routing problems is that found in the traveling times or in the customers' demands. This thesis focuses on the second one, although our approach could be easily extended so that it also considers stochastic traveling times. Due to its relevance in practical applications, the VRP with stochastic demands has been studied by several authors Balaprakash et al. (2015); Bertsimas (1992); Juan et al. (2011a); Ritzinger et al. (2016), while the multi-depot version of the VRP with stochastic demands (MDVRPSD) is much less studied in the literature Calvet et al. (2016); Zuhori et al. (2012).

2.1.2 The Location Routing Problem (LRP)

The LRP comprises all decision levels in Supply Chain Management, i.e. strategic, tactical, and operational levels. Strategic decisions are related to the number and size of facilities to be open, while tactical and operational ones are associated to customer allocation to opened facilities and the corresponding routes to serve customer demands, respectively. In terms of classical optimization problems, the LRP is the combination of both the Facility Location Problem (FLP) with the Vehicle Routing Problem (VRP), which are known to be NP-hard (Nagy and Salhi, 2007). Due to computational constraints, the first works addressing the LRP attempted to solve it by firstly solve a FLP and then use the solution found to solve the associated VRPs. However, thanks to the increasing computational power, recent published works solve the LRP in a more integrated way. The LRP has a wide range of applications including, among others, food and drink distribution, waste collection, or disaster logistics (Nagy and Salhi, 2007).

The benefits derived from taking into account routing decisions while locating facilities were quantified for the first time by Salhi and Rand (1989). The authors showed that solving a location problem and a routing problem separately does not necessarily lead to optimal solutions. Despite the importance of the LRP in supply chain management, the number of published works available in the literature is scarce compared to other logistic problems (e.g. vehicle routing problem and its variants). However, in recent years the number of publications related to the topic has increased considerably.

Since the LRP combines two NP-hard problems, exact methods have been scarcely used. Thus, for instance, Belenguer et al. (2011) or Akca et al. (2009) solved instances with up to 50 customers and 5-10 depots, while Baldacci et al. (2011) or Contardo et al. (2014a) solved instances with up to 200 customers and 10-14 depots. Constructive clustering-based heuristics have been proposed by Barreto et al. (2007); Boudahri et al. (2013), and Lopes et al. (2008) to solve the LRP. Concerning metaheuristic approaches, the less used are population based algorithms Prins et al. (2006a); Ting and Chen (2013) while most employed are neighborhood-based approaches Duhamel et al. (2010); Prins et al. (2006b); Quintero-Araujo et al. (2016). Some matheuristics methods have been considered by Contardo et al. (2014a); Escobar et al. (2014); Prins et al. (2007).

Some applications of the LRP have been studied in Mousavi and Tavakkoli-Moghaddam (2013) where the authors studied a real-life LRP found in cross-docking operation. In addition, Muñoz Villamizar et al. (2013) studied the problem of locating capacitated urban distribution centers and its integration with the routing problem with capacitated vehicles.

Regarding stochasticity, different uncertain parameters have been considered in literature, e.g. travel times, customers service request, customer demands, etc. A LRP with stochastic customer request is presented in Albareda-Sambola et al. (2007) who considered uncapacitated vehicles to perform routing tasks. Customers request for service is not known in advance and is modeled by means of Bernoulli distribution. Probabilistic travel times are included in Ghaffari-Nasab et al. (2012). The authors solved a bi-objective LRP in which the analyzed objectives are the total costs and the maximum delivery time to the customers. In case of stochastic demands, they have been modeled by means of fuzzy numbers (Mehrjerdi and Nadizadeh, 2013; Zarandi et al., 2013) and random variables (Marinakis, 2015; Marinakis et al., 2016).

2.1.3 Other RVRPs in City Logistics

2.1.3.1 The Waste Collection Problem with Stochastic Demands (WCPSD)

Probably the first work to deal with municipal solid waste collection was introduced by Beltrami and Bodin (1974). Since then, various solution techniques for different variants of the Waste Collection Problem (WCP) and its extensions have been proposed. While some works formulating the WCP as an Arc Routing Problem (ARP) can be found (Bautista et al., 2008; Ghiani et al., 2005), the following discussion focuses on recent publications using VRP formulations. ARP formulations fit better for the collection of household refuse in small bins from private homes while VRP models are more suitable for the collection of waste from larger containers, which are often located close to retailers, construction sites, or waste collection points of building blocks in metropolitan areas. More extensive literature reviews are provided by Beliën et al. (2014); Ghiani et al. (2014); Golden et al. (2001) and, Han and Ponce-Cueto (2015).

Most works on the deterministic WCP are case studies with some problem extension, e.g.: combined routing and vehicle scheduling. For example, Baptista et al. (2002) elaborated an extension of the Christofides and Beasley heuristic for the multi-period WCP (Christofides and Beasley, 1984), modeled as a periodic VRP (PVRP) to combine vehicle scheduling over multiple time periods with route planning to improve municipal waste collection in a Portuguese city. Also addressing a multi-period WCP, Teixeira et al. (2004) developed a cluster-first route-second heuristic to schedule and plan waste collection routes for different waste types in a case study in Portugal with over 1600 collection sites. Nuortio et al. (2006) presented a guided variable thresholding metaheuristic to solve a multi-period WCP with several thousand collection points in Eastern Finland. Hemmelmayr et al. (2013) addressed the PVRP with different waste types and up to 288 containers, which they solved with a Variable Neighborhood Search (VNS) metaheuristic. They also discussed the single period WCP with multiple depots, in which the landfills serve as vehicle depots and disposal sites at the same time. Later, Hemmelmayr et al. (2014) discussed the integrated vehicle routing- and container allocation problem using the same real-life problem set, which they solved with a combination of a VNS metaheuristic for the routing part and a mixed integer linear programming-based exact method for the allocation. Ramos et al. (2014) extended the typical objective of minimizing routing costs in order to include environmental concerns, considering multiple waste types and numerous vehicle depots in a case study in Portugal.

Regarding route planning for waste collection, Kim et al. (2006) developed an extension of Solomon's insertion algorithm (Solomon, 1987) to optimize routes of a North American waste management service provider, considering a capacitated vehicle fleet, time windows, and driver lunch breaks. Furthermore, they provided a benchmark set of 10 realistic instances based on the original case study ranging from 102-2100 nodes. This benchmark set has been used by several authors to test their solving approaches (Benjamin and Beasley, 2010; Buhrkal et al., 2012; Ombuki-Berman et al., 2007). Recently, Markov et al. (2016) presented a multiple neighborhood search heuristic for a real-word application of the waste collection VRP with intermediate facilities. The authors considered a heterogeneous vehicle fleet and flexible depot destinations in their approach.

2.1.3.2 The Site Dependent Asymmetric Vehicle Routing Problem with Heterogeneous Fleet (HSDAVRP)

The Site Dependent Vehicle Routing Problem (SDVRP) extends the classical VRP by incorporating compatibility dependencies among customers and vehicle types. The fleet consists of several vehicle types, each of them with limited number of available vehicles. Not every customer can be visited by every vehicle type, e.g. customers located in high congestion areas can not be visited by large vehicles. The objective is to find a set of routes that minimize the total traveled distance. It can be characterized as a multilevel routing problem (Chao et al., 1999). Since it is an extension of the VRP, the SDVRP is NP-Hard (Lenstra and Rinnooy Kan, 1981). The SDVRP was first introduced by Nag et al. (1988) who presented four heuristics to solve it. Chao et al. (1999) presented a heuristic procedure consisting of *(i)* balancing the workload among the different vehicle types and solving it with the savings heuristic, and *(ii)* improvement of solutions by means of uphill and downhill movements of one customer at a time. They also proposed 12 new benchmark instances. Cordeau and Laporte (2001) presented the SDVRP as a special case of the Periodic VRP (PVRP) and solved it by adapting a Tabu Search algorithm conceived for the PVRP. Chao and Liou (2005) developed a method that combines Tabu Search with deterministic annealing in which deviation values are used to carry out intensification and diversification during the search. More recently, modeled site dependency by means of time windows constraints. The authors proposed two metaheuristics (Ant Colony Optimization-ACO and Tabu Search-TS). Both methods were quite similar in terms of quality of the solutions, but ACO was slightly better.

In real-life settings, distances will depend upon the specific location of the nodes and also on the structure of the road network. Regarding oriented networks, real distances might not have to be symmetric (Rodríguez and Ruiz, 2012). However, the literature related to asymmetric distance (costs) matrix is more scarce than its symmetric counterpart. The Asymmetric VRP (AVRP) has been studied by Laporte et al. (1986) who proposed a branch and bound algorithm capable of solving instances with up to 260 nodes. Fischetti et al. (1994) proposed two bound procedures based on the so-called additive approach for the AVRP and a branch and bound algorithm tested with both real-life and random test problems. Vigo (1996) extended two classical heuristics -the Clarke & Wright Savings (CWS) (Clarke and Wright, 1964) and Fischer-Jaikumar (Fisher and Jaikumar, 1981)- to tackle the asymmetric version of the CVRP. In addition, a new heuristic procedure is proposed to solve instances up to 300 nodes. This heuristic uses the additive approach of Fischetti et al. (1994) to generate initial infeasible solutions which are then improved by insertion procedures combined with intra and inter-route arc exchanges. The algorithms proposed by Nagata (2007) and Pisinger and Ropke (2007) are recognized by their performance in both versions symmetric and asymmetric. More recently, Herrero et al. (2014) proposed a multi-start algorithm based on a randomized version of the CWS heuristic. In this work, a weighted savings list and specific local searches for the asymmetric case are proposed obtaining competitive gaps when compared to state-of-the-art methods. Leggieri and Haouari (2016) developed a matheuristic with three sequential stages to deal with the AVRP. In a first phase, they reduce the problem by discarding non-promising arcs, then a feasible solution is obtained and, finally, it is improved by solving a sequence of two or three Asymmetric Capacitated VRP (ACVRP) reduced instances.

This thesis deals with different variants of the aforementioned RVRP. The main characteristics of each of them are compared, in table 2.2, against the taxonomy proposed by Lahyani et al. (2015). Although some of then do not fit in the definition proposed by this author, and considering that the definition of RVRPs is still in construction, they are considered as RVRPs in this thesis.

2.2 Solving Methodologies

Operations Research aims to determine the best possible (optimal) solution for a complex problem subject to a set of constraints, which are usually associated to scarce resources. Depending on the function to be optimized, the optimal solution will correspond to a maximum or a minimum. Optimization problems might be solved by exact or approximate methods. The choice of a given type of method relies on the complexity of the problem to be solved.

It is well-known that most of the problems in logistics and transportation are combinatorial optimization problems (COP). In COP, the feasible region is composed by combinations of the problem data which implies that the number of feasible solutions grows exponentially when the size of the problem increases. For this reason, these problems are known in the literature as NP-Hard. NP-hardness means that there are not exact methods providing an optimal solution in a polynomial time for any size of a given problem. Thus, exact methods

Table 2.2 Characteristics of the RVRPs addressed in this thesis according to the taxonomy proposed by Lahyani et al. (2015)

		MDVRPSD	AMDVRPSD	MOAMDVRPSD	CLRP	CLRPSD	HSDAVRP	WCPSD
	1.1							
	1.1.1							
	1.1.2							
	1.1.3				X		X	
	1.1.4	X	X	X		X		X
	1.2							
	1.2.1	X	X	X			X	X
	1.2.2							
	1.2.3				X	X		
	1.2.4							
	1.2.5							
	1.3							
	1.3.1						X	X
Strategic & Tactical Characteristics	1.3.2	X	X	X	X	X		
	1.4							
	1.4.1	X	X	X	X	X	X	
	1.4.2							X
	1.4.3							
	1.4.4							
	1.5							
	1.5.1							
	1.5.2	X	X	X	X	X	X	X
	1.6							
	1.6.1	X	X		X	X	X	X
	1.6.2			X				
	1.7							
	1.7.1	X	X	X	X	X	X	X
	1.7.2							
	2.1							
	2.1.1							
	2.1.1.1	X	X	X	X	X		X
	2.1.1.2						X	
	2.1.2							
	2.1.2.1	X	X	X			X	X
	2.1.2.2				X	X		
	2.1.3							
	2.1.3.1							
	2.1.3.2	X	X	X	X	X	X	X
	2.1.4	X	X	X	X	X	X	X
	2.1.5							
	2.1.5.1							
	2.1.5.2	X	X	X	X	X	X	X
Opeartional Characteristics	2.1.6							X
	2.2							
	2.2.1							X
	2.2.2							
	2.2.3							X
	2.2.4							X
	2.2.5							X
	2.3							
	2.3.1							X
	2.3.2							
	2.4						X	
	2.5	X	X	X	X	X	X	X
	2.6							
	2.6.1	X	X		X	X	X	X
	2.6.2			X				

can be used only for small instances as well as for too relaxed instances far away from real-life situations, leading to the increasing interest in the development of approximate solution methods.

2.2.1 Exact Methods

According to Talbi (2009), exact methods obtain optimal solutions guaranteeing their optimality. However, as previously said, they can be applied only to small-sized instances of complex problems. Among the classical exact methods we can find Branch and Bound, Branch and Cut, Branch and Price (commonly known as Branch and X family), Dynamic Programming (DP), Constraint Programming (CP), etc. Regarding the Branch and X family, the search for a solution is carried out over the whole search space by building a tree whose root node is the problem and the corresponding search space. Leaf nodes are potential solutions while internal ones are subproblems of the search space. Dynamic programming is based on the recursive division of a problem into simpler subproblems. Constraint Programming is used to model a problem in terms of variables, its domains, and constraints relating them. CP generates short and simple programs easily adaptable to changing requirements in which constraints are used to restrict and guide the search.

2.2.2 Approximate Algorithms

2.2.2.1 Heuristics

A heuristic is a procedure aiming to obtain an initial solution or an improved one for an optimization problem. These procedures are based on common sense and try to provide solutions of reasonable quality in very short computational times. However, they can not guarantee the optimality of the obtained solution. Zanakis and Evans (1981) state that heuristics are “simple procedures, often guided by common sense, that are meant to provide good but not necessarily optimal solutions to difficult problems, easily and quickly”. They also recommend to use heuristics when:

- An exact method is available, but it is computationally unattractive.
- There is no need of optimal solution.
- There is inexact or limited data.
- There are resource limitations like time or budget constraints.
- They are intermediary steps for other procedures.

Heuristic methods can be classified in two main groups: constructive heuristics and improvement heuristics. The aim of constructive heuristics is to create a first feasible solution. The most famous routing heuristics belonging to this group are Nearest Neighborhood Heuristic, Cheapest Insertion Heuristic and the Clarke & Wrigth Savings (CWS) algorithm. Local Search (LS) is one of the most recognized heuristic of the second group. Given a current solution *s* from the feasible region *S*, LS consists of finding, if possible, in the neighborhood of *s* (*N(s)*) a new solution *s'* with a lower cost than *s*, otherwise *s* is called a local optima. *K*-Optimal neighborhoods (see Fig. 2.1) are one of the most used local search strategies. They consist of withdrawing *k* arcs from the solution and replace them by *k* new arcs. This strategy was proposed by Lin and Kernighan (1973) and its complexity is $O(n^k)$, therefore *k* is usually 2 or 3.

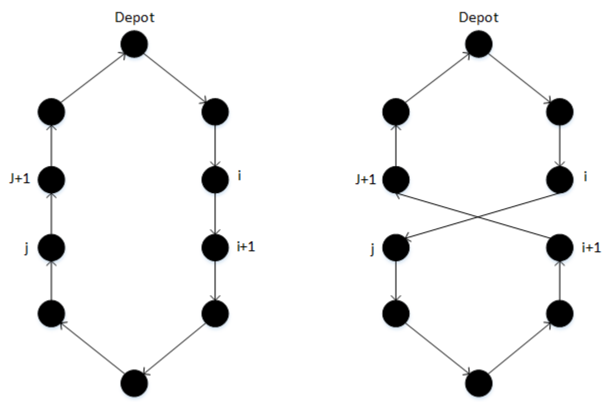


Figure 2.1 An example of 2-Opt exchange

2.2.2.2 Biased Randomization of Heuristics

As heuristics are mainly deterministic in nature, same problem inputs will lead to the same results on each execution of the procedure. To overcome such inconvenient, randomization, i.e. include some random steps (choices) within the algorithm, appears as an alternative to generate different outcomes at each execution of the heuristic (Motwani and Raghavan, 1996). However, randomization in its purest form could destroy the logic behind the heuristic procedure and bad quality solutions could appear during the construction/improvement process. Therefore, in order to keep the original logic of good heuristics, some guidance (bias) needs to be added within the randomized steps.

In the construction process of a feasible solution, Biased Randomization (BR) (Juan et al., 2013a) guides random choices towards the most promising movements by means of skewed probability distributions (e.g. geometric, triangular descendent, etc.). BR is similar to the greedy randomized adaptive search procedure (GRASP) elaborated by Feo and Resende (1995). In contrast to GRASP however, which is based on a restricted candidate list from which solution elements are chosen according to a uniform selection probability distribution, BR allows all eligible elements to be selected at every solution construction step. At each iteration, higher probabilities are assigned to elements with the highest expected objective function improvements.

2.2.2.3 Metaheuristics

Metaheuristics are algorithms conceived to escape from local optima. They are a sort of "templates" with some components that must be tuned up for each problem in order to obtain good solutions. Metaheuristics must incorporate intensification and diversification procedures. In intensification, promising regions are explored more thoroughly in the hope of finding better solutions. In diversification, unexplored regions must be visited to be sure that all regions of the search space are evenly explored and that the search is not confined to only a reduced number of regions (Talbi, 2009). Figure 2.2 shows an example of the evolution of costs when applying metaheuristics. Once a local optima is achieved, the metaheuristic tries to escape from it, by accepting non-improving solutions, with the hope of finding the global optima in another region of the search space.

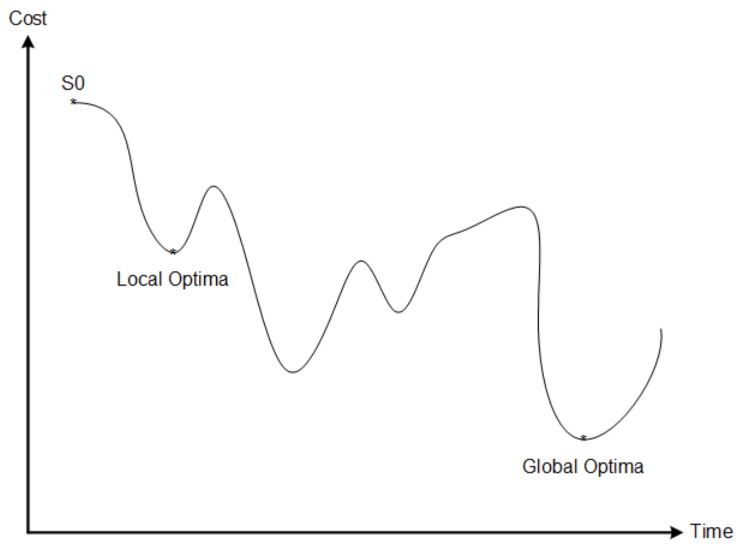


Figure 2.2 Cost reduction by using metaheuristics

Metaheuristics can be classified according to the number of current solutions at each iteration. Therefore, there are single-solution and population-based metaheuristics (Vidal et al., 2013). In the first group, search algorithms operate on a single solution at each iteration and try to improve the quality of the solution by exploring its neighborhoods iteratively. Tabu Search (Glover, 1986), Simulated Annealing (Kirkpatrick et al., 1983), Iterated Local Search (Lourenço et al., 2010) and GRASP (Resende and Ribeiro, 2003) are examples of single solution metaheuristics. Tabu Search (TS) behaves like a LS algorithm but it accepts non-improving solutions to escape from local optima when all neighbors are non-improving solutions. When a local optima is reached, the best solution in the neighborhood (non-improving) is selected. In order to avoid cycles, TS memorizes the recent search trajectory and prohibites it during a given number of iterations. This memory is called the tabu list which is a short-term memory that must be updated at each single iteration. Indeed, we have to check at each iteration if a generated solution does not belong to this list. TS also consider aspiration criteria, i.e. the possibility of allow the use of tabu movements (those movements stored in the tabu list) if they provide a good solution. Simulated Annealing (SA), as indicated by his name, simulates the annealing process which requires heating and then slowly cooling of a substance (e.g. a metal) to obtain a strong crystalline structure. If the initial temperature and the cooling rate are not well chosen, imperfections are obtained. In an optimization problem, the objective function is analogous to the energy state of the system while the global optimum corresponds to the ground state of the system. SA is a stochastic and memoryless algorithm in the sense that it does not use any information gathered during the search. At each iteration a random neighbor is generated. If it improves the cost function it is always accepted, otherwise is accepted with a given probability depending on the current temperature and the degradation of the objective function. Iterated Local Search (ILS) applies a local search operator to an initial solution which is then improved through successive cycles of perturbation and local search steps. New solutions are accepted as the new current solution under some conditions. This iterative steps are executed until a give stopping criterion is reached. GRASP is an iterative greedy heuristic. At each iteration, two steps are executed: the construction of a feasible solution by using a randomized greedy algorithm and a local search applied to the constructed solution. The iterations are completely independent, and so there is no search memory. Variable Neighborhood Search (VNS) is based on the construction of different solution neighborhoods and the following descent phase to define a local minimum in the corresponding neighborhood structure. Neighborhood structures are changed by applying shaking operators to the current solution, next local search schemes are applied to find the corresponding local optimum. It is based on the following principles: *(i)* a local minimum with respect to one neighborhood structure is not necessary so with another, *(ii)* a global minimum is a local minimum with respect to all possible neighborhood structures and, *(iii)* local minima with respect to one or several structures are usually similar to each other in some aspects.

Population-based methods usually start with a set of solution as an initial population, and then try to obtain good solutions by iteratively selecting existing solutions from a population according to their fitness and then combining them in order to get solutions with higher quality. Ant Colony Optimization (ACO) (Colorni et al., 1991) and Genetic Algorithms (GA) (Holland, 1975) belong to this class. ACO imitates the cooperative behavior of real ants to solve optimization problems. The main interest of real ant's behavior is the use of collective behavior to perform complex task such as finding the shortest path between two points. Genetic Algorithms are based on the principles of the evolution and natural selection theories in order to find from a given population (alternative solutions) the individuals that are well adapted (best performing solutions) to the environment conditions (problem constraints). To do that, an initial population is obtained (randomly) and at each generation (iteration) some genetic operators (crossover, mutation, replacement) are applied in order to find the best individual or population.

2.2.3 Simheuristics

Solving large-scale and NP-hard COPs is already a difficult task. If uncertainty is also considered in the form of stochastic components, then the solving process becomes even more challenging. In our view, simheuristic algorithms are one of the most efficient solving approaches to deal with stochastic COPs. These approaches integrate simulation methods inside a metaheuristic framework in order to deal with the stochastic components of the COP (Juan et al., 2015a). In Figure 2.3 we can appreciate the general schema of a simheuristic. It operates as follows: given a stochastic problem setting, the random variables are transformed into deterministic values by considering expected values; then, the resulting deterministic problem can be solved using an efficient metaheuristic; next, the promising solutions provided by the metaheuristic for the deterministic problem is evaluated under a stochastic scenario by running a short simulation process in order to have estimates about the quality of the solution in the stochastic world. Then, solutions are ranked according to their stochastic costs. This process is executed until a given stopping criterion (usually time) is reached. Next, an intensive simulation process (with high number of iterations) is executed on the elite stochastic solutions in order to refine the estimates. Once again the solutions are ranked by stochastic costs. To finish, risk/reliability analysis is performed and the best stochastic solution is reported. It is to note that, in each of the simulation runs, the stochastic variables are depicted from the best-fit probability distribution.

Different simheuristic algorithms have been presented in the literature and applied to routing problems. Stochastic demands in VRPs are, for example, addressed in Juan et al. (2011a, 2013b). Similarly, the arc routing problem with stochastic demands is discussed in

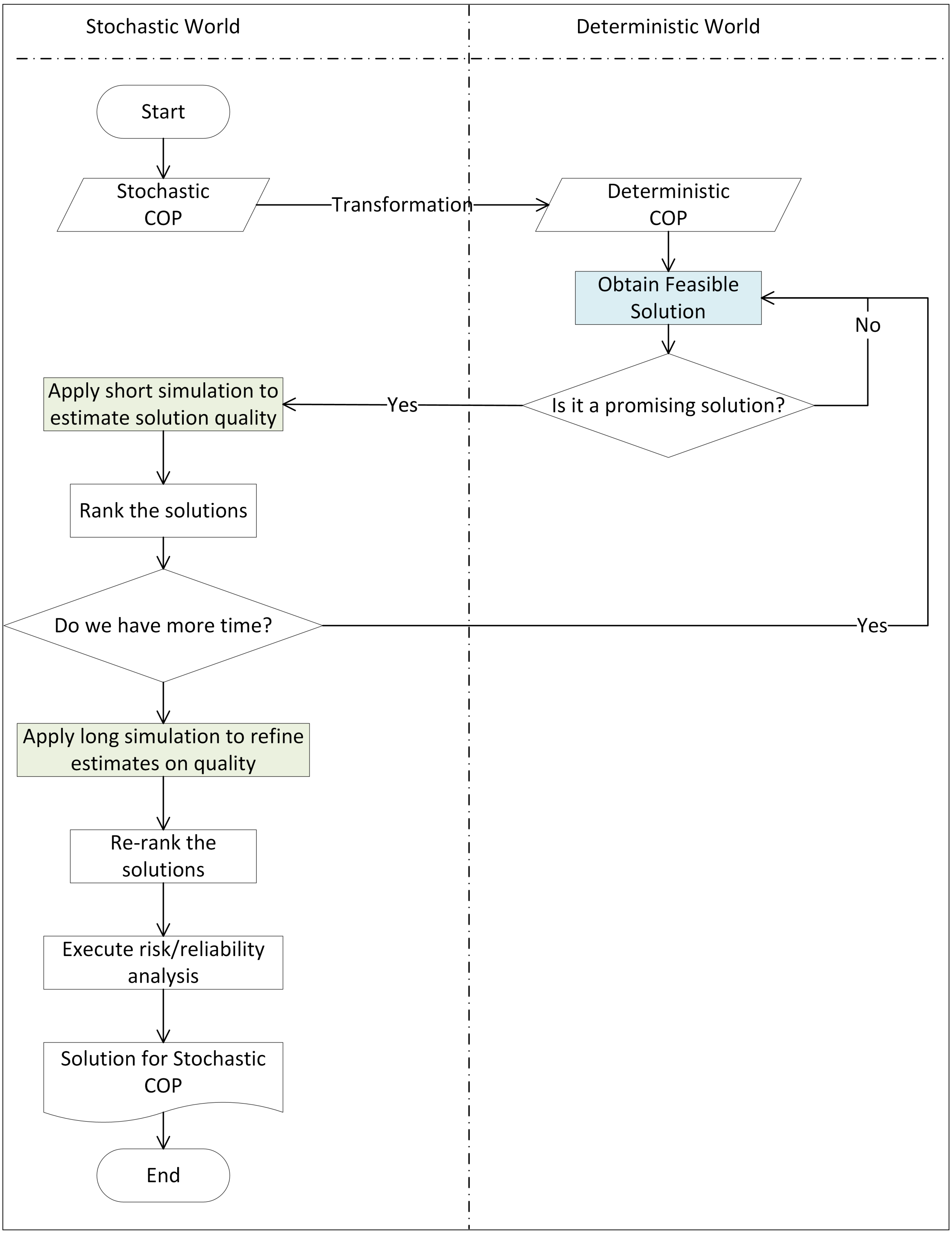


Figure 2.3 General scheme of simheuristics. Adapted from Juan et al. (2015a)

Gonzalez-Martin et al. (2016). Furthermore, simheuristics have been applied to tackle the inventory routing problem with stochastic demands (Juan et al., 2014d), in which integrated decisions about inventory management and routing activities are made. Other applications of simheuristics can be found in the field of flow-shop problems (Juan et al., 2014a) or in dynamic home-service routing with synchronized ride-sharing (Fikar et al., 2016).

2.3 Horizontal Cooperation

Current business environments are shaped by globalized markets, real-time communication, and rapidly changing customer demands. Accordingly, companies are forced to efficiently reorganize their logistic processes to stay competitive by quickly reacting to market changes. In that sense, alliances or partnerships among companies are essential to reduce transportation and logistics (T&L) costs while increasing customer service levels. Some authors establish differences between horizontal cooperation and horizontal collaboration. According to Spekman et al. (1998), cooperation is the threshold level of interaction, while collaboration requires high levels of trust, commitment and information sharing among supply chain partners. Nadarajah (2008) state that "collaboration indicates a stronger relationship, between firms or supply chains, than cooperation". However, most of the available literature refers to both terms as synonyms. Even though this thesis deals with some collaboration concepts, from this point forward, this thesis will use the term Horizontal Cooperation (HC). In the context of land-side T&L, mainly vertical cooperation between companies on different supply chain layers –through concepts such as vendor managed inventories (VMI), efficient customer response (ECR), etc.– has been widely discussed, while the literature on HC in T&L is still an emerging topic (Leitner et al., 2011; Pomponi et al., 2015). The European Union defines HC as "concerted practices among companies operating at the same level(s) in the market (European Commission, 2001)". This definition is extended by Bahinipati et al. (2009), who state that HC is "a business agreement between two or more companies at the same level in the supply chain or network in order to allow ease of work and co-operation towards achieving a common objective". Cost savings generated by the implementation of HC strategies include the potential reduction of negative environmental impacts associated with transportation activities (Lera-López et al., 2012; Ubeda et al., 2011). The importance of sustainable L&T is underlined by the fact that road transportation is estimated to account for around 18% of total greenhouse gas emissions in the European Union (Hill et al., 2011). Even higher percentages have been reported for other parts of the world, such as the Asia and Pacific region (United Nations, 2011) or the United States (United States Environmental Protection Agency, 2014).

Figure 2.4 shows a graphical example of different strategies to follow when executing transportation tasks. On the one hand (left), a non-cooperative strategy is considered when each company plans on its own its operation. Trucks of a given company are loaded at the company's central depot and serve its customers who are located in a scattered area. As a consequence, route length is optimized from a single company perspective. On the other hand (right), a cooperative scenario is considered when some assets (depot capacity, vehicle capacity and customer information) are shared among the different companies and, as a result, transportation is jointly planned. As can be seen, benefits like shorter, more balanced and (usually) less pollutant routes are obtained.

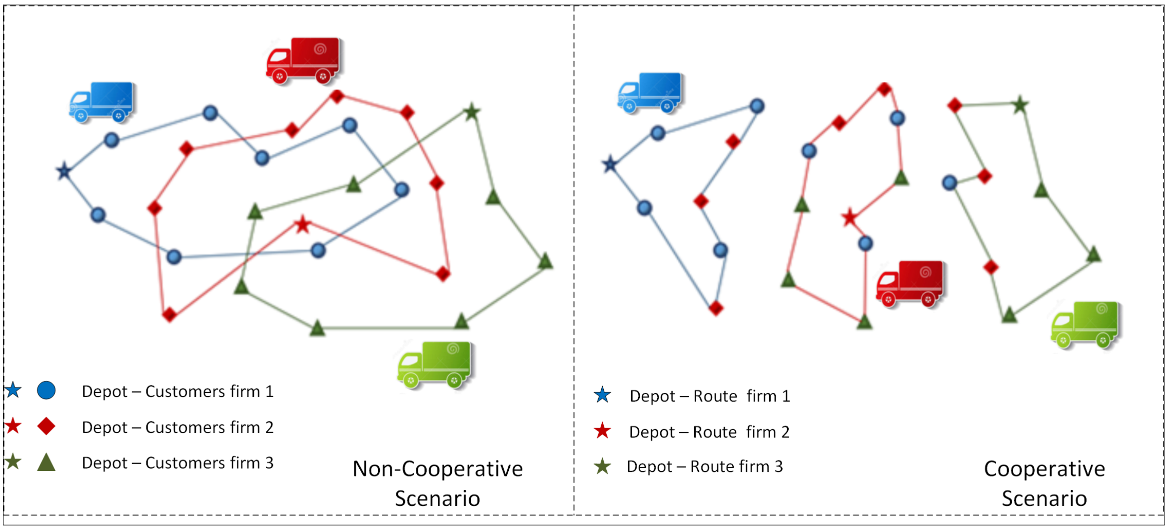


Figure 2.4 Graphical comparison of non-cooperative(left) and cooperative (right) strategies in transportation

2.3.1 Horizontal Cooperation in Logistics and Transportation

One of the first works on the topic was presented by Caputo and Mininno (1996), who discussed different policies including the standardization of electronic documents, pallets, and cartons as well as multi-supplier warehouses, coordinated route planning, and load consolidation to support HC in the Italian grocery industry. Another early work on HC was elaborated by (Erdmann, 1999), who proposed a simulation model to quantify the potentials of different levels of HC among freight carriers. The main strategies to facilitate the quantitative analysis of potential benefits of HC are: *(i)* the implementation of information sharing, *(ii)* load consolidation centers, *(iii)* conjoint route planning and, *(iv)* shared distribution resources.

Cruijssen and Salomon (2004) studied how orders sharing between freight carriers can lead to savings between 5%-15% due to improved transport planning. Joint route planning under varying market conditions was analyzed by Cruijssen et al. (2007a). Özener et al. (2011) discussed how customer exchanges among freight carriers with different levels of information sharing can lead to cost savings for the involved companies. Nadarajah (2008) showed potential route savings and increased vehicle utilization through collaborative vehicle routing and a strategic location of consolidation points for less-than-truckload (LTL) carriers. HC in the context of conjoint transportation planning of LTL shipments was also studied by Wang and Kopfer (2014), who introduced exchange mechanisms for customer request re-allocations and compare this scenario to isolated planning. Furthermore, HC has been investigated in the context of backhauling, with the aim of combining delivery and pickup operations to increase vehicle utilization levels (Belloso et al., 2017a). An optimization approach addressing backhauling routes as possibility to implement HC strategies among companies was presented by Adenso-Díaz et al. (2014), who developed a GRASP algorithm to solve the problem of conjoint delivery routes. A similar problem was addressed by Bailey et al. (2011), who estimated that the percentage of cost savings for empty backhaul routes can reach up to 27% through consolidated shipments. The potential costs and emission savings through backhauling in a case study of a Spanish food distributor was discussed by Ubeda et al. (2011). Juan et al. (2014c) and Belloso et al. (2017b) analyzed the VRP with clustered backhauls as a particular case of HC. Wang et al. (2014) mixed subcontracting with HC to increase operational efficiency. The resulting problem included heterogeneous fleet (own fleet plus subcontracted vehicles). More recently, Pérez-Bernabeu et al. (2015) presented a work on the quantification of potential savings in road transportation through HC. The authors analyzed cooperation between carriers and shippers controlled by the same companies in a semi-cooperative scenario (equivalent to a MDVRP) and two non-cooperative scenarios (multiple VRPs with clustered and scattered customer distributions). The reported results suggest that cooperative supply chain planning typically outperforms its non-cooperative counterpart in terms of both distances and CO_2 emissions, with distance based savings of up to 15% and even higher reductions of the environmental routing impact. Real-life applications of HC in urban distribution can be found in the work of Montoya-Torres et al. (2016). The authors compared non-collaborative transportation with a collaborative scenario related to tactical and operational decision-making using real-data from three retail companies located in the city of Bogotá, Colombia. In this case, stochastic demands are assumed to be known before route planning. Possible benefits through HC were quantified in terms of total distance, CO_2 emissions, number of routes, and vehicle utilization levels. Results showed benefits ranging from a reduction of 9% in the number of routes, with distance savings up to

25% while CO_2 emissions decreased. Caballini et al. (2016) proposed a mathematical model for cooperative planning of different truck carriers serving a seaport in order to reduce unproductive trips. They tested two cooperation strategies using real data from the port of Genoa, Italy. Both strategies lead to higher profits when compared to the initial non-cooperative scenario.

Very few works have been presented showing the advantages of cooperation along the integrated routing and location decision process. Groothedde et al. (2005) introduced a design methodology for collaborative hub networks (CHN) in the context of fast moving consumer goods in the Netherlands. An average logistics cost reduction of 14% was achieved for origin-destination relations that used the CHN strategy.

Even though HC is receiving increased attention, different impediments still prevent a widespread application of conjoint activities among companies. On the one hand, HC requires a high level of trust between participating companies, since many of them are usually competitors and reluctant to share valuable information (Özener and Ergun, 2008). On the other hand, supply chains are specifically designed for different industries or retailers, making an active cooperation among supply chain members more difficult. Another key issue for HC practices is the fact that benefits associated with cooperative strategies cannot be easily quantified for a single company, but are rather visible on an aggregated supply chain level (Cruijssen et al., 2007b). One interesting approach to fulfill this gap is Game Theory, as proposed by Lozano et al. (2013). In addition, fair cost and benefit allocation among HC participants has been addressed by Audy et al. (2012), Dai and Chen (2012), and Krajewska et al. (2008). Generally, the success of any partnership is highly dependent on commitment, trust, and information sharing between the participating organizations (Singh and Power, 2009). For an extensive literature review on HC in T&L, the reader is referred to Cruijssen et al. (2007c).

2.3.2 Different Stages of HC Agreements

Lambert et al. (1999) were the first to propose a HC taxonomy depending on the time horizon of the cooperation agreement. They identified three types of HC: type I is related to short-term cooperation, which is mainly operations oriented; type II involves business planning integration among partners; type III refers to strategic alliances among companies on the same supply chain level. A similar classification of cooperation agreements was suggested by Verstrepen et al. (2009). The authors highlighted differences in the scope and intensity of HC initiatives along operational, tactical, and strategic planning levels. While they suggested that operational cooperation is mainly focused on joint execution and the sharing of information, whereas HC on a tactical planning level involves more intensive planning and shared investments. Finally, strategic cooperation is aimed at joint long-term partnerships according to their framework. Furthermore, the paper described the typical life cycle of such partnerships and suggested a conceptual framework for managing HC in logistics.

Leitner et al. (2011) defined reduced costs, increased responsiveness, and improved service levels as the relevant benefits of HC. The authors also developed a two-dimensional taxonomy to characterize different levels of HC, based on the level of cooperation and the product flow consolidation potential. Recently, Pomponi et al. (2015) elaborated a theory-based framework for HC in logistics, developing coherent pairs of aims and shared assets for different cooperation stages, including operational, tactical, and strategic levels. While these authors characterized operational HC as related to shared information with the aim of cost reductions, cooperation on a tactical level involves shared logistics facilities and enables concepts such as multi-modal deliveries. In their view, the most advanced HC agreement is based on strategic cooperation, which includes joint investments and a high degree of commitment between the participating organizations. Generally, all discussed works stressed the importance of mutual trust among companies to enable a successful partnership, whereby higher trust is necessary as cooperation agreements are enhanced. Moreover, most authors mentioned that the development of different HC stages is a continuous process. Thus, a successful supply chain cooperation typically starts with combined activities that involve a low involvement of the participating actors, before more advanced cooperation projects are started.

2.4 Chapter Conclusions

In this chapter we have reviewed the existing literature related to the topic of this thesis. First of all, we have presented the VRP and some of its well-known variants. In addition, we have included some of the definitions of RVRP proposed in some recently published articles. Next, a literature review on the RVRP analyzed in this thesis has been presented. Moreover, some of the solving approaches have been considered, including exact, approximate methods and simheuristics. Finally, we have introduced the concept of horizontal, more specifically in logistics and transportation. We have identified two issues to be addressed in this thesis through the development of different solving approaches, including simheuristics: *(i)* the need for more realistic scenarios (RVRP) to support decision-making processes in city logistics; and *(ii)* the clear necessity of quantifying the benefits of incorporating HC strategies in different degrees (stages) of implementation.

Chapter 3

Horizontal Cooperation in Urban Distribution

The contents of this chapter are based on the following works:

- Quintero-Araujo C.L., Gruler A., Juan A.A. (2016). "Quantifying Potential Benefits of Horizontal Cooperation in Urban Transportation Under Uncertainty: A Simheuristic Approach". In: Luaces O. et al. (eds) Advances in Artificial Intelligence. CAEPIA 2016. *Lecture Notes in Computer Science*, vol 9868, 280-289. Springer, Cham. ISSN: 1611-3349. (*Scopus*)

- Quintero-Araujo, C.L; Gruler, A.; Juan, A.; De Armas, J.; Ramalhinho, H. (2017). "Using Simheuristics to Promote Horizontal Collaboration in Stochastic City Logistics". Progress in Artificial Intelligence. ISSN: 2192-6352. DOI: 10.1007/s13748-017-0122-8 *Accepted for Publication*.

- Muñoz-Villamizar, A.F.; Quintero-Araujo, C.L.; Montoya-Torres, J.R.; Faulin, J. (*Under Review*). "Short- and Mid-term Evaluation of the Use of Electric Vehicles in Urban Freight Transport Cooperation Networks: A Case Study". Transportation Research Part D: Transport and Environment. ISSN: 1361-9209. (*JCR*)

- Quintero-Araujo, C.L.; Juan, A.; Montoya-Torres, J.R.; Muñoz-Villamizar, A.F. (2016). "A Simheuristic Algorithm for Horizontal Cooperation in Urban Distribution". *Proceedings of the 2016 Winter Simulation Conference*, 2193-2204. Washington D.C., USA. December 11-14. ISBN: 978-1-5090-4485-6. (*ISI Proceedings, Scopus*)

Goods distribution in urban and metropolitan areas concerns both pick-up and delivery in retail, parcel and courier services, waste transport, transport of equipment for the construction industry, and a broad range of other types of transport (Russo and Comi, 2010). One approach to perform urban distribution of goods consists of: *(i)* storage of goods inside a logistics facility (warehouse, depot, etc.) and *(ii)* the corresponding route planning to deliver such goods to retail points (convenience stores). Traditionally, each company serves its own customers from its central depot using its own (or subcontracted) fleet of vehicles. However, Horizontal cooperation (HC) arises as a new strategy that can be implemented between companies in order to reduce operational costs, among other benefits. Under some general circumstances, HC in urban freight delivery can be modeled as a multiple depot vehicle routing problem (MDVRP).

The MDVRP consists on finding a set of routes whose total distance is minimal, in such a way that: *(i)* each route starts and ends at the same depot, *(ii)* each customer is visited exactly once, and *(iii)* the total demand of each route satisfies vehicle capacity (Montoya-Torres et al., 2015). This is a challenging problem because it integrates the allocation of delivery points to depots and its routing process Juan et al. (2015b). The MDVRP hence belongs to the class of NP-hard problems. Therefore, the design of approximate algorithms to efficiently solve this problem is required. In this chapter we analyze the case of cooperative goods distribution in both scenarios: mono-objective with stochastic demands and multi-objective with different planning horizons. In the first case, demand values are known once the vehicle arrives to the customer. Thus, this thesis proposes an approach combining optimization with MCS, which is more appropriate to tackle this problem setting. In particular, the approach used belongs to the so-called simheuristics framework. In the second case, a multi-objective function is proposed to explore the relationships between the delivery cost and the environmental impact while considering different vehicle types (fuel-engined vs electrical). Experiments with different costs and demands forecast are performed as well to analyze short- and medium-term impacts related to the use of electric vehicles in the configuration of the cooperative transport network.

3.1 Cooperative Distribution under Uncertainty

Two different scenarios related to urban freight distribution with stochastic demands are compared: *(i)* a non-cooperative case, which is equivalent to solving one capacitated VRP for each company (assuming each company is represented by a single depot); and *(ii)* a cooperation case, which can be modeled as a multi-depot VRP since customer information and company resources are shared among the different organizations.

3.1.1 Non-Cooperative Scenario

Decision making is completely decentralized in the non-cooperative scenario. No customer information and/or resources are shared between companies on the same supply chain level. It is assumed that each company serves its own set of customers, $I = \{1, 2, ..., n\}$. The random demands $D_i > 0$ at each client i are fulfilled by a homogeneous fleet of capacitated vehicles stationed at a central depot, 0. Travel costs C_{ij} (e.g. distance, time, emissions, etc.) between any two nodes are known. Under these circumstances, company-specific delivery routes can be established by solving the capacitated VRP. With the objective of minimizing total costs, problem constraints include that every customer is only served by one vehicle, that all routes start and end at the central depot, and that no vehicle can stop twice at the same customer. While we consider a VRP to model the deterministic case, a VRP with stochastic demands is considered for the case under uncertainty.

3.1.2 Cooperative Scenario

In contrast to the previous case, customer orders are exchanged between cooperating companies in the cooperative scenario. This leads to aggregated decisions in which vehicle capacities, customer information, and storage space within logistic facilities are shared among the companies participating in the cooperation agreement. From an optimization point of view, this scenario corresponds to a MDVRP. In contrast to the single-depot VRP described above, this problem setting includes a customer-depot assignment phase, during which clients are assigned to different vehicle depots according to their geographic proximity. Especially in scattered environments such as urban areas, this allows for the establishment of efficient customer-depot allocation maps, from which the delivery routes are then created. As done for the non-cooperative scenario, a multi-depot VRP in its deterministic and stochastic demands versions is considered.

3.1.2.1 The Vehicle Routing Problem with Multiple Depots

According to Renaud et al. (1996), the MDVRP can be formalized as follows. Let $G = (V, E)$ where V is a set of nodes and E is a set of arcs connecting each pair of nodes. V is composed by the subsets of N customers and the subset of M depots, V_c and V_d, respectively. Each customer υ_i has a nonnegative demand d_i. Each arc has an associated cost, C_{ij}. The fleet is composed by K vehicles, each one with capacity P_k. In addition, each tour might have a length limit T_k. Let consider a binary decision variable X_{ijk} equal to 1 if the arc (i, j) is visited by the vehicle k, and 0 otherwise. Auxiliary variables y_i are introduced to help sub-tour elimination constraints. The following mathematical model for the MDRVRP was proposed by Kulkarni and Bhave (1985).

$$\text{Min} \sum_{i=1}^{N+M} \sum_{j=1}^{N+M} \sum_{k=1}^{K} C_{ij} X_{ijk} \tag{3.1}$$

Subject to:

$$\sum_{i=1}^{N+M} \sum_{k=1}^{K} X_{ijk} = 1 \qquad \forall j \in V_c \tag{3.2}$$

$$\sum_{j=1}^{N+M} \sum_{k=1}^{K} X_{ijk} = 1 \qquad \forall i \in V_c \tag{3.3}$$

$$\sum_{i=1}^{N+M} X_{ihk} - \sum_{j=1}^{N+M} X_{hjk} = 0 \qquad \forall h = 1, 2, \dots N + M, \forall k \in K \tag{3.4}$$

$$\sum_{i=1}^{N+M} d_i \sum_{j=1}^{N+M} X_{ijk} \leq P_k \qquad \forall k \in K \tag{3.5}$$

$$\sum_{i=1}^{N+M} \sum_{j=1}^{N+M} C_{ij} X_{ijk} \leq T_k \qquad \forall k \in K \tag{3.6}$$

$$\sum_{i=N+1}^{N+M} \sum_{j=1}^{N+M} X_{ijk} \leq 1 \qquad \forall k \in K \tag{3.7}$$

$$\sum_{j=N+1}^{N+M} \sum_{i=1}^{N+M} X_{ijk} \leq 1 \qquad \forall k \in K \tag{3.8}$$

$$Y_i - Y_j + (M + N) X_{ijk} \leq N + M - 1 \qquad \forall i \neq j \in V_c, \forall k \in K \tag{3.9}$$

$$x_{ijk} \in \{0, 1\} \qquad \forall (i, j) \in V, \forall k \in K \tag{3.10}$$

Equation (3.1) describes the objective function which consists in the minimization of the costs of arcs used in the routes. Constraints (3.2) and (3.3) ensure that each customer is visited by one and only one vehicle. Constraints (3.4) guarantee the continuity of each route. Vehicle capacity constraints are represented by expressions (3.5). Constraints (3.6) ensure the cost constraint of each route. Constraints (3.7) and (3.8) are to guarantee vehicle availability. Inequalities (3.9) are sub-tour elimination constraints. Finally, (3.10) define the decision variables.

3.1.2.2 MDVRP with Stochastic Demands

In this chapter, we assume that customers demands are not known in advance, i.e. they are revealed when the vehicle arrives to the customer's site. However, routes need to be planned in advance, based on the expected value of the demand (usually this value is based on the customer's history). The uncertainty of customers demands could cause an expected feasible solution to become infeasible when the total demand of a given route is higher than the capacity of the vehicle serving that route. This situation is known as a route failure. Whenever a route failure occurs, a corrective action consisting on: *(i)* going to the depot, *(ii)* reload the vehicle, *(iii)* go back to the last visited customer to serve it and, *(iv)* resume the planned (original) route. As a consequence, the total costs of the planned routes is increased by incorporating the costs of such corrective action. No further assumptions are made on the demands other than that they follow a well-known theoretical or empirical distribution – either discrete or continuous – with existing mean denoted by $E[D_i]$. In this context, the goal is to find a feasible solution (set of routes) minimizing the expected delivery costs while satisfying all customer demands and vehicle capacity constraints.

3.1.3 Solving Approach

Our solution approach to the MDVRPSD consists of two main phases. First, we create different customer-depot allocation maps which we evaluate using the randomized version of the CWS to solve the deterministic counterpart of the stochastic problem. This process is integrated into an ILS framework to create numerous allocation maps. Then, we apply MCS to evaluate the behavior of the most promising allocation maps in a stochastic environment.

To create different customer-depot allocation maps we use a biased round-robin criterion. That is, a distance based priority list of potential customers for depot k is created based on the marginal savings μ_i^k of serving a customer i from each depot $k \in V_d$, compared to serving it from the best alternative depot k^* (such that $\mu_i^k = c_i^{k^*} - c_i^k$). Next, the nodes are randomly assigned. Each depot iteratively 'chooses' an unassigned customer to serve from its priority list. At each step, the probability of adding the customer with the highest potential savings to the map is defined by parameter $\alpha (0 \leq \alpha \leq 1)$. This parameter defines the specific geometric distribution used to assign the diminishing probability distributions for each edge, whereby all edges are potentially eligible.

Once all customers have been assigned, the created map is evaluated using the extended version of the CWS based on biased randomization as described by Juan et al. (2011b). In order to test different customer-depot allocation maps, we implement the described procedure into an ILS framework. Hereby, we consider the deterministic counterpart of the stochastic problem by using expected demands at each customer. After finding an initial solution (which is set as $currentBest$) and the corresponding allocation map, the map is perturbed by applying a destroy-and-repair strategy, in which $p\%$ of customers are exchanged among the depots. The resulting allocation map is evaluated again using the biased-ranzomized CWS algorithm. Accordingly, the current best solution is updated when necessary. Furthermore, we include an acceptance criterion which allows a solution worsening of $currentBest$ in

Algorithm 1: Establishment of Promising Solutions

Inputs: V_d; I; α; p
//Depots, customers, distribution parameter, customers to be exchanged
M ← ∅
//Set of Promising Solutions
Priority List ← establish customer priorities $\forall d \in V$
establish customer-depot allocation map(α)
$initSol$ ← solve map using randomized CWS
$initSol = currentBest$
while *pertubtime not reached* **do**
  pertubate current map(p)
  $newSol$ ← solve map using randomized CWS
  if $newSol < currentBest$ || *acceptance criterion is met* **then**
    $currentBest = newSol$
  end
end
return Set M of promising deterministic solutions

some cases. More specifically, we accept the current best solution to worsen to a certain extend when the last iteration from x to x^* was an improvement ($f(x) > f(x^*)$), and the difference between the current best solution and the new solution x^{**} is not bigger than the last improvement step ($|f(x) - f(x^*)| < f(x^{**}) - f(x^*)$). This increases the solution search space and avoids the algorithm running into local minima. The described ILS procedure is run for $pertubTime$ seconds, during which the m most promising (deterministic) solutions are defined. See Algorithm 1 for an overview over the applied approach.

This solution set is then evaluated in a stochastic scenario. Hereby, we assume a positive correlation between high-quality deterministic solutions and their stochastic counterpart with relatively low-variances. By simulating only the most promising deterministic customer-depot allocation maps we keep the computational effort manageable. To test the behavior of each solution considering stochastic demands, we repeatedly sample random demands using MCS (Raychaudhuri, 2008). That is, during each of a total of $nIter$ simulation runs, the expected demand D_i of each customer i is sampled from a probability function using the expected demands as mean and considering a demand variance $Var[D_i]$. In our case we use a log-normal distribution, but any other theoretical (e.g. Weibull) or empirical probability distribution providing positive values could have also been used.

Through the repeated simulation of customer demands, the stochastic costs can be estimated. As vehicle capacities are limited, route failures can occur as previously explained. Accordingly, we penalize a route failure by adding additional costs for a round trip from the current customer to the depot and back. The overall stochastic solutions are estimated by summing the costs of all round trip failures during each simulation run n and dividing it by the total number of simulation runs, see Equation (3.11). Route failures also affect the reliability of the solution. For each route, we estimate its reliability as in Equation (3.12). Therefore, the reliability of the solution is obtained by multiplying the reliabilities of the corresponding routes.

$$expectedStochCosts = \frac{\sum_{n=1}^{nIter} RouteFailCost_n}{nIter} \tag{3.11}$$

$$RouteReliability = (1 - \frac{\sum\limits_{n=1}^{nIter} RouteFailuresCount_n}{nIters}) \times 100\% \tag{3.12}$$

The simulation allows for a reliable estimate of the expected total costs of each suggested MDVRP solution by summing the deterministic costs and $expectedStochCosts$. At this stage we suggest the use of short and long simulation runs. By applying a short simulation with $nIterShort$ iterations to each promising solution a first estimate of the overall stochastic solution can be obtained. After this first simulation, the promising solutions are re-ranked to define e elite solutions through a more reliable simulation by using more simulation runs $nIterLong$. Finally our approach returns a list of MDVRPSD solutions. See Algorithm 2 for a description of the simulation procedure.

In addition, we have included the concept of safety stocks as a buffer capacity to face demand uncertainty (Juan et al., 2011a). The idea of using such buffer is to reduce the probability of suffering a route failure. Routes are constructed (planned) using a reduced capacity of the vehicle (VC') which is computed as $VC' = (1 - \%SS) \times VC$, where VC is the original vehicle capacity and $\%SS$ is the established safety stock value. During the aforementioned simulation process, the original capacity VC is used.

3.1.4 Experiments & Results

The aforementioned algorithm was implemented as a Java application and tested on a MacBook Pro Core i5 @2GHz processor with 8GB RAM. In order to allow the assessment of the two considered scenarios, we have carried out experiments with different benchmark instances from both theoretical and real-life settings.

Algorithm 2: Simulation of Stochastic Demands

Input: M; $nIter$; $Var[d_i]$
//Set of promising deterministic Solutions, number of Simulation runs (short and long), demand variance level
E ← ∅
//Set of Elite Solutions
for *each solution* ∈ M **do**
  run short simulation ($nIterShort$)
  estimate $expectedStochCosts$
  if *solution among best e stochastic solutions* **then**
    include solution in E
  end
end
for *each solution* ∈ E **do**
  run long simulation ($nIterLong$)
end
return Set reliable stochastic MDVRPSD solutions

Table 3.1 Tested instances and their features

Instance name	Depots	Customers	Vehicles x depot	Vehicle capacity	BKS
P01	4	50	4	80	576.87
P02	4	50	2	160	473.53
P03	5	75	3	140	641.19
P05	2	100	5	200	750.03
P09	3	249	12	500	3858.66
P10	4	249	8	500	3631.11
P18	6	240	5	60	3702.85
P19	6	240	5	60	3827.06
P20	6	240	5	60	4058.07
P22	9	360	5	60	5702.16

3.1.4.1 Theoretical Benchmarks

In order to allow the assessment of the aforementioned scenarios, we have carried out preliminary tests using ten benchmark instances with different from different sizes proposed by Cordeau et al. (1997) for the MDVRP. Their features are shown in Table 3.1.

Each instance was transformed to fit the non-cooperative scenario by using a greedy distance-based heuristic (round robin tournament) which iteratively assigns each customer to its closest facility. Both scenarios were tested using biased randomization-based algorithms already available in the literature. The non-cooperative scenario was solved by using the

SR-GCWS-CS proposed in Juan et al. (2011b), whereas the cooperative case was solved by means of the BR-ILS algorithm explained in Section 3.1.3.

After some preliminary tests, the following values were established for the different parameters during the execution of tests:

- $nIterShort$ (short simulation runs): 30
- $nIterLong$ (long simulation runs): 5000
- α (geometric distribution parameter for customer allocation) : 0.05-0.8
- p (percentage of customers allocated to new depots): 10% - 50%
- m (number of promising solutions): 10
- e (number of elite solutions): 5

Table 3.2 presents the comparative results among non-cooperative (NC) and cooperative (HC) scenarios in a deterministic environment ($Var[D_i] = 0\%d_i$). Next to the instance specifications, this table reports the deterministic costs of scenario as well as the benefits generated by implementing HC. On average, HC leads to route savings of 3.74% with values rising up to 5.91%. Regarding CO_2 emissions, savings account for 2.90% on average.

Table 3.2 Results for the deterministic version

	Non-cooperative		**Cooperative**		**Gap**		
Instance	Cost(1)	CO_2(2)	Cost(3)	CO_2(4)	(1) - (3)	(2) - (4)	(3) w.r.t. BKS
P01	612.69	528.64	582.34	504.62	-4.95%	-4.54%	0.94%
P02	507.27	427.82	485.32	414.33	-4.32%	-3.15%	2.48%
P03	677.35	572.83	649.99	563.09	-4.04%	-1.70%	1.37%
P05	788.66	676.49	776.57	673.44	-1.53%	-0.45%	3.54%
P09	4039.43	3538.21	3946.26	3450.76	-2.31%	-2.47%	2.27%
P10	3895.55	3380.75	3748.01	3287.66	-3.79%	-2.75%	3.22%
P18	4097.04	3471.12	3854.67	3297.92	-5.91%	-4.99%	4.10%
P19	4097.04	3471.12	3891.99	3329.42	-5.00%	-4.08%	1.69%
P20	4097.04	3471.12	4063.64	3443.35	-0.82%	-0.80%	0.13%
P22	6145.56	5206.68	5852.68	4994.22	-4.77%	-4.08%	2.64%
Average					-3.74%	-2.90%	2.23%

It is important to notice that, although HC practices contribute to reduce global costs, the distribution of savings might vary from one company (depot) to another. This can be clearly seen in Table 3.3, where costs have been detached by depot in both the non-cooperative (NC) and the cooperative (HC) scenarios. As expected, when using HC some depots decrease their

Table 3.3 Cost distribution among depots

	Scenario	***P01***	***P02***	***P03***	***P05***	***P09***	***P10***	***P18***	***P19***	***P20***	***P22***
Depot 1	NC	162.13	136.80	82.19	433.20	1768.46	984.15	682.84	682.84	677.27	682.84
	HC	173.62	87.04	79.62	387.52	1596.48	883.53	642.84	646.93	677.27	662.15
Depot 2	NC	220.67	179.31	145.16	355.46	1289.80	1043.09	682.84	682.84	679.93	682.84
	HC	159.23	183.07	128.96	389.05	1261.04	927.38	739.45	643.08	664.00	646.47
Depot 3	NC	115.94	102.70	146.75		981.17	941.18	682.84	682.84	682.84	682.84
	HC	86.44	141.62	185.42		1088.73	935.29	678.54	727.08	677.27	674.07
Depot 4	NC	113.95	88.46	181.14			927.13	682.84	682.84	686.69	682.84
	HC	163.04	73.59	133.84			1001.81	631.65	676.69	690.55	588.38
Depot 5	NC			122.11				682.84	682.84	682.84	682.84
	HC			122.11				624.01	585.34	664.00	670.47
Depot 6	NC.							682.84	682.84	682.84	682.84
	HC							538.19	612.88	690.55	623.27
Depot 7	NC										682.84
	HC										651.16
Depot 8	NC										682.84
	HC										646.86
Depot 9	NC										682.84
	HC										689.84
Total	NC	612.69	507.27	677.35	788.66	4039.43	3895.55	4097.04	4097.04	4092.41	6145.56
	HC	582.33	485.32	649.99	776.57	3946.26	3748.01	3854.67	3891.99	4063.64	5852.68

costs, while others increase them. Therefore, additional agreements among companies have to be taken into account regarding a fair distributions of the global savings provided by HC practices.

After analyzing the effects of HC in a deterministic environment, we now extend this analysis to the stochastic environment, i.e., one in which uncertainty is present and, therefore, a simulation-optimization approach –as the one introduced in the previous section– is required.

Table 3.4 shows the results for a low-variance demand ($Var[D_i] = 5\%\ E[D_i]$). For each scenario, we include the expected total costs and the expected reliability of the best-found solution. The last two columns depicts the improvements achieved by the cooperative scenario in terms of expected total cost and reliability. It can be seen that the cooperative scenario outperforms –in terms of total expected costs– the non-cooperative case in all considered instances. Additionally, the reliability of the solutions increases in the cooperative scenario, i.e., route failures occur less frequently. Similar results are shown in Table 3.5 and Table 3.6 for medium-variance demand ($Var[D_i] = 10\%\ E[D_i]$), and high-variance demand ($Var[D_i] = 15\%\ E[D_i]$).

Table 3.4 Results with $Var[D_i] = 5\%\ E[D_i]$

	Non-cooperative		**Cooperative**		**Gap**	
Instance	Expected Total Costs	Expected Reliability	Expected Total Costs	Expected Reliability	Expected Total Costs	Expected Reliability
P01	638.06	96.31%	591.35	100.00%	-7.32%	3.83%
P02	511.64	97.72%	491.83	100.00%	-3.87%	2.33%
P03	682.25	98.84%	671.41	100.00%	-1.59%	1.17%
P05	790.29	99.57%	773.09	100.00%	-2.18%	0.43%
P09	4113.53	97.93%	4047.19	98.56%	-1.61%	0.64%
P10	3914.09	99.30%	3902.52	98.51%	-0.30%	-0.80%
P18	4228.57	91.25%	3855.56	100.00%	-8.82%	9.59%
P19	4227.91	91.37%	3923.45	100.00%	-7.20%	9.45%
P20	4227.57	91.39%	4080.35	100.00%	-3.48%	9.42%
P22	6341.26	91.38%	5899.48	100.00%	-6.97%	9.43%
Average					-4.33%	4.55%

3.1.4.2 Real Case Settings

In order to study the performance of the proposed procedure in a more realistic environment, simulation experiments were undertaken on using real data employed in the works of Muñoz Villamizar et al. (2015) and Montoya-Torres et al. (2016). This dataset contains the

Table 3.5 Results with $Var[D_i] = 10\%\ E[D_i]$

	Non-cooperative		Cooperative		Gap	
Instance	Expected Total Costs	Expected Reliability	Expected Total Costs	Expected Reliability	Expected Total Costs	Expected Reliability
P01	644.34	95.30%	591.35	100.00%	-8.22%	4.93%
P02	514.17	97.03%	491.83	100.00%	-4.34%	3.06%
P03	686.92	97.85%	671.41	100.00%	-2.26%	2.20%
P05	802.23	97.84%	773.09	100.00%	-3.63%	2.21%
P09	4178.24	96.08%	4083.71	99.97%	-2.26%	4.05%
P10	3949.39	98.47%	3921.84	98.87%	-0.70%	0.41%
P18	4294.17	88.68%	3855.62	99.99%	-10.21%	12.75%
P19	4291.28	88.65%	3923.51	99.99%	-8.57%	12.79%
P20	4292.20	88.67%	4080.35	100.00%	-4.94%	12.78%
P22	6439.76	88.64%	5899.56	99.99%	-8.39%	12.80%
Average					-5.35%	6.80%

Table 3.6 Results with $Var[D_i] = 15\%\ E[D_i]$

	Non-cooperative		Cooperative		Gap	
Instance	Expected Total Costs	Expected Reliability	Expected Total Costs	Expected Reliability	Expected Total Costs	Expected Reliability
P01	650.40	94.42%	591.35	100.00%	-9.08%	5.91%
P02	512.92	98.63%	491.83	100.00%	-4.11%	1.39%
P03	690.49	97.04%	671.41	100.00%	-2.76%	3.05%
P05	796.21	98.18%	773.09	100.00%	-2.90%	1.85%
P09	4205.89	95.37%	4111.02	95.20%	-2.26%	-0.18%
P10	3983.54	97.89%	3936.38	97.94%	-1.18%	0.05%
P18	4336.48	87.32%	3855.88	99.94%	-11.08%	14.45%
P19	4332.61	87.40%	3923.74	99.94%	-9.44%	14.35%
P20	4337.97	87.11%	4080.45	99.97%	-5.94%	14.76%
P22	6502.50	87.32%	5899.89	99.94%	-9.27%	14.45%
Average					-5.80%	7.01%

location of the three major convenience stores (proximity shops) operating in Bogotá, D.C. (Colombia). Bogotá is the capital of and the largest city in Colombia. It is the fifth largest city in Latin America and twenty-fifth in the world (Citi Mayors, 2011). The selection of Bogotá as the city under study is at least twofold. Size and dynamics of Bogotá allow having a complex and complete example of the behavior of cities in emerging economies. Modern convenience stores offer not only food, snacks, and drinks, but also daily services, including payment of bills (e.g., utilities), purchase of tickets (e.g., trains/buses, concerts, or sport events) and many others. Current locations of proximity shops of selected companies are obtained using a geographical information system (GIS). Company E has a total of 16 stores, Company O has a total of 35 stores, and Company M has 10 stores. The selected vehicle for urban freight transport was the Renault Kangoo Van, with 800 kg of payload and 119 g/km CO_2 emissions (Renault, 2015). Finally, ten different sets of demands (instances) for all the 61 delivery points were generated. The algorithm was modified to include asymmetric distances by using a weighted savings list associated to the arc connecting nodes i and j which is computed as defined in Herrero et al. (2014):

$$\hat{S}_{ij} = \beta \times max\ (S_{ij}, S_{ji}) + (1 - \beta) \times min\ (S_{ij}, S_{ji}), \beta \in [0.5, 1] \tag{3.13}$$

In equation (3.13), S_{ij} is the saving associated to the arc (i, j) and S_{ji} is the saving associated to the arc (j, i).

We have compared the proposed approach to the work of Muñoz Villamizar et al. (2015), in which a hierarchical approach using mathematical programming was proposed to solve the same problem. Tables 3.7 and 3.8 present a comparison of results for the route length (travel distance) and load, respectively, for each of the ten tested instances. Table 3.7 reports the values, in kilometers, of the total length of the delivery routes for each company under study, as well as the total distance of the three companies together. The last column reports the percentage deviation (gap) between these two approaches. The last row of the table presents the average values of length routes. Table 3.8 presents results obtained for the values of the total load transported by vehicles in terms of the units of product demand. Note that our simulation-based approach was able to improve the solutions for route length, provided by the hierarchical approach of Muñoz Villamizar et al. (2015), in every instance. Route length improvements have an average of around 7%. On the other hand, our approach re-distributes load of company O to company M by an average of 3.1%, while company E continues transporting, on average, the same load. This implies that our approach not only improves routing solution, but also improves the customer allocation to depots.

In order to better assess the behavior of the proposed procedure, an extended simulation experiment was carried out. To this end, we compared the performance of the proposed procedure in terms of the total distribution cost under a stochastic demand behavior. High and mid values of the variance of demand were considered, respectively 50% and 20%, for each of the ten instances previously tested. In addition, a safety stock is allowed with values of 1% and 5% of the vehicle capacity. Table 3.9 presents the average values of key performance metrics allowing the comparison of results for these scenarios. The total stochastic cost corresponds to the total distribution cost under stochastic behavior (i.e. distance cost plus failure costs). The distance cost is the deterministic cost (distance) of planned routes. The failure

Table 3.7 Route length comparison (km) between our approach and a former one.

	Results from Muñoz Villamizar et al. (2015)				Our Best Results				
Scenario	**Dist. E**	**Dist. O**	**Dist. M**	**Total Dist.**	**Dist. E**	**Dist. O**	**Dist. M**	**Total Dist.**	**Gap %**
1	72.6	47.74	94.79	215.13	74.6	52.49	82.92	210.01	-2.38
2	72.1	50.99	104.42	227.51	49.12	49.84	112.87	211.83	-6.89
3	68	61.34	100.47	229.81	47.5	47.54	114.94	209.98	-8.63
4	64.5	59.39	104.12	228.01	63.85	46.44	96.77	207.06	-9.19
5	69.8	45.89	99.32	215.01	74.85	53.59	83.57	212.01	-1.40
6	104	57.64	96.79	258.43	64.6	34.64	110.07	209.31	-19.01
7	67.3	54.24	95.02	216.56	62.3	53.84	93.72	209.86	-3.09
8	71.3	50.59	102.04	223.93	48.1	49.84	111.47	209.41	-6.48
9	74.3	50.09	95.69	220.08	49	49.84	110.32	209.16	-4.96
10	57.05	67.24	98.47	222.76	49.12	49.84	112.37	211.33	-5.13
Average	72.1	54.52	99.11	225.72	58.3	48.79	102.9	210	-6.97

Table 3.8 Total load comparison between our approach and a former one.

	Results from Muñoz Villamizar et al. (2015)				Our Best Results			
Scenario	**Load E**	**Load O**	**Load M**	**Total Load**	**Load E**	**Load O**	**Load M**	**Total Load**
1	720	728	1118	2566	795	797	974	2566
2	734	724	1320	2778	736	679	1363	2778
3	721	723	1144	2588	605	526	1457	2588
4	742	728	1105	2575	795	673	1107	2575
5	723	773	1131	2627	772	737	1118	2627
6	733	722	1252	2707	791	445	1471	2707
7	720	727	1262	2709	769	795	1145	2709
8	721	771	1366	2858	648	655	1555	2858
9	749	738	1356	2843	672	655	1516	2843
10	726	746	1289	2761	706	589	1466	2761
Average	728.9	738	1234.3	2701.2	728.9	655.1	1317.2	2701.2

cost is related to the corrective action executed in order to satisfy the total demand of clients (round trip customer-depot).

Box-and-whisker plots are presented in Figures 3.1 and 3.2 comparing the total stochastic cost and the reliability values by the different values of variance and safety stock. After these figures, we conclude that there is a clear difference in the quality of solutions with low variance and low safety stock level versus high variance and high level of safety stock. It might not be surprising that total costs are higher for the highest variance of demand (i.e., 1.89% higher on average). Nevertheless, a higher reliability is achieved for the highest safety stock level (i.e., 3.97% higher on average). Therefore, it can be concluded that safety stock avoids failures in delivery in a greater proportion than the generated over cost. Another interesting feature is the small variance in the reliability for just 5% of safety stock.

Table 3.9 Comparison of best results with different safety stock and variance levels.

	Variance = 20%, Safety Stock = 1%				Variance = 50%, Safety Stock = 5%			
Instance	**Total Stochastic Cost (km)**	**Distance Cost (km)**	**Failure Costs (km)**	**Reliability**	**Total Stochastic Cost (km)**	**Distance Cost (km)**	**Failure Costs (km)**	**Reliability**
1	223.79	223.29	0.5	97.30%	228.01	227.95	0.07	99.60%
2	229.46	228.52	0.94	94.70%	238.11	238.1	0.02	99.90%
3	222.64	222.3	0.34	97.30%	230.58	230.53	0.05	99.60%
4	223.45	222.82	0.63	95.40%	230.3	230.25	0.05	99.70%
5	227.96	227.21	0.75	96.70%	230.8	230.75	0.04	99.70%
6	228.49	227.73	0.76	95.40%	229.54	229.5	0.04	99.80%
7	228.4	227.58	0.82	95.60%	230.63	230.57	0.06	99.70%
8	231.29	230.69	0.6	96.90%	233.91	233.88	0.04	99.80%
9	231.73	231.39	0.35	98.10%	234.82	234.77	0.05	99.80%
10	228.76	228.45	0.31	98.40%	230.61	230.59	0.02	99.80%

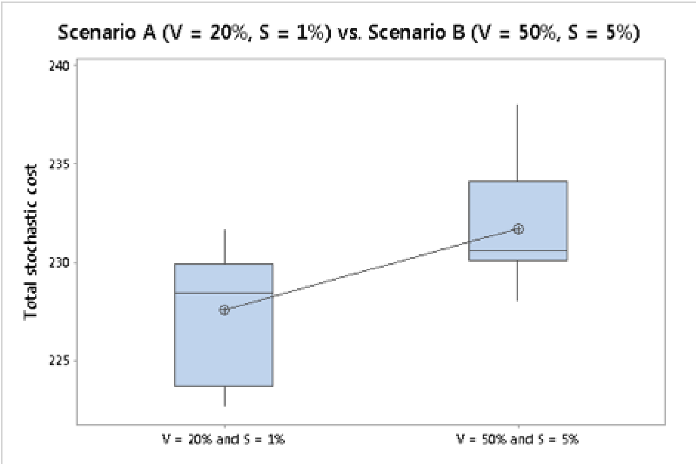


Figure 3.1 Comparison between scenarios for stochastic costs.

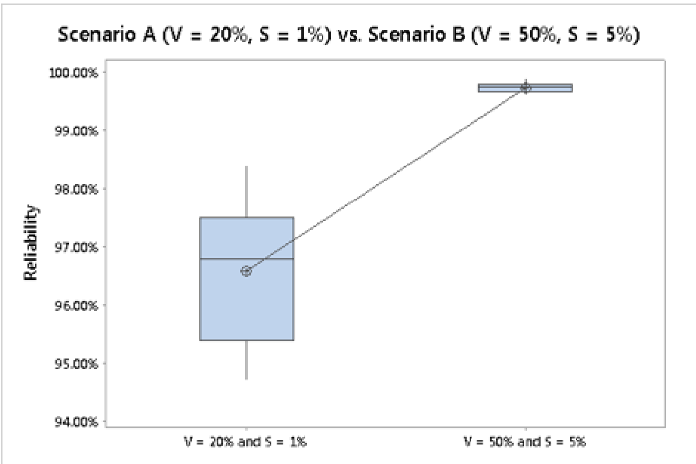


Figure 3.2 Comparison between scenarios for reliabilities.

3.2 Multi-Objective Cooperative Urban Freight Distribution with Electric Vehicles

As pointed out before, the VRP is a central problem in transportation (Bektaş et al., 2016). The standard objective function for traditional VRP is to minimize the total traveling distance, while many of the works on the Green VRP (GVRP) consider the reduction of pollutants, such as nitrogen oxides (N_2O), particulate matter, and greenhouse gases (GHG). Some works directly add those items into the objective function, while many more consider fuel consumption related terms (Demir et al., 2014b), since fuel consumption can sometimes be used as a surrogate measure for the emissions of air pollutants. The simultaneous consideration of economic and environmental objectives leads to a more complex optimization problem. Furthermore, an important characteristic of real-life logistics problems found in enterprises is that decision-makers, very often, have to simultaneously deal with multiple objectives. These objectives are sometimes contradictory (e.g., minimizing number of vehicles and maximizing service level). As pointed out by Pérez-Bernabeu et al. (2015), very few papers have discussed horizontal cooperation through multi-objective / multi-criteria decision-making models. There are very few papers in the literature on the MDVRP that consider multiple objectives (Montoya-Torres et al., 2015). In the context of GVRP, using electric vehicles represents a promising opportunity for reducing costs and pollution caused by transport and mobility operations. Despite the fact that some limitations, such as high initial investments, have hampered their diffusion, there is continuous technological progress to improve them (Felipe et al., 2014; Feng and Figliozzi, 2013). As pointed out by Arslan et al. (2015), the use of electric vehicles in the logistic operations led to several new problems flourishing in the literature such as pollution-routing problem (Bektaş and Laporte, 2011; Demir et al., 2014a; Franceschetti et al., 2013; Çağrı Koç et al., 2016), green-vehicle routing problem (Erdoğan and Miller-Hooks, 2012; Felipe et al., 2014; Jabir et al., 2015; Ćirović et al., 2014), location optimization of alternative fuel stations (Yıldız et al., 2016), and mixed-fleet routing problems (Goeke and Schneider, 2015; Schneider et al., 2014). These studies establish the environmental and operational impacts of electric vehicles from the logistic perspective. As stated by Lin et al. (2014), GVRP have just arisen in the literature in recent years and there is a continuing need to enrich the related studies either through theoretical contributions or by real applications.

3.2.1 Methodology

Our methodology, based on the one of Montoya-Torres et al. (2016); Muñoz Villamizar et al. (2013), is composed of three main phases. Phase 1 defines the characteristics of the urban freight transport network. Phase 2 solves customer allocation and routing sub-problems; and, finally, phase 3 allocates the type of vehicles and creates an efficient relative frontier. Details of each phase are described next.

3.2.1.1 Characterization of Urban Transport Network

In this phase, we identify elements of the case under study. Key elements are: location of depots and delivery points (e.g., stores), demand of each delivery point, distances/cost between nodes (i.e. travel distances between depots and delivery points and between delivery points themselves). In addition, we consider the different characteristics of the available vehicle types (e.g. power source, autonomy, CO_2 emissions, capacities, etc.)

As this approach seeks to assess the environmental impact, emission factors for each vehicle type must be calculated in order to compute total CO_2 emissions. These emission factors are computed considering *(i)* the emissions generated by the production of the energy and, *(ii)* the emissions due to the transportation operation itself. As energy can be generated using different sources (e.g., oil, natural gas, nuclear, hydroelectric or solar), production of energy has different costs and emissions depending on both the local diversity of power plants and distribution network efficiency. Therefore, CO_2 emissions will be different for each country where this approach is applied. In addition, energy consumption depends on both the given use and the efficiency of the vehicles, i.e., costs and emissions generated in the delivery process directly depend on the activity and usage of fleet vehicles. Estimations of these factors will be shown further in the experiments section.

3.2.1.2 Costumers' Allocation and Routing

In this phase, we use the Algorithm 1 described in subsection 3.1.3.

3.2.1.3 Allocation of Vehicle Types and Efficient Relative Frontier

After routes are defined minimizing the distance, a multi-objective evaluation is performed to evaluate the impact of the use of electric vehicles compared to gasoline vehicles, using a relativized efficient frontier. It is important to recall that very few papers have discussed horizontal cooperation or MDVRP through multi-objective / multi-criteria decision-making models. This relativized efficient frontier is proposed by Muñoz Villamizar et al. (2017).

The efficient frontier is the set of non-dominated solutions for the combination of different objectives. Depending on the decision maker preferences, a different solution could be chosen from the efficient frontier. In our approach, two impacts are taken into account in this evaluation: economic and environmental costs (CO_2 emissions). However, other objective functions, as social impact, could be simultaneously evaluated using this relativization methodology. This is, as each impact has different units (i.e. US$ for the costs and CO_2 emissions for the environmental impact), it is convenient to perform the relativization of each of them. Thereby, every impact can be evaluated in the same objective function as a weighted-sum of factors. The proposed procedure is different from other known multi-objective approaches and determines the type of required vehicles for each route defined in the previous phase. It is important to clarify that this sequential approach implies that results of the previous phase are inputs for this one. The relativized efficient frontier is created using three different objective functions (i.e., f_1, f_2 and f_3), presented next. Note that our approach uses one objective function for each evaluated impact (i.e., f_1 for economic cost and f_2 for environmental impact) and an additional function that aggregates the two previous ones (i.e. f_3). First objective function, f_1, computes the economic cost of using a specific combination of gasoline and electric vehicles in the routes (e.g., route 1 uses an electric car, route 2 a gasoline car, etc.). In our approach, economic cost is calculated using the purchase price of each vehicle, its maintenance cost and the cost of used energy (i.e., gasoline or electricity) in transport operation. Objective function f_2 computes the environmental impact. Environmental impact is estimated using the CO_2 emissions created by the production of the energy and the emissions created by the consumption of the energy itself. According to this, our approach evaluates every possible combination of allocation of vehicle types to each route, by computing f_1 and f_2 separately. Best solutions obtained so far, for each objective function, are kept as the basis solution f_1^* and f_2^*. Then, objective function f_3 is computed (see Equation 3.14) with every possible combination of allocation of vehicle used in previous step. It is important to emphasize that functions f_1 and f_2, along with f_1^* and f_2^*, must be evaluated previously and are inputs of f_3.

$$f_3 = \alpha \times \frac{f_1}{f_1^*} + (1-\alpha) \times \frac{f_2}{f_2^*} \tag{3.14}$$

Note that the objective function f_3 is used to calculate a relativized solution. This relativization occurs giving different weights to each impact (i.e. α weight for economic cost and $1-\alpha$ weight for CO_2 emissions). According to the preferences of the decision maker, different weights for each impact can be evaluated. It should be noted that the minimum value for this third function is 1, as a result of the relativization. Then, for each selected weight of each impact (i.e. α and 1–α), the best solution of f_3 obtained so far, is kept as the basis solution. Finally, the efficient frontier is created using the best results in third function, f_3, for all combinations of selected weights.

3.2.2 Experiments & Results

For the short-term evaluation (i.e. 1 year), weekly demands for all the 61 delivery points was randomly generated from a uniform distribution between the 1% and the 10% of the maximum vehicle load capacity. For the mid-term evaluation (i.e. 5 years), annual increases of 5% and 25% are added to this random generation. In order to replicate the experiments, full origin-destination matrices and stochastic demand sets are available upon request. It is also assumed that availability of the necessary vehicles achieves a 100% of service level.

Selected vehicles for urban freight transport were Renault Kangoo Van (gasoline vehicle) and Renault Kangoo Z.E. (electric vehicle). Characteristics of these used vehicles are resumed in Table 3.10. Note that both models have the same payload and are from similar category, thus they can be comparable one each other. As mentioned before, the economic cost components that we consider in this study are the cost of used energy (i.e., electricity or gasoline), the price of each vehicles and the yearly maintenance cost (Table 3.11).

Table 3.10 Characteristics of each vehicle type (Renault Colombia, 2016)

	Kangoo Van (Gasoline Car)	Kangoo Z.E. (Green Car)
Price	US$ 15,423.73	US$ 28,813.56
Payload	650Kg	650Kg
Energy Consumption	4.3 litres/100km	16.2 kWh/100Km*
CO_2 emissions	112 g/Km	0 g/Km

Table 3.11 Approximate yearly maintenance cost (US$) per vehicle type (Audatex, 2016).

	Kangoo Van (Gasoline Car)	Kangoo Z.E. (Green Car)
Year 1	US$ 324	US$ 138
Year 2	US$ 430	US$ 457
Year 3	US$ 351	US$ 269
Year 4	US$ 733	US$ 524
Year 5	US$ 667	US$ 138

Alternatively, environmental components of the distribution process are: the CO_2 emissions by the production of the energy (i.e. electricity or gasoline) and the emissions by the consumption of the energy itself. It is to note that each country has a mix of power plants that use different energy sources; so, the economic cost and the CO_2 emissions will be different for obtaining electricity or gasoline in each country. According to the Colombian Ministry of Mines and Energy, 64% of electricity in the country is produced by water resources, 31% by thermal resources, and other sectors such as wind energy is now being explored (Comisión de Regulacion de Energia y Gas, 2015). The price of electricity in Bogotá is \$0.18/kWh (CODENSA, 2016) and the price of gasoline is \$0.67 per liter (GlobalPetrolPrices.com, 2016). Colombia has a rate of 0.199 kg of CO_2 emissions per kWh of electric energy produced and 2.33 kg of CO_2 emissions per litre of gasoline produced (Unidad de Planeación Minero Energética , 2016). These factors are used to calculate the quantity of emissions created by the use of each energy source. Finally, with this data, costs and CO_2 emissions per kilometer were calculated for both type of vehicles and are presented in Table 3.12. Note that CO_2 emissions per kilometer are computed as the sum of the emissions generated by the usage of the vehicle and the ones generated by producing its respective energy source (i.e. gasoline or electricity).

Table 3.12 Variable costs and emissions per vehicle type

	Kangoo Van (Gasoline Car)	Kangoo Z.E. (Green Car)
Cost / km	0.029 US\$ /km	0.023 US\$/ km
CO_2 emissions / km	0.212 kg/km	0.032 kg/km

As an initial comparison, results for routing of Muñoz Villamizar et al. (2017) and our results are presented in Figure 3.3. Notice that our approach was able to improve the routing solutions provided by the heuristic method of Muñoz Villamizar et al. (2017), in an average of 10.3%. This value is equivalent to an average reduction of 23 km in routing distances per instance. Nevertheless, given the cost of traveling one kilometer (less than 0,029 US\$/kilometer), money savings are not as significant as the distance reduction.

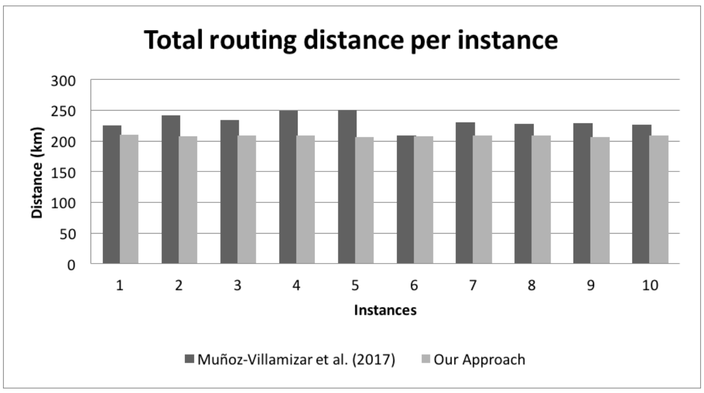


Figure 3.3 Distances comparison of our results vs Muñoz Villamizar et al. (2017)

Finally, complete results of Muñoz Villamizar et al. (2017) with updated data and our approach are presented in Tables 3.13 and 3.14, respectively; while efficiency frontier for both approaches are shown in Figure 3.4. Different values of α (i.e. α=weight for cost and 1–α=weight for CO_2 emissions) were proposed to show the behavior of the efficiency frontier. Improved results in cost (f_1) and emissions (f_2) functions, and hence in the efficiency frontier, are due to the improvement of the solution method. This is, the proposed approach makes a better customer allocation and an improved vehicle routing. Small improvements in cost functions are due to the low costs of traveling compared to the purchasing cost of each vehicle. Therefore, we can state a preliminary good performance of the proposed method.

Table 3.13 Results from Muñoz Villamizar et al. (2017)

α	Cost function f_1	Environmental function f_2	Relative function f_3	% of electric vehicles
1.00	61,702	49.2	1.00	0%
0.98	63,041	47.6	1.56	3%
0.78	71,074	40.1	1.66	18%
0.58	83,125	30.0	1.70	40%
0.33	96,514	19.5	1.71	65%
0.13	105,887	12.8	1.72	83%
0.03	112,582	8.7	1.69	95%
0.00	115,260	7.4	1.00	100%

Table 3.14 Summary of results

α	Cost function f_1	Environmental function f_2	Relative function f_3	% of electric vehicles
1.00	61,701	44.2	1.0	0%
0.89	63,040	43.0	1.6	3%
0.88	73,751	34.2	1.7	23%
0.87	84,463	26.2	1.7	43%
0.86	97,853	17.0	1.7	68%
0.85	108,564	10.3	1.7	88%
0.82	113,920	7.3	1.7	98%
0.00	115,259	6.7	1.0	100%

3.2.2.1 Short Term Evaluation

Weekly demands for all the 61 delivery points were randomly generated from a uniform distribution in order to analyze short impacts in the use of electric vehicles in the configuration of the transport network. Therefore, 52 different instances were evaluated with the proposed approach to simulate the complete transport operation for a full year. This experiment allows a better comparison between the costs of acquiring the vehicles and the costs of the

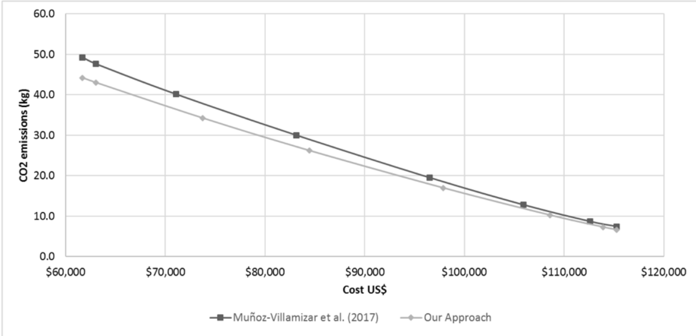


Figure 3.4 Comparison of our results vs Muñoz Villamizar et al. (2017)

transportation activities. Results for this scenario are presented in Table 3.15 and Figure 3.5. As mentioned before, different values of α were proposed to fully show the behavior of the efficiency frontier. For this one-year evaluation, the cheapest option is to keep the entire gasoline fleet. However, after considering a 0.04 value in the weight for CO_2 emissions (i.e., 1-α) the optimal solution is made by a complete electric fleet. This is, the improvement in the environmental impact is, relatively, much greater than the cost overruns of having all electric fleet of vehicles. In this case, having the entire electric fleet of vehicles generates an economic overrun of 22%, but a reduction of almost 88% in the environmental impact; compared to having the entire fleet of gasoline vehicles.

Table 3.15 Results for one-year operation

α	Cost function f_1	Environmental function f_2	Relative function f_3	% of electric vehicles
1.00	129,579	190,927	1.0	0%
0.98	135,407	140,895	1.2	25%
0.97	142,005	97,362	1.2	50%
0.96	149,000	57,168	1.2	75%
0.00	156,727	23,149	1.0	100%

3.2.2.2 Mid Term Evaluation

Finally, for a better understanding of the transportation operation, a period of five years is evaluated. Two additional key aspects have been taken into account in this mid-term evaluation of the use of electrical vehicles. Firstly, the yearly maintenance cost (see Table 3.11) and, secondly, the variations in customer demands are considered over time. For this second aspect, two different yearly increases of 5% and 25% are separately evaluated. This is 260 instances were generated for each annual increase, for a total of 520 weekly demands for all the 61 delivery points.

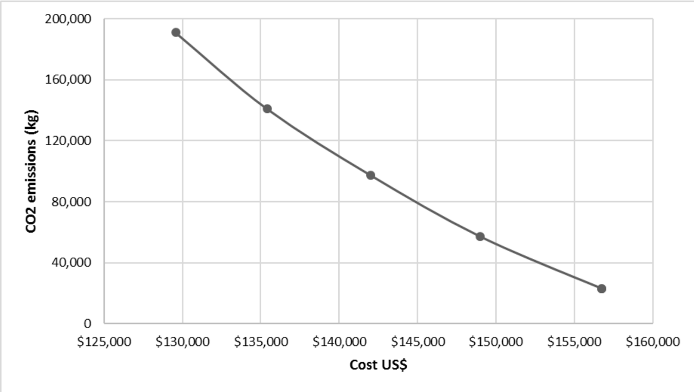


Figure 3.5 Efficient frontier for one-year operation

Annual increase in demand by 5%

Results of applying the proposed approach for a time horizon of 5 years with demand increases of 5% per year are presented in Table 3.16 and Figure 3.6. An unexpected result with two extremes is obtained. For this scenario, the cheapest option is to keep just one gasoline vehicle. Once again, after a 0.04 value in the weight for CO_2 emissions (i.e., 1-α) the optimal solution is to have the entire electric fleet. The main reason for this result is that maintenance costs of gasoline vehicles are, in med-term, higher than maintenance costs of electric vehicles. In this scenario. having the entire electric fleet of vehicles generates an economic overrun of only 2%, but a reduction of almost 29% in the environmental impact, compared to having a 20% of gasoline vehicles (i.e., 1 gasoline vehicle in the fleet).

Table 3.16 Results for five-year operation with yearly increments of 5% in demand

α	Cost function f_1	Environmental function f_2	Relative function f_3	% of electric vehicles
1.00	294,577	167,011	1.00	80%
0.96	294,577	167,011	1.02	80%
0.00	300,388	118,872	1.00	100%

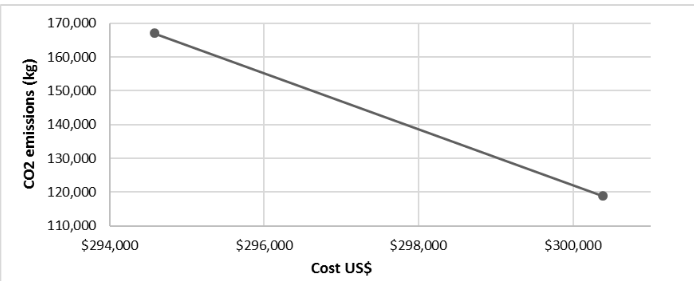


Figure 3.6 Efficient frontier for five-year operation with annual increments of 5% in demand

On the other hand, and for a better understanding of last results, Figure 3.7 shows the number of vehicles required per year when $\alpha = 1$. In this case, the one and only gasoline vehicle is purchased in the third year. This behavior asserts that electric vehicles are more profitable in mid-term, while gasoline vehicles are in the short-term because of the purchasing price of this type of vehicle. It is important to emphasize that demand increase is very low, thus, it is only necessary to purchase an additional vehicle to completely meet the demand during the last 3 years of operation. Since this last vehicle will be used only for 3 years, it is more profitable to buy a gasoline vehicle than an electric one.

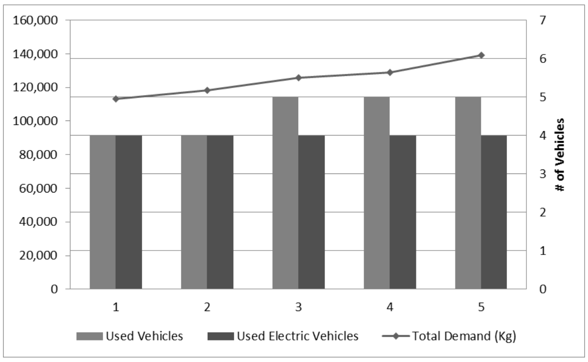


Figure 3.7 Yearly demand and used vehicles with α=1 and demand growth = 5%

Annual increase in demand by 25%

Last scenario evaluates a 25% annual increase in demand for 5 years. Results of applying the proposed approach are presented in Table 3.17 and Figure 3.8. In this scenario. the cheapest option is to keep one half of gasoline fleet and the other half electric; while only after a 0.56 value in the weight for CO_2 emissions (i.e., 1-α) the optimal solution is to have the entire electric fleet. In this scenario. having the entire electric fleet of vehicles generates an economic overrun of only 8%. but a reduction of almost 56% in the environmental impact; over having a 50% of gasoline vehicles (i.e., 5 gasoline vehicle in the fleet).

Table 3.17 Results for Five-Year Operation with Yearly Increments of 25% in Demand

α	Cost function Z_1	Environmental function Z_2	Relative function Z_3	% of electric vehicles
1.00	454,564	318,045	1.00	50%
0.97	456,721	239,100	1.03	60%
0.92	462,131	187,585	1.04	70%
0.86	470,512	160,416	1.05	80%
0.44	480,026	143,020	1.04	90%
0.00	492,327	140,295	1.00	100%

This solution initially seems different from the obtained in the previous scenarios. However, the results have the same explanation. Figure 3.9 shows the number of vehicles required per year as demand grows. When only the economic impact is taken into account (i.e. α=1). In this case, a fixed number of electric vehicles is purchased from the very first year (i.e., 4 vehicles) and as demand increases only in the second year a new electric vehicle is purchased. Then, only gasoline vehicles are purchased to meet customer requirements. Once again is confirmed that electric vehicles are more profitable in a 4-5 years evaluation. while gasoline vehicles are more profitable in a 1-3 years time-horizon.

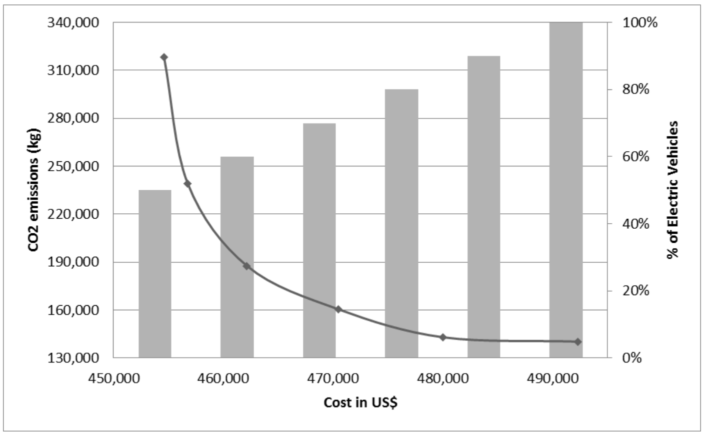


Figure 3.8 Efficient frontier for five-year operation with annual increments of 25% in demand

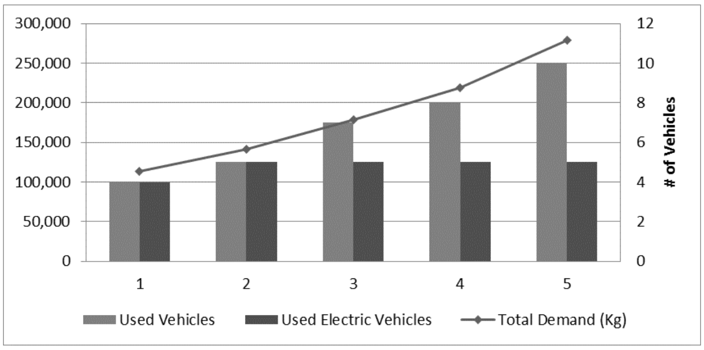


Figure 3.9 Yearly demand and used vehicles with α=1 and demand growth = 25%

Another remarkable aspect of this scenario is that a considerable amount of electric vehicles (EVs) is profitable for any value of α or 1-α (i.e., weight for economic cost and weight for environmental impact, respectively). As it can be seen in Figure 3.10 at least 50% of the fleet of vehicles must be electric for any combination of the multi-objective function. This confirms once again that electric vehicles are economically and environmentally profitable for mid-term evaluation.

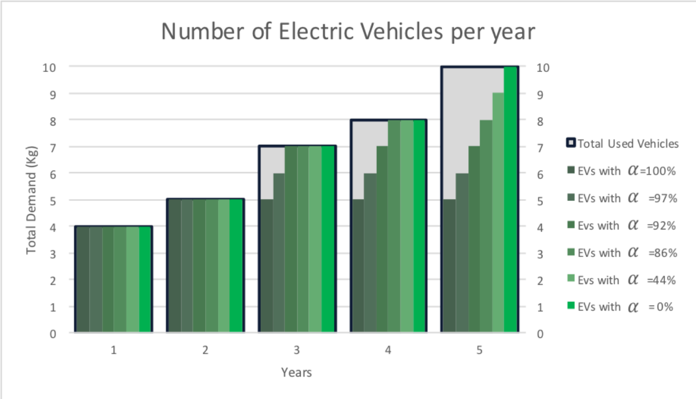


Figure 3.10 Number of used electric vehicles per year according to α values

3.3 Chapter Conclusions

This chapter analyzes how horizontal cooperation strategies can contribute to reduce distribution costs in urban freight transportation under uncertainty. The non-cooperative scenario is modeled as a series of isolated vehicle routing problems with stochastic demands, while the cooperative scenario is modeled as a multi-depot vehicle routing problem with stochastic demands.

In order to solve both scenarios, a simheuristic approach is proposed. Our algorithm combines a biased randomization based iterated local search metaheuristic with Monte Carlo simulation. A set of classical benchmark instances has been adapted and extended in order to perform some computational experiments. According to the results obtained, the cooperative strategy can generate noticeable reductions in total costs for all the considered instances. The reliability of the provided solutions is also reported by the simheuristic algorithm. In addition, our approach has been compared to already published works using a realistic dataset, outperforming their results. Extended simulation experiments were executed to evaluate the impact of the variance of demand (stochastic behavior) in the distribution costs. Results showed that safety stock policy and the variance of demand influence total distribution costs and process reliability. Furthermore, we have evaluated the use of electric vehicles in urban freight transport cooperative networks. Several aspects were taken into account to fully evaluate the transport operation in short- and mid-term scenarios, from both economic and environmental perspectives. Purchasing and maintenance vehicles costs and the cost of used energy (i.e., electricity or gasoline). were considered as economic costs. On the other hand, CO_2 emissions by the production of the energy (i.e. electricity or gasoline) and the emissions by the consumption of the energy itself were selected as environmental components. Then, experiments for 1 and 5 years were performed to find an efficient frontier solution regarding the use of electric vehicles for short- and mid-term, respectively. Our findings suggest that purchase of new vehicles (electrics or gasoline) depends on the time horizon left for the operation. This is, electric vehicles are more profitable, both economically and environmentally, for periods of more than 3 years; while gasoline vehicles are better for short-time operation because of their lower purchasing cost.

Chapter 4

The Capacitated Location Routing Problem

The contents of this chapter is based on the following publications:

- Quintero-Araujo, C.L.; Caballero-Villalobos, J.P.; Juan, A.; Montoya-Torres, J.R. (2017) "A Biased-Randomized Metaheuristic for the Capacitated Location Routing Problem". International Transactions in Operational Research, 24: 1079–1098. ISSN: 0969-6016. doi:10.1111/itor.12322 (*JCR*)

- Quintero-Araujo, C.L.; Gruler, A.; Juan, A.; Faulin, J. (*Under Review*) "Using Horizontal Cooperation Concepts in Integrated Routing and Facility Location Decisions". International Transactions in Operational Research. ISSN: 0969-6016. (*JCR*)

- Quintero-Araujo, C.L.; Guimarans, D.; Juan, A. (*Under Review*) "A SimILS Algorithm for the Capacitated Location Routing Problem with Stochastic Demands". Journal of the Operational Research Society. ISSN: 0160-5682. (*JCR*)

- Quintero-Araujo, C.L.; Juan, A. (2015): "Solving the Integrated Location Routing Problem considering Uncertainty and Risk Factors". Proceedings of the ICRA6/Risk 2015 Int. Conference, 655-662. ISBN: 978-84-9844-496-4. Barcelona, Spain

In logistics management, facility location and route planning are linked decisions. However, in most real-life situations, these decisions are taken in an independent way. On the one hand, the size and location of logistics facilities is decided without considering its effects on routing plans. On the other hand, customers are served from facilities to which they were previously allocated, usually. To overcome this situation, the scientific community has recently started to study the location routing problem (LRP). The aim of the LRP is to determine *(i)* the number, size and location of facilities to be opened, *(ii)* the customer allocation to open facilities and *(iii)* the corresponding routes to serve customer demands that minimize total costs (opening + routing + vehicles). In practical terms, the LRP combines the facility location problem (FLP) with the VRP, which are known to be NP-Hard (Nagy and Salhi, 2007). Thus, the LRP is also NP-hard. The location routing problem (LRP) is one of the most complete problems in logistics and transportation because it involves all decision levels in supply chain design and management, that is, the strategic, tactical, and operational levels. A graphical description of this problem is presented in figure 4.1. In fact, the classical approaches used to tackle the LRP are based on solving an FLP as a first step and then solving the associated VRPs. Nowadays, due to the development of computers and optimization techniques, there is an increasing interest in solving the LRP in a more integrated way. The LRP has a wide range of applications including, among others, food and drink distribution, waste collection, or bill deliveries (Nagy and Salhi, 2007).

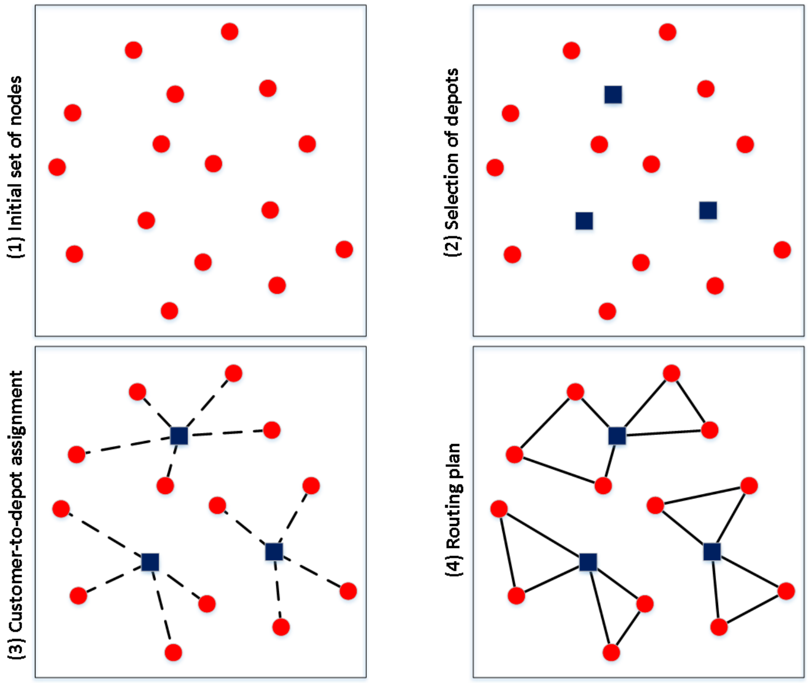


Figure 4.1 An illustrative description of the LRP

The idea of combining depot location with vehicle routing was proposed about 50 years ago. Maranzana (1964) was probably the first publication on the LRP, which stated that "the location of factories, warehouses and supply points in general . . . is often influenced by transport costs" (p. 261). The benefits obtained by considering vehicle routing decisions while locating depots were quantified for the first time by Salhi and Rand (1989). These authors showed that solving a location problem and routing problem separately does not necessarily lead to optimal solutions. There are several variants for the LRP depending on the characteristics of the depots (capacitated or not), vehicles (capacitated or not, homogeneous or heterogeneous fleet), costs (symmetric or asymmetric), or the consideration of uncertain (stochastic) parameters.Taking this into account, this chapter addresses the Capacitated Location Routing Problem (CLRP) in both versions: with deterministic and stochastic demands.

4.1 Deterministic Version

4.1.1 Problem Statement

The CLRP can be described on a graph $G = (V, A, C)$, where the set of nodes $V = I \cup J$ includes: *(i)* a set of n customers, $I = \{c_1, c_2, \dots, c_n\}$; *(ii)* a set of m potential depot locations, $J = \{d_1, d_2, \dots, m\}$. A is the set of arcs connecting each par of nodes, while C is the cost matrix of traversing arcs. A set K of unlimited homogeneous vehicles with capacity Q is available. It is also assumed that each arc $a \in A$ satisfies the triangle inequality. Let S be a subset of nodes, $\delta^+(S)$ ($\delta^-(S)$) be the set of arcs leaving (entering) S, and $L(S)$ the set of arcs with both ends in S. Customer demands are deterministic and known in advance. The capacity of each depot and its opening costs are known. Depots might have equal or different capacities between them. Each customer must be served by a single vehicle departing from the depot to which the customer has been allocated. A solution for the CLRP consists in determining which depots must be opened, the customer allocation to open depots, and design of vehicle routes for serving customers from their corresponding depot. The following constraints must be satisfied: *(i)* the total demand of customers assigned to one depot must not exceed its capacity, *(ii)* each route begins and ends at the same depot, *(iii)* each vehicle performs at most one trip, *(iv)* each customer is served by one single vehicle (split deliveries are not allowed), and *(v)* the total demand of customers visited by one vehicle fits its capacity.

According to Prins et al. (2006b), the CLRP can be formulated as a mixed integer linear programming (MILP) model using the following parameters and variables:

- O_j : opening cost of depot j
- $DepCap_j$: capacity of depot j
- d_i: demand of customer i
- Q: capacity of each vehicle
- VF: fixed cost for using a vehicle
- C_a: cost of traversing the arc a
- Y_j : binary variable to represent if the depot location j is opened or not
- X_{ij} : binary variable to represent if customer i is assigned to the facility j or not

- f_{ak}: binary variable to indicate if arc a is used in the route performed by vehicle k or not

$$\text{Min Z=} \sum_{j\in J} O_j Y_j + \sum_{a\in A} \sum_{k\in K} C_a f_{ak} + \sum_{k\in K} \sum_{a\in\delta^+(J)} VF f_{ak} \tag{4.1}$$

Subject to:

$$\sum_{k\in K} \sum_{a\in\delta^-(i)} f_{ak} = 1 \qquad \forall i \in I \tag{4.2}$$

$$\sum_{i\in I} \sum_{a\in\delta^-(j)} d_i f_{ak} \leq Q \qquad \forall k \in K \tag{4.3}$$

$$\sum_{a\in\delta^+(j)} f_{ak} - \sum_{a\in\delta^-(j)} f_{ak} = 0 \qquad \forall k \in K, \forall j \in V \tag{4.4}$$

$$\sum_{a\in\delta^+(i)} f_{ak} \leq 1 \qquad \forall k \in K, \forall i \in I \tag{4.5}$$

$$\sum_{a\in L(S)} f_{ak} \leq |S| - 1 \qquad \forall S \subseteq I, \forall k \in K \tag{4.6}$$

$$\sum_{a\in\delta^+(j)\cap\delta^-(I)} f_{ak} + \sum_{a\in\delta^-(i)} f_{ak} \leq 1 - X_{ij} \qquad \forall i \in I, \forall j \in J, \forall k \in K \tag{4.7}$$

$$\sum_{i\in I} d_i X_{ij} \leq DepCap_j Y_j \qquad \forall j \in J \tag{4.8}$$

$$f_a, X_{ij}, Y_i \in \{0, 1\} \qquad \forall a \in A, \forall k \in K, \forall i \in I, \forall j \in J \tag{4.9}$$

The objective function, presented in equation 4.1, is the minimization of total costs – which include opening costs, distance-based costs, and usage of vehicles costs. Constraints 4.2 are to guarantee that each customer is served once. Expressions 4.3 are vehicle capacity constraints. Inequalities 4.4 and 4.5 guarantee the continuity of each route and return of a route to the depot from which it has started. Constraints 4.6 are to eliminate sub-tours. Constraints 4.7 guarantee that a customer is only assigned to a depot if there are routes serving that depot. Constraints 4.8 specify that depot capacity cannot be violated. Constraints 4.9 define the decision variables.

4.1.2 A Biased-Randomized Iterated Local Search for the Deterministic LRP

Two main ideas are the basis of our solving approach. The first one is the use of very simple (with few parameters to avoid long fine tuning processes) and, at the same time, fast heuristics to solve complex problems. The second one is to involve all decisions at each phase of the algorithm, i.e. using an integrated approach. Another key point of our approach is the use of biased randomization techniques to obtain new solutions. Biased randomization techniques (Juan et al., 2013a) are applied at different stages of the algorithm. During the iterative construction of a feasible solution, solution elements are hereby randomly chosen according to a skewed probability function, biased towards the most promising elements. While our algorithm is flexible enough to apply any non-uniform distribution, we use the single-parameter geometric distribution. More specifically, biased randomization is used during *(i)* the generation of customer-depot allocations, and *(ii)* the subsequent planning of delivery routes.

Our solving approach consists of two phases: *(i)* generation of feasible solutions and selection of the most promising ones; and *(ii)* improvement or refinement of the selected solutions. To generate feasible solutions we decompose the original problem into a set of successive and less complex problems by using simple and fast procedures. In this case, the CLRP can be easily transformed into the MDVRP once we have decided the open depots. Once the customers are allocated to the depots, the MDVRP becomes a m-CVRP (m defining the number of open depots). Each CVRP can be solved by a fast and high quality heuristic, e.g. the Clarke & Wright Savings Heuristic (Clarke and Wright, 1964). The second phase is the improvement of customer allocation and routing for each of the top solutions found in the first phase.

4.1.2.1 Selection of Promising Solutions

In order to obtain feasible solutions, the first step is to estimate the number of facilities required to serve all customers' demands. We start by computing a lower bound ($lowerbound$) on the number of facilities to be opened by dividing the expected total demand by the highest capacity of the set of depots. Then, 30 feasible combinations of open depots are generated for each value of l, ($lowerbound \leq l \leq m$). For each of these sets of combinations, the associated CLRP is solved by means of a fast allocation and routing heuristic. Then, the average cost is computed for each l. We keep the l value with the lowest average cost as a promising number of open depots. The value of $lowerbound$ is then updated as the maximum between its original value and $l - 1$. Also, the value of $upperbound$ is set to $l + 1$.

Next, we randomly determine sets of l^* 'candidate' facilities (with $lowerbound \leq l^* \leq upperbound$), during at most $nInitialIters$. Then, customers are allocated to different depots according to the savings s_{id} of serving any customer i from any depot d. The value of s_{id} is defined as the cost difference of serving customer i from depot d instead of the closest alternative depot d^*, such that $s_{id} = c_{id} - c_{id^*}$. Once each depot specific savings list has been created, the customer-depot allocations are defined in an iterative round-robin tournament. In turn, each depot chooses a customer to serve according to the geometric distribution parameter β, which defines the probability of the most promising customer being assigned to the current depot (Juan et al., 2015b). Next, delivery routes are constructed using a biased randomized version of the Clarke-and-Wright savings heuristic (CWS) (Clarke and Wright, 1964). This procedure is based on the calculation of savings values for all edges in the problem. According to the defined savings, a feasible routing solution is constructed. In the biased randomized CWS, the node connections are ranked according to their expected savings at each edge selection step. The probabilities for each edge are calculated according to the geometric distribution parameter α, which defines the probability of the edge with the highest savings value to be chosen (Juan et al., 2011b).

4.1.2.2 Improvement Phase

In this step, the aim is to determine new customer-depot allocations and the corresponding new routes in order to improve the $baseSols$ already obtained. It is to note that the set of open depots of each solution does not change. This improvement is done by an ILS algorithm.

As a first step, we extract the allocation map for each $baseSol$ from the $nbaseSols$ and apply a perturbation procedure on it for a total of $maxPerturbIter$ times. The perturbation procedure is used to obtain new customer-depot allocations. For each open depot we randomly select a node from its allocation map and try (due to capacity constraints) to assign it together with its nearest nodes to another open depot. Then, in order to complete a new CLRP solution ($newSol$), we apply the biased-randomized version of the CWS heuristics (SR-GCWS-CS algorithm) proposed by Juan et al. (2011b). This routing heuristic is executed a total of $maxRoutingIter$ times on each new customer-depot allocation. After that, a local search procedure is applied on the $newSol$ to obtain $newSol^*$, if necessary, we update both the best solution found so far –$bestSol$– and $baseSol$. If the $newSol$ is worse than $bestSol$ we apply an acceptance criterion to update our $baseSol$ and, therefore, to escape from local optima. We accept a non-improving $newSol$ when the difference between the cost of $newSol$ and the cost of $bestSol$ is lower than 1.5 times the last improvement achieved.

At the end of the $maxPerturbIter$ we report the solution with the lowest total costs – Sum of opening costs, vehicles usage cost and distance cost– ($bestSol$) obtained from all $baseSols$. The pseudo-code corresponding to this phase is presented in Algorithm 3.

Algorithm 3: BR-Iterated Local Search

```
Input: inputs, parameters
initialize(variables)
baseSols ← createInitialSolutions(inputs, parameters)
costs(bestSol) ← BigM
foreach baseSol ∈ baseSols do
    while stopping criteria not reached do
        newSol ← perturbate(baseSol)
        improving ← true
        while improving do
            newSol* ← localSearch(newSol)
            if costs(newSol*) < costs(newSol) then
                newSol ← newSol*
            end
            else
                improving ← false
            end
        end
        delta ← costs(newSol*) - costs(baseSol)
        if delta < 0 then
            baseSol ← newSol*
            credit ← 1.5 × delta
        end
        else
            if delta < credit then
                baseSol ← newSol*
                credit ← 0
            end
        end
    end
    if costs(baseSol) < costs(bestSol) then
        bestSol ← baseSol
    end
end
return bestSol
```

4.1.3 Results & Analysis

To cope with the deterministic version we have implemented, as Java application, the ILS algorithm presented in 4.1.2. Java allows a rapid, platform independent development of algorithms that can be used to test the potential of the method.

Some tests were carried out using three well-known benchmark sets available in the literature for the CLRP. All three benchmark sets consider capacity constraints in both depots and vehicles. The first set is known as Prodhon's set which was introduced by Belenguer et al. (2011) and contains 30 instances. These instances consider 5 and 10 potential facilities as well as 20, 50, 100 and 200 customers. The values for the vehicle capacity are 70 and 140. Each instance name has the form $coordnCustomers - nFacilities - X - Y$ where $X = \{1, 2, 3\}$ and $Y = \{70, 140\}$ represent the number of clusters of customers and the capacity of the vehicles. The second set is known as Barreto's set and was introduced by Barreto (2004). This set involves 17 instances with the number of customers varying from 12 to 150 and the number of depots ranging from 2 to 15. The third set is known as Akca's set and was introduced in Akca et al. (2009). This set is composed by 12 instances with 30 and 40 customers and 5 depots. The number of clusters of customers vary from 1 to 3.

For each instance, twenty random seeds were used to carry out the test of the proposed algorithm. After several executions, the following parameters provided the best results in terms of solution quality and time consumed by our algorithm:

- Iterations for map perturbations ($maxPerturbIter$) =350,
- Iterations for randomized Clarke and Wright routing ($maxRoutingIter$)=150,
- Iterations for splitting ($maxSplittingIter$)=150,
- Geometric distribution parameter for biased allocation maps (P_m)= $0.05 \leq P_m \leq 0.8$,
- Geometric distribution parameter for randomized CWS (P_r)= $0.07 \leq P_r \leq 0.23$,
- Percentage of nodes to re-allocate (r) = $0.1 \leq r \leq 0.5$.

Our results have been compared with to top-5 performers algorithms in terms of percentual gap with respect to the best-known solutions (BKS) for each of the aforementioned sets of benchmark instances.

Table 4.1 shows the results of our algorithm for Prodhon's instances, compared to the following works: GRASP+ILP (Contardo et al., 2014b), GVNTS (Escobar et al., 2014), MACO (Ting and Chen, 2013), ALNS (Hemmelmayr et al., 2012) and SALRP (Yu et al., 2010). It includes the comparison in terms of percentage gaps and also shows the computational time consumed to obtain the best solution reported as well as the number of parameters used by each algorithm. At the bottom of the table we present the CPU index given by the Passmark performance test (PassMark, 2015). Higher values of the CPU index correspond to faster CPUs. As can be seen in Table 4.1, our algorithm has been capable to match 10 of the 30 BKSs while its average gap is 0.35%. Moreover, the average computational time is 346.82 seconds which is about 30% of the average time consumed by the top performing algorithm available up to date in the literature for this set.

Table 4.2, summarizes the results obtained for Barreto's set. It must be noted that only our algorithm and the GRASP+ILP algorithm from Contardo et al. (2014b) have been tested over the whole set of instances. It can bee seen that our algorithm has achieved 11 out of 17 BKSs with an average gap of 0.20% with respect to the BKS. Regarding this benchmark set, our algorithm is quite competitive to other state-of-the-art algorithms except to the SALRP algorithm (Yu et al., 2010).

Similarly, Table 4.3 presents the summary of results for Akca's set. To the best of our knowledge, the most competitive results previously reported for this set are due to Contardo et al. (2011, 2013). Our algorithm has matched 12 of 12 BKSs. There are four instances for which our results seem to be slightly better than the current BKSs that have been proven to be optimal. In fact, the differences are due to different decimal precision. Moreover, we have noticed that in the aforementioned works, the results are presented with different decimal precision and in some cases these differ between the different tables. In our case, we did not apply rounding procedures to the variable values and, therefore, we consider that our results are the correct values for the BKSs. This balance between the quality of the solutions provided and computational time consumed by our algorithm combined with its easiness to be implemented in real scenarios, makes the proposed approach an interesting tool to support the design of supply chains.

First of all, it must be noted that despite its relative simplicity, our biased-randomized approach to solve theCLRP is quite competitive in terms of percentage gap with respect to the BKS—average gaps of 0.35%, 0.20%, and 0.00% for Prodhon's, Barreto's, and Akca's benchmark sets, respectively. We tried to analyze the results of the different algorithms using a one-way ANOVA test but the hypothesis of normality of the residuals could not be validated. Therefore, we used a Kruskal– Wallis nonparametric test (Corder and Foreman, 2009) to assess the quality of the results in terms of percentage Gap with respect to the BKSs. According to the p-values obtained ($p - value = 0.25$), there is no statistically significant difference in terms of gap.

4.2 CLRP with Stochastic Demands

4.2.1 Characteristics

In this section, we deal with a CLRP variant with stochastic demands (CLRPSD), meaning that customers' demands are not known in advance. Thus, demand uncertainty might cause

Table 4.1 Results on Prodhon's instances

	BKS	GRASP+ILP (2014)			GVNTS (2014)			MACO (2013)			ALNS (2012)			SALRP (2010)			OUR APPROACH (2016)		
INSTANCES	TOTAL COST	ZBest	CPU Time	Gap ZBest (%)	ZBest	CPU Time	Gap ZBest(%)	ZBest	CPU Time	Gap ZBest(%)	ZBest	CPU Time	Gap ZBest(%)	ZBest	CPU Time	Gap ZBest (%)	ZBest	CPU Time	Gap ZBest (%)
coord20-5-1.dat	54793	54793	1.7	0	54793	2	0	54793	4.08	0	54793	39	0	54793	19.8	0	54793	4.91	0
coord20-5-1b.dat	39104	39104	2.6	0	39104	3	0	39104	4.78	0	39104	54	0	39104	15	0	39104	9.18	0
coord20-5-2a.dat	48908	48908	1.5	0	48945	2	0.08	48908	3.92	0	48908	38	0	48908	19.3	0	48908	4.61	0
coord20-5-2b.dat	37542	37542	2.8	0	37542	3	0	37542	5.45	0	37542	67	0	37542	15	0	37542	8.19	0
coord50-5-1.dat	90111	90111	15	0	90111	13	0	90111	24.47	0	90111	101	0	90111	74.7	0	90111	24.78	0
coord50-5-1b.dat	63242	63242	18.4	0	63242	9	0	63242	21.31	0	63242	65	0	63242	57.7	0	63242	30.76	0
coord50-5-2.dat	88298	88298	17.5	0	89342	12	1.18	88298	24.19	0	88443	99	0.16	88298	95	0	88298	22.37	0
coord50-5-2b.dat	67308	67373	22	0.1	67951	10	0.96	67308	20.13	0	67340	200	0.05	67340	58.6	0.05	67373	23.89	0.1
coord50-5-2bis.dat	84055	84055	27.3	0	84126	8	0.08	84055	24.66	0	84055	107	0	84055	74.7	0	84126	20.47	0.08
coord50-5-2bBIS.dat	51822	51883	21	0.12	52213	9	0.75	51822	16.83	0	51822	98	0	51822	66.1	0	51883	27.81	0.12
coord50-5-3.dat	86203	86203	16.6	0	86203	18	0	86203	32.78	0	86203	101	0	86456	74	0.29	86203	30.93	0
coord50-5-3b.dat	61830	61830	22.9	0	61885	20	0.09	61830	25.7	0	61830	137	0	62700	58.2	1.41	61830	41.24	0
coord100-5-1.dat	274814	275457	230.4	0.23	276137	75	0.48	276220	116.59	0.51	275636	520	0.3	277035	348.6	0.81	275813	118.23	0.36
coord100-5-1b.dat	213615	214056	230.2	0.21	216154	59	1.19	214323	134.52	0.33	214735	1190	0.52	216002	268.9	1.12	214918	95.49	0.61
coord100-5-2.dat	193671	193708	121.9	0.02	193896	76	0.12	194441	237.28	0.4	193752	463	0.04	194124	348.6	0.23	194585	138.64	0.47
coord100-5-2b.dat	157095	157178	100	0.05	157180	82	0.05	157222	144.33	0.08	157095	859	0	157150	211.5	0.04	157221	161.43	0.08
coord100-5-3.dat	200079	200339	97.3	0.13	200777	69	0.35	201038	178.75	0.48	200305	454	0.11	200242	250.3	0.08	200977	175.34	0.45
coord100-5-3b.dat	152441	152466	100.1	0.02	153435	68	0.65	152722	151.58	0.18	152441	684	0	152467	196.7	0.02	152441	157.62	0
coord100-10-1a.dat	287695	287892	2621.8	0.07	287864	203	0.06	291134	105.28	1.2	296877	210	3.19	291043	270	1.16	291306	197.49	1.26
coord100-10-1b.dat	230989	234080	1067.2	1.34	232599	117	0.7	235348	81.81	1.89	235849	188	2.1	231763	202.6	0.34	235359	215.26	1.89
coord100-10-2.dat	243590	243695	236.1	0.04	245484	52	0.78	245263	122.47	0.69	244740	136	0.47	245813	260.6	0.91	243957	257.43	0.15
coord100-10-2b.dat	203988	203988	258.5	0	204252	42	0.13	205524	85.03	0.75	204016	261	0.01	205312	199.3	0.65	204652	252.23	0.33
coord100-10-3.dat	250882	252927	723.3	0.82	254558	82	1.47	254302	112.09	1.36	253801	202	1.16	250882	338.1	0	253205	209.75	0.93
coord100-10-3b.dat	204317	204664	584.4	0.17	205824	78	0.74	204786	79.7	0.23	205609	224	0.63	205009	240.3	0.34	205117	213.08	0.39
coord200-10-1.dat	475294	475327	3960.4	0.01	477009	320	0.36	478843	941.78	0.75	480883	752	1.18	481002	1428.1	1.2	478735	1364.52	0.72
coord200-10-1b.dat	377043	377327	4006	0.08	377716	239	0.18	378865	562.05	0.48	378961	1346	0.51	383586	1335.8	1.74	378844	1127.14	0.48
coord200-10-2.dat	449006	449291	4943	0.06	449006	231	0	451457	703.66	0.55	450451	1201	0.32	450848	1795.8	0.41	450462	1559.19	0.32
coord200-10-2b.dat	374280	374575	3486	0.08	374717	290	0.12	374972	403.53	0.18	374751	1349	0.13	376674	1245.1	0.64	374726	1229.44	0.12
coord200-10-3.dat	469433	469870	4075.1	0.09	471978	330	0.54	475155	878.83	1.22	475373	1251	1.27	473875	1776	0.95	473546	1502.7	0.88
coord200-10-3b.dat	362653	363103	7887.6	0.12	362827	214	0.05	365401	490.92	0.76	366902	1137	1.17	363701	1326.4	0.29	364968	1180.12	0.64
AVERAGE			1129	0.12		91	0.37		191	0.4		451	0.44		422	0.42		346.82	0.35
Number of BKS			11			7			12			12			10			10	
Number of parameters			22			14			14			9			7			6	
CPU Index			9586			1398			374			1234			4046			4055	

Table 4.2 Results on Barreto's instances

	BKS	GRASP+ILP (2014)			GVNTS (2014)			MACO (2013)			ALNS (2012)			SALRP (2010)			OUR APPROACH (2016)		
INSTANCES	TOTAL COST	ZBest	CPU Time	Gap ZBest (%)	ZBest	CPU Time	Gap ZBest(%)	ZBest	CPU Time	Gap ZBest(%)	ZBest	CPU Time	Gap ZBest(%)	ZBest	CPU Time	Gap ZBest (%)	ZBest	CPU Time	Gap ZBest (%)
Perl-12x2	203.98	203.98	0.3	0	*	*	*	*	*	*	*	*	*	203.98	6.8	0	203.98	0.25	0
Gas-21x5	424.9	424.9	1.7	0	424.9	4	0	424.9	5.64	0	424.9	25	0	424.9	18.3	0	424.89	1.27	0
Gas-22x5	585.11	585.11	2.9	0	585.1	6	0	585.1	4.69	0	585.11	21	0	585.11	16.6	0	585.11	1.87	0
Min-27x5	3062.02	3062.02	3.5	0	*	*	*	*	*	*	3062.02	38	0	3062.02	23.3	0	3062.02	4.2	0
Gas-29x5	512.1	512.1	5.4	0	512.1	7	0	512.1	8.59	0	512.1	40	0	512.1	23.9	0	512.1	4.4	0
Gas-32x5	562.22	562.22	6.2	0	562.2	20	0	562.22	13.05	0	562.22	58	0	562.22	27	0	562.22	5.05	0
Gas-32x5b	504.33	504.33	7.9	0	504.33	15	0	504.33	9.56	0	504.33	55	0	504.33	25.1	0	504.33	4.74	0
Gas-36x5	460.37	460.37	8.6	0	460.37	22	0	464.37	13.14	0.87	460.37	61	0	460.37	31.7	0	460.37	4.6	0
Chr-50x5ba	565.62	574.66	17.1	1.6	580.4	22	2.61	565.62	29.16	0	565.6	73	0	565.62	52.8	0	565.62	21.5	0
Chr-50x5be	565.6	569.49	17.7	0.69	*	*	*	*	*	*	*	*	*	*	*	*	565.6	23.08	0
Perl-55x15	1112.06	1112.06	47.4	0	*	*	*	1112.58	28.81	0.05	*	*	*	1112.06	112.4	0	1112.38	105.04	0.03
Chr-75x10ba	844.4	844.58	87.9	0.02	853.8	45	1.11	844.88	58.72	0.06	853.47	207	1.07	844.4	126.8	0	850.13	134.62	0.68
Perl-85x7	1622.5	1625.84	81.8	0.21	*	*	*	1623.14	77.86	0.04	*	*	*	1622.5	213.1	0	1625.55	129.83	0.19
Das-88x8	355.78	355.78	209.6	0	361.6	97	1.64	355.78	99.53	0	*	*	*	355.78	226.9	0	355.78	156.61	0
Chr-100x10	833.43	840.67	492	0.87	837.1	111	0.44	836.75	83.92	0.4	833.43	403	0	833.43	330.8	0	840.57	423.09	0.86
Min-134x8	5709	5719.25	750.2	0.18	5789	134	1.4	5709	136.63	0	5712.99	460	0.07	5709	522.4	0	5778.68	627.22	1.22
Das-150x10	43919.9	43952.3	1842.1	0.07	44578.9	199	1.5	44131.02	166.95	0.48	44309.2	613	0.89	43919.9	577	0	44096.49	1267.4	0.4
Average			210.72	0.21		56.83	0.72		52.59	0.13		171.17	0.17		145.93	0		192.63	0.2
Number of BKS			10			6			7			9			16			11	
Number of parameters			22			14			14			9			7			6	
CPU Index			9586			1398			374			1234			4046			4055	

Table 4.3 Results on Akca's instances

	BKS	Contardo et al. (2011)			Contardo et al. (2013)			Our Approach (2016)		
Instance Name	**TOTAL COST**	**ZBest**	**CPU Time**	**Gap ZBest (%)**	**ZBest**	**CPU Time**	**Gap ZBest (%)**	**ZBest**	**CPU Time**	**Gap ZBest (%)**
Cr30x5a-1	819.51	819.51	2.45	0	819.52	3.23	0	819.51	1.25	0
Cr30x5a-2	821.5	821.5	3.72	0	821.5	8.77	0	821.45	2.25	-0.01
Cr30x5a-3	702.3	702.3	0.5	0	702.3	0.91	0	702.29	3	0
Cr30x5b-1	880.02	880.02	4.57	0	880.02	9.05	0	880.02	3.22	0
Cr30x5b-2	825.32	825.32	1.24	0	825.32	2.55	0	825.32	1.25	0
Cr30x5b-3	884.6	884.6	1.23	0	884.6	3.25	0	884.58	1.03	0
Cr40x5a-1	928.1	928.1	14.67	0	928.1	140.31	0	928.1	12.5	0
Cr40x5a-2	888.42	888.42	11.88	0	888.42	86.31	0	888.42	14.5	0
Cr40x5a-3	947.3	947.3	11.36	0	947.3	76.63	0	947.26	5.1	0
Cr40x5b-1	1052.04	1052.04	10.49	0	1052.04	3115.92	0	1052.04	5.5	0
Cr40x5b-2	981.54	981.54	3.77	0	981.54	7.61	0	981.54	7.75	0
Cr40x5b-3	964.33	964.33	2.68	0	964.33	12.33	0	964.33	2.52	0
AVERAGE			5.71	0		288.91	0		4.99	0
Number of BKS		8			7			12		
CPU Index		9586			9586			4055		

route failures (i.e., the initial vehicle load is lower than the real demand in the route). As a consequence, corrective actions might be needed in order to satisfy all customers' demands. A corrective action implies returning to the depot to reload the vehicle, go back to the customer, serve it, and resume the original planned route. Therefore, the expected stochastic cost due to route failures has to be included in the objective function. Demands can be modeled by any probability distribution providing non-negative numbers. In our case, we use the log-normal distribution due to its great flexibility for modeling positive random variables. This assumption allows us to use the demand value of the deterministic benchmarks for the CLRP as the mean parameter of the distribution and test our algorithm using different variability levels.

4.2.2 A simILS for the CLRP with Stochastic Demands (CLRPSD)

The simheuristic approach proposed to deal with the CLRP with stochastic demands is depicted in Figure 4.2. It can be seen that three different simulation processes are executed during the solving procedure. The first one is to determine the capacity buffer (safety stock) percentage to be used during the route planning process. The second one is a short simulation process used to approximate stochastic costs and reliabilities of promising solutions. The third one is a long simulation process executed on the elite solutions to refine the estimates of the stochastic costs and reliabilities. Taking into account that simulation is a time consuming process, long simulations are carried out on a selected group ($elite$) of solutions. The process used to establish the safety stock percentage is explained in the following.

As presented by Juan et al. (2011a), safety stocks can be used as a strategy to face uncertainty in route planning. However, for some instances the original available capacity could be enough to face demand uncertainty, even for higher variability levels, and safety stocks could not be necessary. Therefore, one of the contributions of this work is the use of MCS to estimate the recommended value of the safety stock percentage ($\%SS$). The process to estimate it consists of the following steps: *(i)* we solve again the routing phase using different values for $\%SS$; *(ii)* the new solutions go through a fast simulation process ($initSimIters = 500$) in order to test their quality in a stochastic environment; and *(iii)* we keep the safety stock level that provides the higher number of best stochastic solutions, among the $initSimIters$, to be used during the rest of the solving procedure.

During the improvement phase of the algorithms we need to apply the following changes to the deterministic solving procedures: *(i)* the real vehicle capacity (VC') is computed as $VC' = (1 - \%SS) \times VC$, where VC is the original vehicle capacity and $\%SS$ is the value obtained during the initial fast simulation process, and *(ii)* all promising solutions are stored in a set of $promisingSols$. In a further stage, each solution considered to be promis-

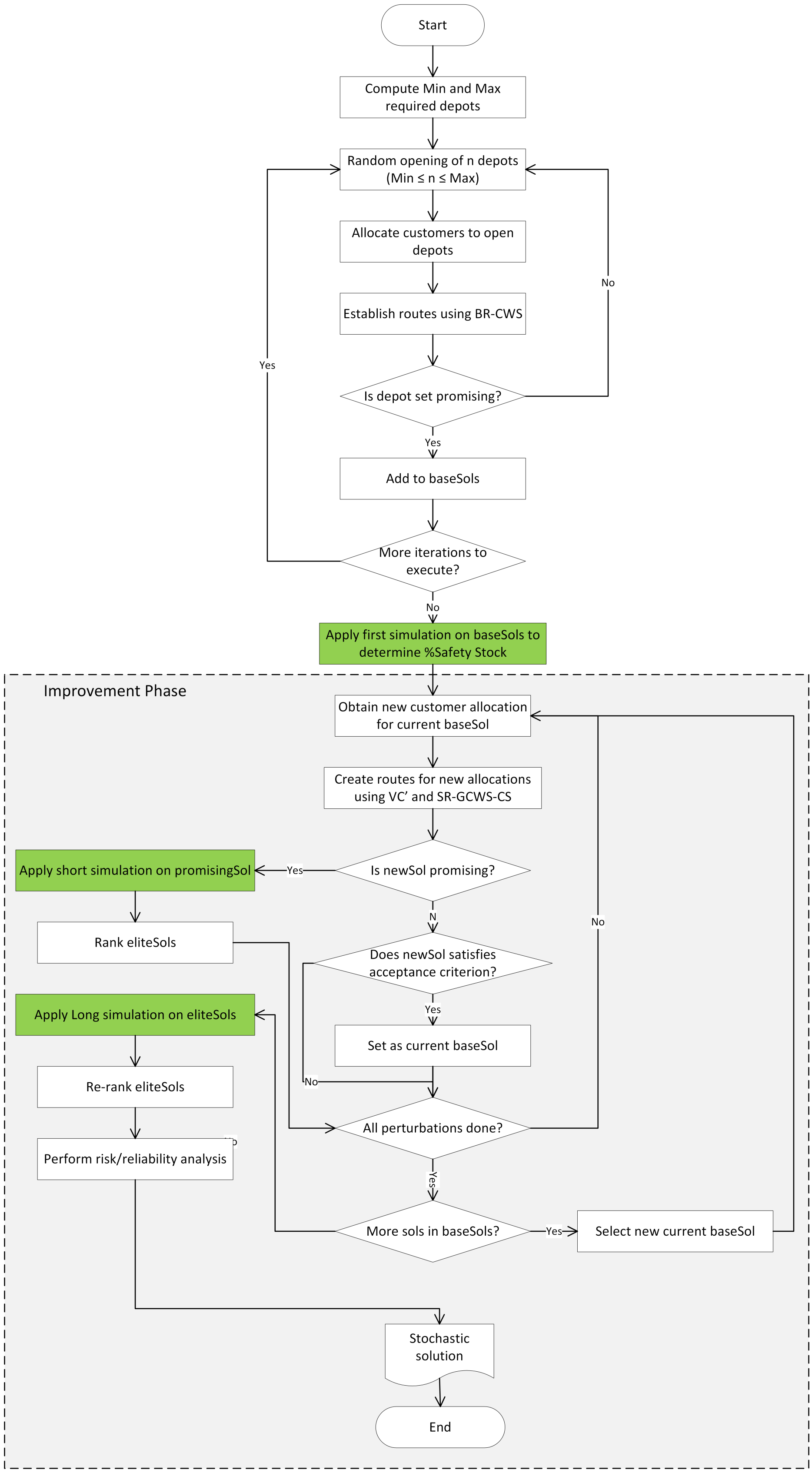


Figure 4.2 Flowchart of our simheuristic approach

ing is tested in a stochastic scenario by means of MCS. We use a second short simulation process ($shortSimIters = 500$) in order to update our list of $nPromising\ eliteSols$. Then each of the $eliteSols$ goes through a long simulation process ($longSimIters = 5000$) to obtain a better estimation of expected stochastic costs and expected reliability (percentage of successfully completed routes). Within the simulation process, our algorithm compares the cost of preventive and reactive re-loading trips, and applies the most convenient one. Once we have visited customer i and the expected value of the demand for the next customer j to be visited leads to a route failure, the stochastic cost $stochCost$ is computed as: $stochCost = Min\{preventiveCost, reactiveCost\}$, where $preventiveCost = C_{i0}+C_{0j}-C_{ij}$ and $reactiveCost = C_{j0} + C_{0j}$. Finally, the solution with the lowest expected total cost is reported.

4.2.2.1 Modifications on the ILS Structure

Some changes have been added to the improvement phase of the algorithm presented in section 4.1.2 to solve the stochastic version of the LRP. They can be summarized as follows:

- The perturbation operator consists in randomly exchanging the depot allocation of $p\%$ of all potential clients. In more detail, the percentage values applied at this point are taken from the range $p = [0.05, 0.1, ..., 0.95]$. Note that this latter version is similar to a variable neighborhood search structure (Hansen et al., 2010), i.e.: we start with the lowest value of p and we keep it while the solution is improved. If it is not possible to improve the solution, we move to the next value of p. For each of the successive values of p, whenever an improvement is found, p is restarted to its initial value. Otherwise, we move towards the next value until all values are considered.

- A simulated annealing-like acceptance criterion for non-improving solutions based on an initial temperature T_0 and a cooling constant $coolingFactor$, as described by Henderson et al. (2003).

- Three new local search operators are added to the existing one. At each iteration, the specific local search operator to be applied is randomly selected. All local search operators are outlined in Table 4.4.

Therefore, four different versions of the solving algorithm are provided to deal with the CLRPSD, which are presented, in the following, as: $rand + DEMON$, $rand + SA$, $p\% + DEMON$, and $p\% + SA$.

Table 4.4 Local search operators

Operator (k)	Description
Customer Swap Inter-Route	Swaps customers randomly chosen between different routes of the same depot.
Inter-Depot Node Exchange	Exchanges two nodes randomly selected from different depots.
2-Opt Inter-Route	Interchanges two chains of randomly selected customers between different depots.
Cross-Exchange	Interchanges positions of 3 random, non-consecutive customers from different depots.

4.2.3 Results & Analysis

Since there are no benchmarks for the CLRPSD, we have adapted the instances of the three aforementioned benchmark sets for the CLRP to fit the stochastic case. Our main assumption is that customer demands follow a particular probability distribution, in our case we have decided to use the lognormal distribution with expected value of the customer demands equal to the deterministic value of the demand provided in the CLRP instances and considering three different variability levels (considering demand variance $Var[D_i]$ =5%D_i, 10%D_i and 20%D_i). Such choice relies on the fact that demands can not have negative values.

For all tested instances and considering a low-variance scenario ($Var[D_i] = 5\%D_i$), Table 4.5 presents the results obtained by each of the 4 versions of the algorithm. For each instance, it shows the best stochastic solution reported, its expected reliability, and the average cost of the obtained solutions. Table 4.6 provides a comparison among the 4 versions for a low variance scenario. It compares the results provided by each method against our best stochastic solution for each benchmark set (Table 4.5 - Column *13*). It can be seen that all methods provide solutions of similar quality, both in terms of expected stochastic costs and expected reliabilities. The $rand + SA$ method is the one that provides the higher number of best solutions (30 over the 59 instances), while $rand + DEMON$ is the version providing the lowest average gaps for all sets. On the other hand, the $p\%+SA$ version seems to have the poorest performance in terms of both average gaps and numbers of best solutions obtained. It must be noted that our strategy of using simulation to determine the "ideal" value of the safety stock percentage seems to work well, since expected total costs are not too different from those of the deterministic solutions. Also, we observe that reliabilities for Akca's and Barreto's instances are over 95% and 92%, respectively. However, in the case of Prodhon's instances is below 80%. This latter result can be explained by the fact that our optimization criterion is not the maximization of reliability but the minimization of total expected costs. To illustrate the trade-off between total expected costs and reliability, we have solved a particular instance (with reliability ≤ 50%) using different safety stock policies. The behavior of stochastic costs and reliabilities is shown in Figure 4.3. It can be seen that the best solution in terms of stochastic costs is the one with 0% safety stock, but its reliability is below 50%. When the safety stock percentage is increased by 1%, reliability goes up to 86% but

Table 4.5 Comparison of results in a low-variance scenario

	rand + DEMON			rand + SA			p% + DEMON			p% + SA			BEST SOLUTION
Instance Name	*Best Solution (1)*	*Reliability BS (2)*	*Average Solution (3)*	*Best Solution (4)*	*Reliability BS (5)*	*Average Solution (6)*	*Best Solution (7)*	*Reliability BS (8)*	*Average Solution (9)*	*Best Solution (10)*	*Reliability BS (11)*	*Average Solution (12)*	*(13)*
PRODHON'S SET													
coord100-10-1.dat	294626.39	65.00%	297793.79	294626.39	65.00%	297870.52	295724.01	47.00%	298259.7005	295724.01	47.00%	298265.6085	294626.39
coord100-10-1b.dat	236796.93	91.00%	238140.66	236796.93	91.00%	238147.50	237608.57	92.00%	238824.8715	237608.57	92.00%	239085.124	236796.93
coord100-10-2.dat	245473.87	44.00%	247073.58	246158.40	57.00%	246987.50	245996.88	52.00%	246929.097	245884.38	54.00%	246877.068	245473.87
coord100-10-2b.dat	205240.22	93.00%	205802.40	205241.37	93.00%	205709.76	205216.71	96.00%	206027.1115	205541.57	93.00%	206054.212	205216.71
coord100-10-3.dat	255520.93	66.00%	258832.99	255349.96	65.00%	258472.18	256636.91	85.00%	259090.1145	255762.65	59.00%	258639.9085	255349.96
coord100-10-3b.dat	205347.90	88.00%	208657.99	204979.01	89.00%	208483.36	205694.11	91.00%	208748.93	205766.87	100.00%	208609.102	204979.01
coord100-5-1.dat	280517.20	74.00%	282328.43	281060.90	45.00%	282305.10	279719.5	45.00%	282440.905	280727.17	45.00%	282231.672	279719.50
coord100-5-1b.dat	215223.71	93.00%	216304.55	215054.17	91.00%	216169.82	215261.07	85.00%	216534.1135	214935.44	88.00%	216705.8665	214935.44
coord100-5-2.dat	196914.63	37.00%	198006.46	196738.12	36.00%	197996.50	196966.69	40.00%	197929.6845	196799.26	38.00%	197768.2735	196738.12
coord100-5-2b.dat	157710.11	90.00%	158321.34	157712.53	91.00%	158259.09	157470.09	89.00%	157998.7235	157481.07	88.00%	158168.819	157470.09
coord100-5-3.dat	203498.59	47.00%	205328.60	203498.59	47.00%	205248.97	203940.09	53.00%	205156.7865	203940.09	53.00%	205265.065	203498.59
coord100-5-3b.dat	152747.22	87.00%	153873.39	152787.04	86.00%	153882.92	152770.41	87.00%	153741.85	152781.78	86.00%	153745.963	152747.22
coord200-10-1.dat	482454.39	31.00%	484317.17	481720.03	34.00%	484046.66	482586.79	41.00%	483937.1705	483021.33	29.00%	483993.978	481720.03
coord200-10-1b.dat	378782.78	82.00%	379201.12	378629.39	81.00%	379172.57	378394.52	85.00%	378969.6155	378449.62	85.00%	379095.717	378394.52
coord200-10-2.dat	451810.57	39.00%	452900.13	451810.57	39.00%	452912.18	451910.05	38.00%	452584.691	451637.49	45.00%	452605.2105	451637.49
coord200-10-2b.dat	374905.18	85.00%	375537.72	375106.92	87.00%	375684.76	374801.79	78.00%	375393.8925	375008.22	76.00%	375518.7625	374801.79
coord200-10-3.dat	477819.33	67.00%	479239.35	477448.21	29.00%	479019.98	478371.2	24.00%	479370.204	477790.7	32.00%	479236.0835	477448.21
coord200-10-3b.dat	369402.09	98.00%	371518.36	369030.65	90.00%	371850.07	368840.13	93.00%	370942.31	368657.09	88.00%	370798.6675	368657.09
coord20-5-1.dat	55247.55	79.00%	55347.90	55249.00	79.00%	55348.85	55318.99	86.00%	55384.1555	55309.35	87.00%	55382.578	55247.55
coord20-5-1b.dat	39104.00	100.00%	39835.45	39104.00	100.00%	39770.50	39104	100.00%	39698.1	39104	100.00%	39633.15	39104.00
coord20-5-2.dat	48909.92	100.00%	48912.36	48909.34	100.00%	48911.98	48909.83	100.00%	48911.7045	48909.92	100.00%	48912.514	48909.34
coord20-5-2b.dat	37542.00	100.00%	37542.21	37542.00	100.00%	37542.14	37542	100.00%	37542.236	37542	100.00%	37542.2105	37542.00
coord50-5-1.dat	90288.61	96.00%	90526.98	90278.86	97.00%	90504.76	90268.92	97.00%	90711.963	90264.79	97.00%	90646.227	90264.79
coord50-5-1b.dat	63395.42	93.00%	63658.44	63395.42	93.00%	63599.17	63351.49	93.00%	63615.4615	63351.49	93.00%	63697.6405	63351.49
coord50-5-2.dat	89288.34	62.00%	90068.99	89288.34	62.00%	90235.06	90002.44	93.00%	90068.76	90284.04	97.00%	90618.963	89288.34
coord50-5-2b.dat	68337.99	91.00%	68723.40	68342.29	89.00%	68609.44	68363.56	91.00%	68736.8845	68443.42	89.00%	68885.2015	68337.99
coord50-5-2bBIS.dat	51945.66	99.00%	52320.26	51940.11	99.00%	52386.15	51946.37	99.00%	52289.4405	52104.14	100.00%	52344.341	51940.11
coord50-5-2BIS.dat	85376.47	93.00%	86339.79	85366.74	94.00%	86151.59	85237.35	96.00%	86996.971	85579.85	89.00%	86672.4255	85237.35
coord50-5-3.dat	87075.27	99.00%	87807.02	87103.54	99.00%	87849.54	86755.48	87.00%	87880.6885	86556.65	87.00%	87830.2265	86556.65
coord50-5-3b.dat	61936.77	97.00%	62665.64	62124.83	98.00%	62520.17	61856.79	99.00%	62388.7025	61928.89	97.00%	62393.7195	61856.79
AVERAGE		79.53%			77.53%			78.73%			77.80%		
AKCA'S SET													
cr30x5a-1.dat	821.61	94.00%	823.01	821.69	94.00%	823.43	821.72	94.00%	823.85	821.83	94.00%	824.17	821.61
cr30x5a-2.dat	826.01	100.00%	840.48	821.45	100.00%	836.62	821.45	100.00%	841.86	821.47	100.00%	841.53	821.45
cr30x5a-3.dat	706.91	85.00%	716.18	706.85	85.00%	713.79	712.64	84.00%	717.00	706.82	85.00%	715.20	706.82
cr30x5b-1.dat	881.82	98.00%	886.00	881.69	98.00%	887.58	881.14	98.00%	884.21	881.71	98.00%	891.92	881.14
cr30x5b-2.dat	825.32	100.00%	825.32	825.32	100.00%	825.32	825.32	100.00%	825.32	825.32	100.00%	825.32	825.32
cr30x5b-3.dat	886.74	97.00%	887.89	886.76	97.00%	887.87	886.84	97.00%	887.90	886.32	96.00%	887.86	886.32
cr40x5a-1.dat	931.57	100.00%	933.36	929.16	100.00%	934.27	929.18	100.00%	933.35	929.77	100.00%	936.09	929.16
cr40x5a-2.dat	888.80	100.00%	892.68	888.80	100.00%	891.79	888.80	100.00%	892.88	888.80	100.00%	892.79	888.80
cr40x5a-3.dat	953.31	93.00%	955.11	954.07	98.00%	956.28	954.02	98.00%	957.02	954.06	98.00%	958.93	953.31
cr40x5b-1.dat	1059.00	87.00%	1063.93	1057.29	86.00%	1062.72	1059.05	87.00%	1063.02	1059.61	86.00%	1064.30	1057.29
cr40x5b-2.dat	981.59	100.00%	994.95	981.73	100.00%	994.71	981.65	100.00%	994.50	981.76	100.00%	994.22	981.59
cr40x5b-3.dat	972.14	91.00%	977.11	972.10	92.00%	981.78	972.27	91.00%	982.34	972.21	91.00%	986.21	972.10
AVERAGE		95.42%			95.83%			95.75%			95.67%		
BARRETO'S SET													
Christ-100x10.dat	851.17	96.00%	858.40	847.75	98.00%	856.83	851.42	94.00%	859.2105	851.75	95.00%	858.308	847.75
Christ-50x5.dat	566.74	94.00%	572.95	570.45	97.00%	580.06	566.59	95.00%	575.3975	574.31	97.00%	579.592	566.59
Christ-50x5_B.dat	566.51	97.00%	583.79	570.44	100.00%	586.52	572.43	100.00%	584.8175	578.91	97.00%	588.2025	566.51
Christ-75x10.dat	814.09	97.00%	823.23	819.99	79.00%	827.99	816.98	100.00%	824.6165	816.98	100.00%	825.242	814.09
Daskin95-150x10.dat	44358.89	100.00%	44642.28	44313.37	100.00%	44594.39	44461.68	100.00%	44692.9105	44109.22	100.00%	44658.916	44109.22
Daskin95-88x8.dat	358.46	100.00%	360.14	358.46	100.00%	361.27	358.46	100.00%	361.1795	358.5	100.00%	362	358.46
Gaskell-21x5.dat	427.19	88.00%	430.30	427.02	89.00%	430.21	427.22	88.00%	430.167	427.22	88.00%	430.3845	427.02
Gaskell-22x5.dat	585.11	100.00%	585.11	585.11	100.00%	585.11	585.11	100.00%	585.11	585.11	100.00%	585.11	585.11
Gaskell-29x5.dat	512.10	100.00%	512.10	512.10	100.00%	512.10	512.1	100.00%	512.1	512.1	100.00%	512.1	512.10
Gaskell-32x5.dat	562.28	100.00%	562.28	562.28	100.00%	562.28	562.28	100.00%	562.28	562.28	100.00%	562.28	562.28
Gaskell-32x5-2.dat	504.33	100.00%	505.05	504.33	100.00%	505.05	504.33	100.00%	504.418	504.33	100.00%	504.418	504.33
Gaskell-36x5.dat	460.37	100.00%	469.29	460.37	100.00%	469.29	460.37	100.00%	466.687	460.37	100.00%	466.687	460.37
Min-27x5.dat	3062.02	100.00%	3063.73	3062.02	100.00%	3062.97	3062.02	100.00%	3062.652	3062.02	100.00%	3062.813	3062.02
Min92-134x8.dat	5778.65	84.00%	5837.35	5775.24	83.00%	5844.45	5778.91	99.00%	5864.2785	5778.16	85.00%	5874.567	5775.24
Perl83-12x2.dat	205.11	91.00%	205.24	205.11	91.00%	205.24	205.11	91.00%	205.208	205.11	91.00%	205.208	205.11
Perl83-55x15.dat	1131.99	33.00%	1140.51	1132.65	42.00%	1142.23	1134.09	42.00%	1140.0145	1137.23	41.00%	1142.921	1131.99
AVERAGE		92.50%			92.44%			94.31%			93.38%		

Table 4.6 Results with low variance level

	GAP			
	rand + DEMON	*rand + SA*	*p% + DEMON*	*p% + SA*
	(1) - (13)	*(4) - (13)*	*(7) - (13)*	*(10) - (13)*
INSTANCE NAME	**PRODHON'S SET**			
coord100-10-1.dat	0.00%	0.28%	0.21%	0.17%
coord100-10-2b.dat	0.01%	0.01%	0.00%	0.16%
coord100-10-3.dat	0.07%	0.00%	0.50%	0.16%
coord100-10-3b.dat	0.18%	0.00%	0.35%	0.38%
coord100-5-1.dat	0.13%	0.06%	0.15%	0.00%
coord100-5-2.dat	0.09%	0.00%	0.12%	0.03%
coord100-5-2b.dat	0.15%	0.15%	0.00%	0.01%
coord100-5-3.dat	0.00%	0.00%	0.22%	0.22%
coord100-5-3b.dat	0.00%	0.03%	0.02%	0.02%
coord200-10-1.dat	0.15%	0.00%	0.18%	0.27%
coord200-10-1b.dat	0.10%	0.06%	0.00%	0.01%
coord200-10-2.dat	0.04%	0.04%	0.06%	0.00%
coord200-10-2b.dat	0.03%	0.08%	0.00%	0.06%
coord200-10-3.dat	0.08%	0.00%	0.19%	0.07%
coord200-10-3b.dat	0.20%	0.10%	0.05%	0.00%
coord20-5-1.dat	0.00%	0.00%	0.13%	0.11%
coord20-5-1b.dat	0.00%	0.00%	0.00%	0.00%
coord20-5-2.dat	0.00%	0.00%	0.00%	0.00%
coord50-5-1.dat	0.03%	0.02%	0.00%	0.00%
coord50-5-1b.dat	0.07%	0.07%	0.00%	0.00%
coord50-5-2.dat	0.00%	0.00%	0.80%	1.12%
coord50-5-2b.dat	0.00%	0.01%	0.04%	0.15%
coord50-5-2bBIS.dat	0.01%	0.00%	0.01%	0.32%
coord50-5-2BIS.dat	0.16%	0.15%	0.00%	0.40%
coord50-5-3.dat	0.60%	0.63%	0.23%	0.00%
coord50-5-3b.dat	0.13%	0.43%	0.00%	0.12%
AVERAGE	0.08%	0.09%	0.13%	0.16%
NUMBER OF BS	10	13	6	6
	AKCA'S SET			
cr30x5a-1.dat	0.00%	2.14%	2.25%	2.50%
cr30x5a-2.dat	0.00%	0.00%	0.00%	0.00%
cr30x5a-3.dat	0.04%	0.00%	0.03%	0.03%
cr30x5b-1.dat	0.00%	0.01%	0.01%	0.25%
cr30x5b-2.dat	0.00%	0.00%	0.00%	0.00%
cr30x5b-3.dat	0.01%	0.00%	0.00%	0.01%
cr40x5a-1.dat	0.34%	0.56%	0.00%	0.11%
cr40x5a-2.dat	0.00%	0.00%	0.26%	0.26%
cr40x5a-3.dat	0.00%	0.00%	0.14%	0.13%
cr40x5b-1.dat	0.00%	0.18%	0.18%	0.00%
cr40x5b-2.dat	0.00%	0.00%	0.01%	0.01%
cr40x5b-3.dat	0.61%	2.12%	0.00%	0.68%
AVERAGE	0.08%	0.42%	0.24%	0.33%
NUMBER OF BS	6	6	5	3
	BARRETO'S SET			
Christ-100x10.dat	0.40%	0.00%	0.43%	0.47%
Christ-50x5.dat	0.03%	0.68%	0.00%	1.36%
Christ-50x5_B.dat	0.00%	0.69%	1.04%	2.19%
Christ-75x10.dat	0.00%	0.72%	0.35%	0.35%
Daskin95-150x10.dat	0.57%	0.46%	0.80%	0.00%
Daskin95-88x8.dat	0.00%	0.00%	0.00%	0.01%
Gaskell-21x5.dat	0.04%	0.00%	0.05%	0.05%
Gaskell-22x5.dat	0.00%	0.00%	0.00%	0.00%
Gaskell-29x5.dat	0.00%	0.00%	0.00%	0.00%
Gaskell-32x5.dat	0.00%	0.00%	0.00%	0.00%
Gaskell-32x5-2.dat	0.00%	0.00%	0.00%	0.00%
Gaskell-36x5.dat	0.00%	0.00%	0.00%	0.00%
Min-27x5.dat	0.00%	0.00%	0.00%	0.00%
Min92-134x8.dat	0.06%	0.00%	0.06%	0.05%
Perl83-12x2.dat	0.00%	0.00%	0.00%	0.00%
Perl83-55x15.dat	0.00%	0.06%	0.19%	0.46%
AVERAGE	0.07%	0.16%	0.18%	0.31%
NUMBER OF BS	11	11	9	8
AVERAGE	**0.08%**	**0.18%**	**0.17%**	**0.24%**
TOTAL BS	**27**	**30**	**20**	**17**

total costs are also increased. An additional increase of 1% (i.e., 2%) in safety stock level leads to a small increase in costs but a huge one in reliability. On the other hand, after a 4% safety stock level, costs are highly increased but reliability improvements are not important or null.

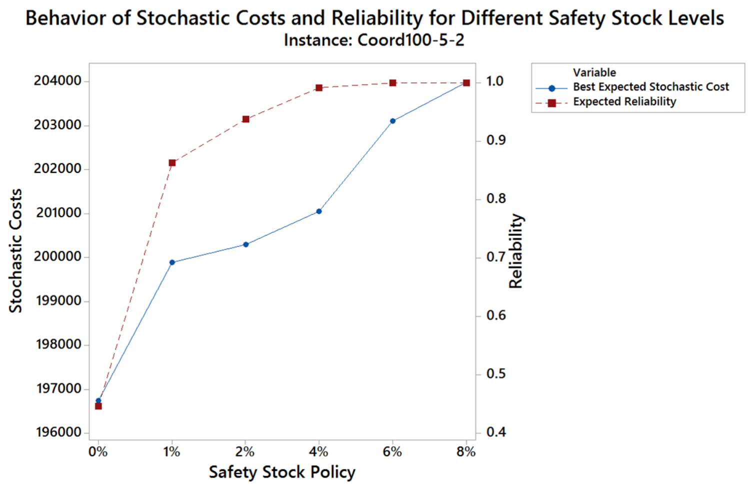


Figure 4.3 Behavior of costs and reliability with different safety stock policies

In addition, figure 4.4 shows the variability of solutions obtained with different safety stock policies. As can be seen, the solution for a safety stock policy of 0% is better, in terms of costs, than the solution obtained with 8%, but the latter has less variability –i.e., it is a low-risk policy. Thus, a risk-averse decision maker could prefer the last policy, while a risk-oriented one could select the first one.

In a similar way, Tables 4.7 and 4.8 summarize the results for mid- and high-variance levels, respectively. It is important to mention that reliabilities show similar behavior to those of the low-variance level, i.e.: higher values for Akca's and Barreto's sets and lower values for Prodhon's set. As expected, when variability levels increase reliabilities tend to decrease. Again, this behavior is generated by the fact that our objective function is the minimization of total expected costs, not the maximization of reliability.

4.3 Extension to Horizontal Cooperation

This section reviews the monetary and environmental impact of different HC strategies based on the integration of routing and facility location decisions on a supply chain level. Different cooperation scenarios are discussed as outlined in Table 4.9. On the one hand, delivery routes and facility locations are individually defined by each company in non-cooperative

Table 4.7 Comparison of results in a mid-variance scenario

	rand + DEMON			rand + SA			p% + DEMON			p% + SA			BEST SOLUTION
Instance Name	*Best Solution (1)*	*Reliability BS (2)*	*Average Solution (3)*	*Best Solution (4)*	*Reliability BS (5)*	*Average Solution (6)*	*Best Solution (7)*	*Reliability BS (8)*	*Average Solution (9)*	*Best Solution (10)*	*Reliability BS (11)*	*Average Solution (12)*	*(13)*
PRODHON'S SET													
coord100-10-1.dat	297607.12	43.00%	300111.624	297607.12	43.00%	300055.066	298141.85	37.00%	299977.853	298141.85	37.00%	299968.327	297607.12
coord100-10-1b.dat	237622.33	70.00%	238961.019	237622.33	70.00%	238841.5815	237714.13	75.00%	239407.0365	237714.13	75.00%	239698.3695	237622.33
coord100-10-2.dat	247609.78	37.00%	248699.1585	247557.24	38.00%	248617.63	247883.28	18.00%	248682.977	247896.21	26.00%	248718.881	247557.24
coord100-10-2b.dat	205346.71	85.00%	206269.8765	205619.01	77.00%	205976.0955	205361.65	77.00%	206206.364	205501.12	80.00%	206247.0025	205346.71
coord100-10-3.dat	256665.15	39.00%	260389.9585	256562.35	39.00%	260269.318	257661.43	61.00%	259981.44	257661.35	85.00%	260012.5855	256562.35
coord100-10-3b.dat	205140.82	95.00%	208745.186	205233.16	97.00%	208099.836	206425.31	97.00%	209353.663	205818.88	87.00%	209321.6185	205140.82
coord100-5-1.dat	283876.99	43.00%	285400.931	284210.03	35.00%	285347.527	283749.9	41.00%	285472.388	283793.69	41.00%	285534.452	283749.90
coord100-5-1b.dat	215697.97	67.00%	216994.7925	215860.43	66.00%	216989.1965	216549.08	95.00%	217489.537	216802.59	82.00%	217476.447	215697.97
coord100-5-2.dat	198697.21	12.00%	199278.2535	198599.72	15.00%	199260.431	198764.7	13.00%	199575.676	198763.74	13.00%	199559.1935	198599.72
coord100-5-2b.dat	158078.07	71.00%	158933.9905	158067.67	75.00%	159016.9955	158068.22	92.00%	158411.3115	157849.7	66.00%	158477.92	157849.70
coord100-5-3.dat	204990.1	23.00%	207681.487	205337.04	28.00%	207622.186	206226.55	52.00%	207773.31	206226.55	52.00%	207814.412	204990.10
coord100-5-3b.dat	153584.42	60.00%	154535.0115	153547.46	60.00%	154556.905	153591.67	58.00%	154415.8695	153572.36	59.00%	154483.6855	153547.46
coord200-10-1.dat	487594.78	56.00%	488391.729	487321.98	47.00%	488132.77	486959.87	14.00%	488707.214	486969.09	29.00%	488675.3055	486959.87
coord200-10-1b.dat	379549.65	54.00%	380460.9555	379674.61	85.00%	380360.884	379774.31	68.00%	380225.8865	379565.38	77.00%	380183.9455	379549.65
coord200-10-2.dat	454651.03	25.00%	455298.20	454426.38	28.00%	455168.16	454456.07	28.00%	455024.9445	454460.45	8.00%	454997.34	454426.38
coord200-10-2b.dat	375796.23	60.00%	376365.30	375533.23	62.00%	376386.68	375421.53	64.00%	376205.833	375555.99	56.00%	376223.22	375421.53
coord200-10-3.dat	480695.38	17.00%	482874.87	480682.29	17.00%	482811.79	480892.99	21.00%	482749.5385	480892.99	21.00%	482760.44	480682.29
coord200-10-3b.dat	369208.51	78.00%	373134.91	370655.65	75.00%	373423.89	369523.13	85.00%	371841.032	369965.65	74.00%	372194.33	369208.51
coord20-5-1.dat	55516.43	77.00%	55595.82	55516.43	77.00%	55591.96	55526.32	77.00%	55626.7925	55522.84	77.00%	55651.22	55516.43
coord20-5-1b.dat	39104.00	100.00%	39835.55	39104.00	100.00%	39770.60	39104	100.00%	39698.2455	39104.00	100.00%	39698.16	39104.00
coord20-5-2.dat	48960.53	97.00%	48969.73	48960.53	97.00%	48969.57	48960.65	97.00%	48967.3105	48957.36	97.00%	48968.33	48957.36
coord20-5-2b.dat	37548.14	100.00%	37555.38	37551.09	100.00%	37556.59	37547.58	100.00%	37555.1055	37548.14	100.00%	37555.78	37547.58
coord50-5-1.dat	90786.23	81.00%	91315.65	90781.90	83.00%	91184.01	90961.65	77.00%	91397.932	90902.24	77.00%	91291.05	90781.90
coord50-5-1b.dat	63714.52	79.00%	64023.49	63714.52	79.00%	63896.41	63685.5	79.00%	64026.08	63696.19	79.00%	64111.26	63685.50
coord50-5-2.dat	90211.48	67.00%	90614.58	90503.10	73.00%	90868.93	90462.21	73.00%	90664.9105	90499.96	73.00%	91150.97	90211.48
coord50-5-2b.dat	68670.53	88.00%	68970.01	68670.91	99.00%	68840.28	68632.11	76.00%	68944.3655	68697.38	78.00%	69080.53	68632.11
coord50-5-2bBIS.dat	52103.43	99.00%	52440.83	52085.86	95.00%	52450.36	52102.48	100.00%	52320.0635	52103.95	99.00%	52402.91	52085.86
coord50-5-2BIS.dat	85990.77	80.00%	87159.95	86128.82	79.00%	86967.80	87470.21	62.00%	88413.526	86563.30	56.00%	88059.14	85990.77
coord50-5-3.dat	87216.45	92.00%	88456.08	87235.69	91.00%	88546.02	87227.83	91.00%	88570.736	87089.14	67.00%	88532.98	87089.14
coord50-5-3b.dat	61944.83	94.00%	62769.82	62391.60	100.00%	62696.86	61925.4	100.00%	62581.9945	61920.53	100.00%	62539.99	61920.53
AVERAGE		66.30%			67.67%			67.60%			65.70%		
AKCA'S SET													
cr30x5a-1.dat	825.92	84.00%	829.66	826.04	84.00%	829.39	826.72	84.00%	830.34	826.79	84.00%	829.95	825.92
cr30x5a-2.dat	821.74	100.00%	841.47	821.97	99.00%	837.26	821.78	100.00%	839.89	821.73	100.00%	837.93	821.73
cr30x5a-3.dat	709.96	75.00%	724.02	709.73	76.00%	720.83	714.95	100.00%	725.27	709.82	76.00%	720.47	709.73
cr30x5b-1.dat	885.98	95.00%	889.57	885.70	95.00%	891.85	885.58	95.00%	891.05	888.21	89.00%	896.79	885.58
cr30x5b-2.dat	825.32	100.00%	825.32	825.32	100.00%	825.47	825.32	100.00%	825.32	825.32	100.00%	825.32	825.32
cr30x5b-3.dat	891.07	86.00%	898.74	893.98	87.00%	899.19	894.52	86.00%	899.12	894.51	86.00%	899.18	891.07
cr40x5a-1.dat	932.54	98.00%	934.77	932.67	97.00%	936.39	932.60	97.00%	935.52	932.64	97.00%	936.32	932.54
cr40x5a-2.dat	888.82	100.00%	895.87	888.83	100.00%	895.60	888.86	100.00%	895.63	888.84	100.00%	895.66	888.82
cr40x5a-3.dat	957.16	93.00%	960.36	957.36	92.00%	961.54	957.14	93.00%	961.22	957.34	93.00%	961.48	957.14
cr40x5b-1.dat	1064.1	98.00%	1071.02	1064.41	97.00%	1066.94	1064.50	97.00%	1071.82	1064.30	98.00%	1068.16	1064.10
cr40x5b-2.dat	992.39	98.00%	1000.08	992.63	98.00%	1000.45	983.60	98.00%	999.30	983.77	98.00%	999.61	983.60
cr40x5b-3.dat	974.94	82.00%	982.13	975.05	82.00%	986.78	975.12	82.00%	988.39	975.52	80.00%	994.85	974.94
AVERAGE		92.42%			92.25%			94.33%			91.75%		
BARRETO'S SET													
Christ-100x10.dat	853.76	88.00%	860.67	854.86	83.00%	860.36	850.60	92.00%	859.471	850.60	92.00%	859.90	850.60
Christ-50x5.dat	571.16	92.00%	575.86	573.25	86.00%	582.28	569.57	82.00%	577.835	572.28	88.00%	582.60	569.57
Christ-50x5_B.dat	571.01	98.00%	585.43	573.64	97.00%	588.21	581.49	90.00%	586.8215	581.93	90.00%	589.28	571.01
Christ-75x10.dat	815.04	95.00%	824.82	818.38	97.00%	830.21	818.20	95.00%	828.5875	818.20	95.00%	828.59	815.04
Daskin95-150x10.dat	44444.82	100.00%	44652.44	44359.72	100.00%	44613.27	44161.74	100.00%	44690.3125	44270.07	100.00%	44754.91	44161.74
Daskin95-88x8.dat	358.46	100.00%	360.20	358.46	100.00%	361.39	358.46	100.00%	361.287	358.54	100.00%	361.94	358.46
Gaskell-21x5.dat	429.46	77.00%	432.31	429.31	78.00%	432.18	429.42	78.00%	432.264	429.42	78.00%	432.20	429.31
Gaskell-22x5.dat	585.11	100.00%	585.11	585.11	100.00%	585.11	585.11	100.00%	585.11	585.11	100.00%	585.11	585.11
Gaskell-29x5.dat	512.10	100.00%	512.10	512.10	100.00%	512.10	512.10	100.00%	512.1	512.10	100.00%	512.10	512.10
Gaskell-32x5.dat	562.28	100.00%	562.28	562.28	100.00%	562.28	562.28	100.00%	562.28	562.28	100.00%	562.28	562.28
Gaskell-32x5-2.dat	504.33	100.00%	505.06	504.33	100.00%	505.06	504.33	100.00%	504.418	504.33	100.00%	504.42	504.33
Gaskell-36x5.dat	460.37	100.00%	469.30	460.37	100.00%	469.30	460.37	100.00%	466.7	460.37	100.00%	466.70	460.37
Min-27x5.dat	3062.02	100.00%	3063.41	3062.02	100.00%	3062.34	3062.02	100.00%	3062.334	3062.02	100.00%	3062.50	3062.02
Min92-134x8.dat	5782.33	93.00%	5846.54	5792.52	68.00%	5845.57	5783.14	93.00%	5884.0895	5781.37	94.00%	5892.06	5781.37
Perl83-12x2.dat	206.07	83.00%	206.35	206.07	83.00%	206.35	206.07	83.00%	206.288	206.07	83.00%	206.29	206.07
Perl83-55x15.dat	1141.07	25.00%	1153.98	1141.82	19.00%	1153.96	1148.11	15.00%	1153.2125	1148.68	25.00%	1155.69	1141.07
AVERAGE		90.69%			88.19%			89.25%			90.31%		

Table 4.8 Comparison of results in a high-variance scenario

	rand + DEMON			rand + SA			p% + DEMON			p% + SA			BEST SOLUTION
Instance Name	*Best Solution (1)*	*Reliability BS (2)*	*Average Solution (3)*	*Best Solution (4)*	*Reliability BS (5)*	*Average Solution (6)*	*Best Solution (7)*	*Reliability BS (8)*	*Average Solution (9)*	*Best Solution (10)*	*Reliability BS (11)*	*Average Solution (12)*	*(13)*
PRODHON'S SET													
coord100-10-1.dat	301069.61	16.00%	302583.62	301069.61	16.00%	302546.32	302326.53	36.00%	305153.21	300916.95	34.00%	302502.98	300916.95
coord100-10-1b.dat	238526.38	83.00%	239974.14	238526.38	83.00%	239855.19	239249.17	55.00%	242150.44	238698.54	51.00%	240201.80	238526.38
coord100-10-2.dat	249105.62	51.00%	250789.16	249205.17	50.00%	250740.07	250734.36	24.00%	251708.79	249356.50	52.00%	250700.15	249105.62
coord100-10-2b.dat	206155.69	64.00%	206864.59	205876.27	64.00%	206635.26	208078.47	56.00%	208653.87	205626.26	64.00%	206952.08	205626.26
coord100-10-3.dat	259310.06	43.00%	262170.16	258139.10	35.00%	262254.70	259831.94	31.00%	264750.20	258341.84	43.00%	261964.11	258139.10
coord100-10-3b.dat	205602.99	76.00%	209517.17	205602.99	76.00%	209003.81	209294.82	76.00%	213255.32	206791.28	67.00%	209990.73	205602.99
coord100-5-1.dat	287827.92	48.00%	289486.86	287637.37	41.00%	289262.41	292385.78	4.00%	294829.48	287244.95	42.00%	289412.63	287244.95
coord100-5-1b.dat	216973.44	82.00%	218129.36	216896.88	77.00%	217933.61	219815.87	58.00%	221813.55	217130.35	88.00%	218287.11	216896.88
coord100-5-2.dat	200123.80	49.00%	201131.59	200123.80	49.00%	201067.54	203107.37	9.00%	204386.92	200539.28	27.00%	201404.38	200123.80
coord100-5-2b.dat	158779.90	45.00%	159264.50	158794.86	45.00%	159441.68	160958.07	35.00%	161570.09	158467.00	61.00%	158942.08	158467.00
coord100-5-3.dat	208166.08	27.00%	210345.54	208231.24	25.00%	210368.85	210404.90	7.00%	212617.82	208751.13	28.00%	210334.58	208166.08
coord100-5-3b.dat	154944.33	56.00%	155662.13	154946.73	55.00%	155608.94	156183.50	60.00%	157144.91	155152.26	28.00%	155785.01	154944.33
coord200-10-1.dat	492792.59	14.00%	494223.47	492511.88	12.00%	494161.05	494891.78	2.00%	498882.05	492671.43	12.00%	493754.62	492511.88
coord200-10-1b.dat	380989.60	50.00%	381981.88	380938.57	46.00%	381932.26	384708.37	25.00%	387137.05	381046.83	50.00%	381693.73	380938.57
coord200-10-2.dat	458331.04	3.00%	459309.05	458041.13	5.00%	459265.45	459785.65	3.00%	461480.11	458460.43	3.00%	459089.84	458041.13
coord200-10-2b.dat	377136.33	33.00%	377822.44	377180.63	49.00%	377707.98	378997.86	41.00%	380146.16	377080.38	62.00%	377690.68	377080.38
coord200-10-3.dat	485618.47	8.00%	487602.74	486238.50	9.00%	487931.47	490631.32	2.00%	492742.57	486652.51	2.00%	488470.75	485618.47
coord200-10-3b.dat	372426.12	40.00%	375314.91	372697.29	38.00%	375304.77	373206.79	39.00%	379421.03	371555.87	45.00%	374277.32	371555.87
coord20-5-1.dat	55742.03	68.00%	55776.45	55734.66	69.00%	55791.77	56524.62	43.00%	56588.29	55756.85	67.00%	55929.93	55734.66
coord20-5-1b.dat	39108.36	100.00%	39838.86	39108.36	100.00%	39773.94	39109.87	100.00%	39832.22	39111.70	100.00%	39703.28	39108.36
coord20-5-2.dat	49182.76	87.00%	49204.75	49181.15	87.00%	49202.14	49182.76	87.00%	49206.02	49184.92	87.00%	49204.37	49181.15
coord20-5-2b.dat	37634.64	97.00%	37650.97	37634.64	97.00%	37650.06	37634.64	97.00%	37650.97	37633.17	97.00%	37648.15	37633.17
coord50-5-1.dat	91779.61	52.00%	92383.33	91776.95	52.00%	92190.97	91860.54	50.00%	92852.69	91791.09	51.00%	92682.72	91776.95
coord50-5-1b.dat	64127.77	77.00%	64553.28	64201.01	76.00%	64553.83	65353.31	66.00%	65757.34	64162.46	78.00%	64698.39	64127.77
coord50-5-2.dat	91555.55	45.00%	91833.92	91632.13	47.00%	91965.93	92771.02	42.00%	93292.52	91663.45	45.00%	92036.86	91555.55
coord50-5-2b.dat	68849.04	79.00%	69231.05	68743.07	94.00%	69110.31	69306.73	84.00%	70335.82	68752.75	93.00%	69356.54	68743.07
coord50-5-2bBIS.dat	52170.89	95.00%	52516.40	52175.06	95.00%	52645.94	52513.13	91.00%	53241.92	52167.69	95.00%	52433.41	52167.69
coord50-5-2BIS.dat	88034.97	48.00%	89321.53	88048.73	49.00%	89135.69	90467.67	49.00%	91528.44	88272.40	48.00%	90165.82	88034.97
coord50-5-3.dat	88004.55	65.00%	89594.55	88222.20	70.00%	89633.52	89610.23	42.00%	90407.67	88279.23	64.00%	89287.05	88004.55
coord50-5-3b.dat	62137.76	86.00%	62964.05	62208.48	84.00%	62938.94	62587.03	96.00%	63386.68	62129.90	86.00%	62793.79	62129.90
AVERAGE		56.23%			56.50%			47.00%			55.67%		
AKCA'S SET													
cr30x5a-1.dat	835.07	66.00%	842.71	834.52	67.00%	841.44	838.62	67.00%	843.37	834.50	67.00%	841.90	834.50
cr30x5a-2.dat	824.80	96.00%	844.28	825.19	96.00%	841.18	825.39	96.00%	852.07	825.34	96.00%	840.64	824.80
cr30x5a-3.dat	713.62	66.00%	730.09	713.60	66.00%	724.48	713.85	65.00%	730.22	717.38	98.00%	726.98	713.60
cr30x5b-1.dat	890.97	86.00%	899.00	891.33	86.00%	902.25	890.97	86.00%	900.52	892.70	87.00%	902.56	890.97
cr30x5b-2.dat	825.36	100.00%	825.57	825.38	100.00%	825.43	825.37	100.00%	825.42	825.37	100.00%	825.42	825.36
cr30x5b-3.dat	901.65	67.00%	919.67	907.14	83.00%	919.27	901.21	68.00%	919.11	907.30	82.00%	919.63	901.21
cr40x5a-1.dat	933.88	87.00%	939.49	935.79	90.00%	941.65	934.36	88.00%	939.97	934.80	87.00%	941.38	933.88
cr40x5a-2.dat	889.69	99.00%	898.13	889.73	99.00%	900.70	889.78	98.00%	898.54	889.60	99.00%	897.90	889.60
cr40x5a-3.dat	962.75	82.00%	966.69	962.63	92.00%	966.43	962.82	91.00%	968.29	962.71	91.00%	967.17	962.63
cr40x5b-1.dat	1071.89	89.00%	1082.61	1072.36	88.00%	1074.09	1072.07	89.00%	1083.89	1072.20	89.00%	1075.65	1071.89
cr40x5b-2.dat	999.96	89.00%	1012.30	991.09	88.00%	1010.38	991.99	88.00%	1011.56	991.75	88.00%	1011.39	991.09
cr40x5b-3.dat	980.81	69.00%	986.99	981.05	69.00%	992.09	981.09	69.00%	996.53	980.73	69.00%	996.66	980.73
AVERAGE		83.00%			85.33%			83.75%			87.75%		
BARRETO'S SET													
Christ-100x10.dat	858.42	82.00%	866.18	858.42	82.00%	865.50	859.40	95.00%	865.68	859.40	95.00%	865.82	858.42
Christ-50x5.dat	574.60	62.00%	579.30	580.92	83.00%	584.64	574.55	62.00%	583.19	578.38	68.00%	586.12	574.55
Christ-50x5_B.dat	574.23	87.00%	587.76	576.33	85.00%	590.84	576.32	85.00%	589.99	575.58	85.00%	591.70	574.23
Christ-75x10.dat	821.27	85.00%	831.95	828.13	82.00%	838.32	823.09	80.00%	835.74	823.09	80.00%	835.74	821.27
Daskin95-150x10.dat	44448.31	100.00%	44653.71	44222.57	100.00%	44572.70	44416.68	100.00%	44656.98	44227.91	100.00%	44661.14	44222.57
Daskin95-88x8.dat	358.46	100.00%	360.24	358.54	100.00%	362.09	358.46	100.00%	360.82	358.46	100.00%	361.60	358.46
Gaskell-21x5.dat	432.34	91.00%	435.29	432.47	90.00%	434.90	432.29	67.00%	435.55	432.81	96.00%	435.77	432.29
Gaskell-22x5.dat	585.11	100.00%	585.11	585.11	100.00%	585.11	585.11	100.00%	585.11	585.11	100.00%	585.11	585.11
Gaskell-29x5.dat	512.10	100.00%	512.10	512.10	100.00%	512.10	512.10	100.00%	512.10	512.10	100.00%	512.10	512.10
Gaskell-32x5.dat	562.28	100.00%	562.30	562.28	100.00%	562.30	562.28	100.00%	562.30	562.28	100.00%	562.30	562.28
Gaskell-32x5-2.dat	504.33	100.00%	505.09	504.33	100.00%	505.09	504.33	100.00%	504.42	504.33	100.00%	504.42	504.33
Gaskell-36x5.dat	460.53	100.00%	469.50	460.53	100.00%	469.50	460.49	100.00%	466.89	460.49	100.00%	466.89	460.49
Min-27x5.dat	3062.03	100.00%	3064.14	3062.05	100.00%	3062.76	3062.03	100.00%	3062.59	3062.05	100.00%	3063.08	3062.03
Min92-134x8.dat	5812.57	96.00%	5859.79	5810.01	58.00%	5882.12	5802.19	74.00%	5899.25	5852.82	97.00%	5916.37	5802.19
Perl83-12x2.dat	207.27	73.00%	207.46	207.27	73.00%	207.46	207.27	73.00%	207.37	207.27	73.00%	207.37	207.27
Perl83-55x15.dat	1139.42	100.00%	1162.41	1145.40	100.00%	1165.04	1144.49	100.00%	1165.36	1158.94	13.00%	1167.45	1139.42
AVERAGE		92.25%			90.81%			89.75%			87.94%		

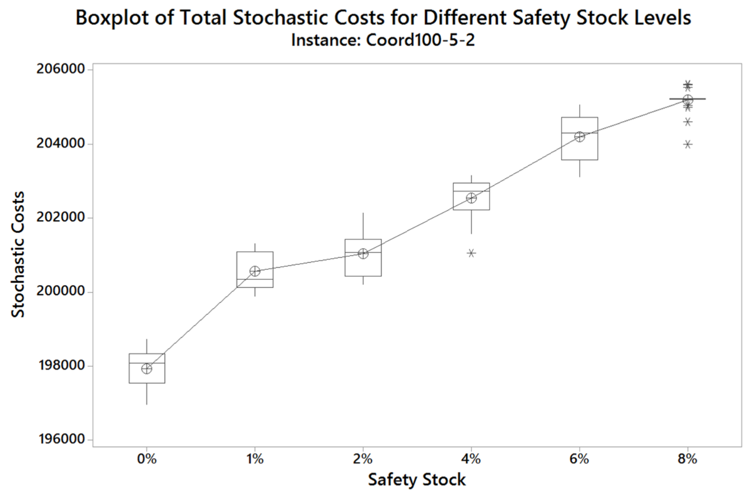


Figure 4.4 Comparison of best stochastic solutions for different safety stock levels

supply chain networks. On the other hand, semi-cooperative (operational) HC in road transportation involves customer service exchanges between different companies by sharing client information and vehicle capacities. This allows for an aggregated routing solution in which customers are assigned to different supply depots according to their geographic proximity. Moreover, a fully-cooperative supply chain approach concerning integrated routing and facility location decisions is discussed. This represents the most advanced form of HC, in which strategic decisions are jointly taken by participating organizations, including the possibility of opening shared logistics facilities (i.e., vehicle depots) (Pomponi et al., 2015; Rezapour et al., 2014). In order to compare the considered scenarios in terms of both monetary and environmental costs, a general solving approach combining biased randomization (Juan et al., 2011b) with variable neighborhood search (Mladenović and Hansen, 1997) is used. This algorithm is able —with minor adjustments— to solve each problem setting associated with different cooperation extensions. Its performance is tested on a range of theoretical and real-life benchmark instances, outperforming previously published results.

4.3.1 Problem Description

As the level of integrated supply chain decision making differs among the discussed scenarios, each considered case of HC corresponds to a different combinatorial optimization problem (COP) (Juan et al., 2014c; Pérez-Bernabeu et al., 2015). Whereas non-cooperative T&L planning involves solving a VRP for each participating company, centralized routing decisions in the semi-cooperative case result in a MDVRP. The case of fully integrated rout-

Table 4.9 Overview of considered HC scenarios

Scenario	Non-cooperative	Semi-cooperative	Fully-cooperative
Joint decisions	None	Route planning, customer allocation	Route planning, customer allocation, facility location investment
Shared resources	None	Customer information, vehicle capacities, logistics facilities	Customer information, vehicle capacities, logistics facilities
Related optimization problem	Company specific VRPs	MDVRP	LRP

ing and facility location planning is represented by the CLRP, in which route planning and facility location decisions are combined.

All scenarios of cooperative delivery route and facility location planning are outlined in Figure 4.5, where the three diamond-shaped nodes represent depots of different companies and each of the other nodes are customers (notice that customers with the same shape belong to the same company). Thus, the initial location of different depots and their associated customers can be seen in Fig. 4.5(a). In non-cooperative supply chains, both routing and facility location decisions are decentralized. Therefore, every company establishes its own routing plans starting and ending at their central depot. From an optimization perspective, this leads to the solution of the NP-hard VRP (Toth and Vigo, 2014) for each company, as it tries to establish efficient delivery tours. An illustrative solution can be observed in Fig. 4.5(b).

In cooperative route planning, the degree of joint supply chain decisions increases. By sharing customer information, storage facilities, and vehicle capacities, route planning can be optimized through a more efficient customer-depot allocation. This situation corresponds to the MDVRP (Montoya-Torres et al., 2015; Pérez-Bernabeu et al., 2015), in which customer allocation and routing decisions are combined. The impact of this operational form of HC in road transportation is visualized in Fig. 4.5(c). As can be intuitively observed, the routing distances are reduced in comparison to the non-cooperative case.

Finally, Fig. 4.5(d) shows the resulting routing map of fully integrated routing and facility location supply chain decisions. Apart from joint delivery route planning, this level of HC includes the shared determination of the most efficient number and location of logistics facilities. This situation is represented by the LRP, which summarizes: *(i)* facility location decisions; *(ii)* customer assignment; and *(iii)* delivery route planning (Prodhon and

Prins, 2014). This simple example illustrates how an integrated routing and location decision might vary the number of depots employed to serve all customers.

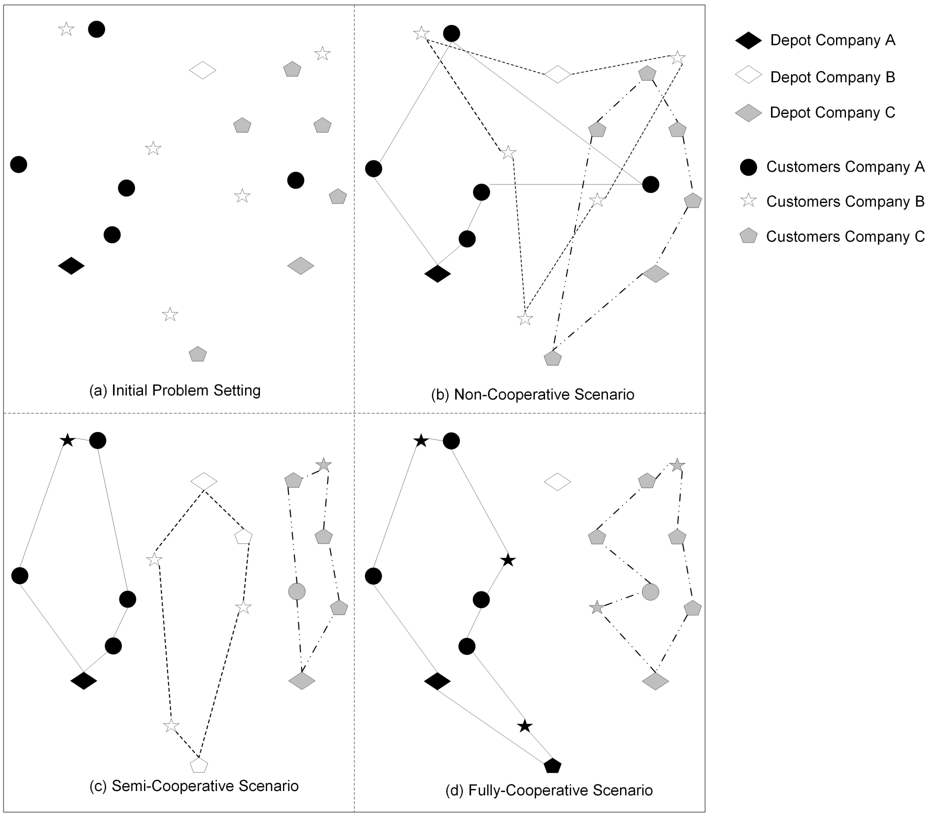


Figure 4.5 Graphical representation of different scenarios

4.3.2 Generic Solving Approach

In order to quantify each scenario, we use the BR-VNS procedure presented in Algorithm 4. This generic procedure is able to solve all problem settings related to integrated routing and facility decisions for different cooperation degrees in road transportation planning: the VRP, the MDVRP, and the LRP.

As the level of aggregated decision-making differs among the different scenarios, small variations must be adopted within the solving framework in order to efficiently solve the related problems for non- and semi-cooperative supply chain planning. Necessary changes are the following:

- In the non- and semi-cooperative cases, the number of depots to be open is no longer a decision variable but rather an algorithm input. Thus, *lowerbound* and *upperbound* are equal to the total number of depots considered in the problem instance.

Algorithm 4: BR-Variable Neighborhood Search

```
Input: inputs, parameters
initialize(variables)
baseSols ← createInitialSolutions(inputs, parameters)
costs(bestSol) ← BigM
foreach baseSol ∈ initSols do
    T = T_0
    while stopping criteria not reached do
        k ← 1
        while k < k_max do
            newSol ← shake(baseSol, k)
            improving ← true
            while improving do
                newSol* ← localSearch(newSol)
                if costs(newSol*) < costs(newSol) then
                    newSol ← newSol*
                end
                else
                    improving ← false
                end
            end
            delta ← costs(newSol*) - costs(baseSol)
            if delta < 0 or (random < (exp-(-delta/T))) then
                baseSol ← newSol*
                k ← 1
            end
            else
                k ← k+ 1
            end
            T ← T×coolingFactor
        end
    end
    if costs(baseSol) < costs(bestSol) then
        bestSol ← baseSol
    end
end
return bestSol
```

- In the non-cooperative scenario, customer allocation is not a decision variable but an instance input. In this case, the biased randomized allocation procedure is turned off and the number of promising solutions $nbaseSols$ is set to 1.

Table 4.10 Estimation of emission factors. Adapted from Ubeda et al. (2011)

Vehicle Load	**Load Percentage**	**Consumption (l/100km)**	**Conversion factor (kg CO_2/l)**	**Emission factor (kg CO_2/km)**
Empty	[0-25%)	29.6		0.773
Low	[25-50%)	32		0.831
Half	[50-75%)	34.4	x 2.61	0.900
High	[75-100%)	36.7		0.958
Full	100%	39		1.018

- As the shaking operators aim to modify customer/depot allocation maps and taking into account that this is not allowed in the non-cooperative scenario, the shaking procedure is not considered in this scenario. In effect, $p\% = 0$ and $k_{max} = 2$ in this case.

4.3.3 Experiment Description

We have adapted the three aforementioned CLRP benchmark sets from the literature to fit each considered scenario, in order to compare the cooperation degrees on integrated routing and location decisions. Each instance consists of a set of possible (capacitated) facility locations and numerous customers to be served by a homogeneous and capacitated vehicle fleet. In order to represent the non- and semi cooperative scenarios, it is assumed that all possible facility locations have to be opened. Customers are randomly assigned to the open depots to represent the non-cooperative case. In the semi-cooperative case, the customer/depot allocations are optimized as described in the applied metaheuristic for the MDVRP (Juan et al., 2015b). An estimation of the environmental impact of different cooperation scenarios is provided according to the load- and distance based CO_2 emission calculations elaborated by Ubeda et al. (2011). CO_2 emissions are hereby calculated according to travel distances and vehicle loads as outlined in Table 4.10. This load dependency leads to asymmetric emission estimations for each established route, depending on the direction the delivery route is completed. Since customers have different demands, the load of the vehicle in a given edge will be different depending on the direction of the route. As a consequence, the CO_2 emissions of that vehicle while traversing each edge will also differ depending on the selected direction. Therefore, CO_2 emissions for each route are calculated in both directions. The reported CO_2 emissions represent the lowest value obtained for both tours.

Additionally, the potential of our approach is demonstrated using the real-life instances proposed by Muñoz Villamizar et al. (2015). These authors discuss the impact of cooperative strategies in the context of city logistics by showing the benefits of operational cooperation, suggesting significant monetary and environmental cost savings through HC strategies. A total of 10 instances are considered. These instances represent different customer demand sets, with 3 depots supplying up to 61 clients scattered around the Colombian capital Bogotá. The authors compare two scenarios, the non-cooperative and cooperative one. While the non-cooperative scenario is similar to the one described in this chapter, their cooperative scenario is equivalent to the semi-cooperative case discussed in this work.

The proposed solving framework was implemented as a Java application and tested on a personal computer with a core i5 processor and 8GB RAM. Each instance was solved using ten different random seeds, whereby the reported results correspond to the best found solution. The following parameters settings are applied for the BR-VNS algorithm to solve the LRP:

- $nIterSols = 300$
- $nInitSols = 2 + \lfloor nodes/100 \rfloor$
- $maxIter = 350$
- $routingIterationsRandomCWS = 150$
- $0.07 \leq \alpha \leq 0.23$
- $0.05 \leq \beta \leq 0.8$
- $T_0 = 50$
- $coolingFactor = 0.984$

4.3.4 Analysis of Results

4.3.4.1 Results on Theoretical Benchmarks

The results concerning opening-, vehicle-, routing-, and total costs as well as associated CO_2 emissions of all scenarios for each benchmark set are listed in Tables 4.11-4.13. In the case of Prodhon's instances, a fixed vehicle cost of 1000 for each used delivery truck is applied, and the reported distances are multiplied by 100 and rounded up to the nearest integer, in order to calculate routing costs. For both the cases of HC during the integrated routing and location planning process, significant cost savings can be expected. While the semi-cooperative case leads to total cost reductions of 24.19% on average, this value increases to 58.6% in strategic level of cooperation. Similarly, the overall environmental impact can be reduced through cooperative strategies. While the reported results for operative cooperation

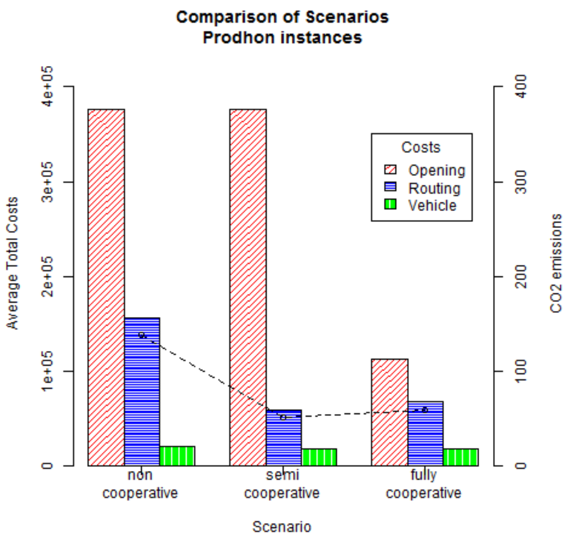


Figure 4.6 Summary average results of Prodhon instances.

suggest CO_2 reductions of up to 61.88%, a fully-cooperative scenario can lead to emission savings of 56.87%.

The benchmark sets of Barreto (2004) and Akca et al. (2009) do not provide any vehicle usage cost approximations. For this reason, no vehicle usage costs are reported for these problem settings. In addition, these sets consider that routing costs are equal to the associated distances. The benchmark set of Barreto (2004) suggests total cost savings of 42.37% and 61.64% for semi- and fully cooperative HC strategies in comparison to decentralized (non-integrated) routing and location decisions. CO_2 emissions can be expected to decrease by 55.78% when applying a fully- instead of a non-cooperative strategy, with emission values decreasing even further in for in semi-cooperative scenario. The problem settings provided by Akca et al. (2009) suggest possible cost savings of 42.07% and 55.37% for the semi- and cooperative scenarios, respectively. Concerning CO_2 emissions, differences of 55.77% and 52.74% are reported. All discussed results are summarized in Figures 4.6-4.8.

4.3.4.2 Results on a Real-life Case

Concerning the non-cooperative scenario, our approach to solve the related VRPs outperforms the results of Muñoz Villamizar et al. (2015) by 4.93% over the 10 real-life instances described in the benchmark paper, as seen in Table 4.14 which reports the sum of routing distances for each company. Similarly, the MDVRP is solved for the cooperative (semi-cooperative) case. As depicted in Table 4.15, our algorithm is on average 4.81% better than previously reported results. The potential distance-based benefits of a fully-cooperative sce-

Table 4.11 Quantified scenario comparison Prodhon's instances

Instance	Non-cooperative scenario (NC)					Semi-cooperative scenario (SC)					Fully-cooperative scenario (FC)					Nc vs SC		NC vs FC	
	opening costs	routing costs	vehicle costs	total costs	CO_2 emissions	opening costs	routing costs	vehicle costs	total costs	CO_2 emissions	opening costs	routing costs	vehicle costs	total costs	CO_2 emissions	total costs	CO_2 emissions	total costs	CO_2 emissions
P1	43960	42576	5000	91536	365	43960	22327	6000	72287	188	25549	24472	5000	55021	208	-21.03	-48.40	-39.89	-43.08
P2	52604	60759	5000	118363	479	52604	19342	3000	74946	166	15497	20607	3000	39104	173	-36.68	-65.35	-66.96	-63.98
P3	46395	46766	5000	98161	403	46395	18926	6000	71321	163	24196	19712	5000	48908	169	-27.34	-59.58	-50.18	-58.11
P4	50170	55457	5000	110627	439	50170	17665	3000	70835	151	13911	20631	3000	37542	174	-35.97	-65.71	-66.06	-60.37
P5	48833	113859	14000	176692	978	48833	52581	12000	113414	458	25442	52822	12000	90264	452	-35.81	-53.16	-48.91	-53.78
P6	48833	83190	7000	139023	715	48833	37449	6000	92282	324	15385	41908	6000	63293	358	-33.62	-54.73	-54.47	-49.88
P7	56340	106922	15000	178262	922	56340	42114	12000	110454	368	29319	46979	12000	88298	406	-38.04	-60.13	-50.47	-56.01
P8	56340	75527	8000	139867	653	56340	30486	6000	92826	261	29319	32314	6000	67633	275	-33.63	-60.00	-51.64	-57.90
P9	32277	72163	8000	112440	615	32277	26955	6000	65232	236	18763	27120	6000	51883	233	-41.99	-61.60	-53.86	-62.18
P10	30891	121186	15000	167077	1671	30891	55995	12000	98886	496	19785	52871	12000	84656	458	-40.81	-70.30	-49.33	-72.61
P11	48665	101552	15000	165217	872	48665	44758	13000	106423	387	18961	55307	12000	86268	472	-35.59	-55.65	-47.79	-45.91
P12	48665	74627	8000	131292	647	48665	32347	6000	87012	281	18961	37021	6000	61982	315	-33.73	-56.63	-52.79	-51.29
P13	231677	205589	25000	462266	1795	231677	114907	25000	371584	1013	132890	120083	24000	276973	1041	-19.62	-43.60	-40.08	-42.01
P14	231677	131367	15000	378044	1138	231677	67070	12000	310747	588	132890	71008	12000	215898	610	-17.80	-48.34	-42.89	-46.36
P15	257351	165372	25000	447723	1447	257351	64819	25000	347170	567	102246	70248	24000	196494	606	-22.46	-60.81	-56.11	-58.12
P16	257351	108279	15000	380630	1467	257351	43765	11000	312116	382	102246	44427	11000	157673	382	-18.00	-73.96	-58.58	-73.98
P17	235497	167591	25000	428088	1466	235497	67152	24000	326649	589	88287	89260	24000	201547	775	-23.70	-59.84	-52.92	-47.13
P18	235497	111985	15000	362482	968	235497	45264	12000	292761	392	88287	54002	11000	153289	465	-19.23	-59.48	-57.71	-51.91
P19	532149	213619	30000	775768	1852	532149	68406	27000	627555	594	165068	102669	26000	293737	886	-19.11	-67.92	-62.14	-52.15
P20	532149	159666	19000	710815	1368	532149	49227	13000	594376	424	154942	69510	12000	236452	598	-16.38	-69.01	-66.74	-56.30
P21	510425	206014	29000	745439	1773	510425	68448	26000	604873	596	149586	66641	23000	239227	695	-18.86	-66.40	-67.91	-60.83
P22	510425	154552	18000	682977	1315	510425	47455	13000	570880	409	149586	42456	13000	205042	363	-16.41	-68.89	-69.98	-72.38
P23	501936	197223	29000	728159	1692	501936	62637	26000	590573	542	136123	92082	25000	253205	791	-18.90	-67.96	-65.23	-53.27
P24	501936	154868	17000	673804	1322	501936	43111	13000	558047	373	136123	52008	11000	199131	447	-17.18	-71.79	-70.45	-66.20
P25	984087	386144	50000	1420231	3374	984087	112151	49000	1145238	983	266151	164764	47000	477915	1431	-19.36	-70.88	-66.35	-57.61
P26	984087	258583	28000	1270670	2266	984087	76309	24000	1084396	666	253840	104306	22000	380146	901	-14.66	-70.62	-70.08	-60.23
P27	1113968	333256	50000	1497224	2916	1113968	113687	50000	1277655	996	280370	123205	48000	451575	1062	-14.67	-65.85	-69.84	-63.57
P28	1113968	217490	29000	1360458	1883	1113968	71440	22000	1207408	629	280370	72608	23000	375978	625	-11.25	-66.61	-72.36	-66.82
P29	1003017	324132	50000	1377149	2828	1003017	147613	48000	1198630	1304	272528	156128	46000	474656	1357	-12.96	-53.87	-65.53	-52.01
P30	1003017	220785	27000	1250802	1905	1003017	87683	22000	1112700	773	234660	109891	22000	366551	950	-11.04	-59.42	-70.69	-50.13
Average																**-24.19**	**-61.88**	**-58.60**	**-56.87**

Table 4.12 Quantified scenario comparison Barreto's instances

Instance	Non-cooperative scenario (NC)				Semi-cooperative scenario (SC)				Fully-cooperative scenario (FC)				NC vs SC		NC vs FC	
	opening costs	routing costs	total costs	CO_2 emissions	opening costs	routing costs	total costs	CO_2 emissions	opening costs	routing costs	total costs	CO_2 emissions	total costs	CO_2 emissions	total costs	CO_2 emissions
B1	200.0	149.6	349.6	128.9	200.0	95.8	295.8	83.0	100.0	104.0	204.0	89.7	-15.40	-35.63	-41.66	-30.47
B2	250.0	786.4	1036.4	655.5	250.0	322.8	572.8	270.1	100.0	324.9	424.9	282.8	-44.73	-58.8	-59.00	-56.86
B3	250.0	1357.1	1607.1	1075.6	250.0	554.0	804.0	452.6	50.0	535.1	585.1	451.9	-49.97	-57.93	-63.59	-57.99
B4	1360.0	6978.4	8338.4	5765.1	1360.0	2666.2	4026.2	2248.5	544.0	2518.0	3062.0	2108.4	-51.72	-63.28	-63.28	-63.43
B5	250.0	1236.2	1486.2	1014.4	250.0	408.8	658.8	337.0	100.0	412.1	512.1	351.7	-55.67	-65.54	-65.54	-65.33
B6	250.0	1089.9	1339.9	901.2	250.0	484.0	734.0	406.1	50.0	512.2	562.2	441.9	-45.22	-54.93	-58.04	-50.96
B7	250.0	1039.6	1289.6	841.4	250.0	456.5	706.5	383.3	50.0	454.3	504.3	383.1	-45.21	-54.46	-60.89	-54.46
B8	250.0	837.8	1087.8	695.7	250.0	374.0	624.0	325.3	50.0	426.0	476.0	369.8	-42.64	-53.25	-56.24	-46.85
B9	200.0	984.4	1184.4	838.4	200.0	461.1	661.1	396.9	80.0	485.6	565.6	421.3	-44.18	-52.66	-52.24	-49.76
B10	200.0	976.8	1176.8	836.4	200.0	444.7	644.7	387.5	80.0	485.6	565.6	425.8	-45.22	-53.67	-51.94	-49.09
B11	3600.0	1273.3	4873.3	1035.3	3600.0	340.3	3940.3	286.9	720.0	392.4	1112.4	342.0	-19.15	-72.29	-77.17	-66.97
B12	400.0	1879.8	2279.8	1599.7	400.0	648.6	1048.6	565.9	120.0	730.1	850.1	638.7	-54.01	-64.62	-62.71	-60.07
B13	2604.0	748.9	3352.9	647.4	2604.0	498.5	3102.5	426.4	1116.0	509.1	1625.1	440.6	-7.47	-34.13	-51.53	-31.95
B14	914.0	892.8	1806.8	699.4	914.0	229.4	1143.4	185.9	83.6	272.7	356.3	237.0	-36.72	-73.42	-80.28	-66.11
B15	400.0	2043.1	2443.1	1714.1	400.0	722.7	1122.7	614.0	80.0	760.5	840.5	658.1	-54.05	-64.18	-65.60	-61.61
B16	2144.0	17230.9	19374.9	14845.2	2144.0	4948.8	7092.8	4199.3	804.0	4993.5	5797.5	4351.7	-63.39	-71.71	-70.08	-70.69
B17	50000.0	88210.5	138210.5	72837.5	50000.0	25311.9	75311.9	21127.9	15000.0	29190.6	44190.6	24967.1	-45.51	-70.99	-68.03	-65.72
Average													**-42.37**	**-58.85**	**-61.64**	**-55.78**

Table 4.13 Quantified scenario comparison Akca's instances

Instance	Non-cooperative scenario (NC)				Semi-cooperative scenario (SC)				Fully-cooperative scenario (FC)				NC vs SC		NC vs FC	
	opening costs	routing costs	total costs	CO_2 emissions	opening costs	routing costs	total costs	CO_2 emissions	opening costs	routing costs	total costs	CO_2 emissions	total costs	CO_2 emissions	total costs	CO_2 emissions
A1	500	1380.6	1880.6	1171.3	500	658.4	1158.4	573.5	200	619.5	819.5	538.1	-38.40	-51.04	-56.42	-54.06
A2	500	1529.1	2029.1	1294.3	500	586.5	1086.5	509.5	200	621.5	821.5	532.6	-46.45	-60.63	-59.52	-58.85
A3	500	1127.9	1627.9	957.5	500	509.6	1009.6	433.4	200	502.3	702.3	436.9	-37.99	-54.74	-56.86	-54.38
A4	500	1434.8	1934.8	1214.1	500	600.8	1100.8	515.6	200	680.0	880.0	597.2	-43.11	-57.54	-54.52	-50.81
A5	500	1517.1	2017.1	1292.0	500	589.2	1089.2	503.9	200	625.3	825.3	539.0	-46.00	-61.00	-59.08	-58.28
A6	500	1307.0	1807.0	1110.5	500	695.5	1195.5	597.0	200	684.6	884.6	596.6	-33.84	-46.24	-51.05	-46.27
A7	500	1424.2	1924.2	1212.2	500	648.7	1148.7	550.8	200	728.1	928.1	623.4	-40.31	-54.56	-51.77	-48.57
A8	500	1688.6	2188.6	1446.1	500	655.1	1155.1	554.2	200	688.4	888.4	594.9	-47.22	-61.67	-59.41	-58.86
A9	500	1464.6	1964.6	1235.1	500	706.9	1206.9	603.6	200	747.3	947.3	650.3	-38.57	-51.13	-51.78	-47.34
A10	500	1756.9	2256.9	1495.6	500	784.7	1284.7	669.4	200	852.0	1052.0	747.3	-43.08	-55.24	-53.39	-50.03
A11	500	1808.6	2308.6	1523.7	500	673.5	1173.5	573.1	200	781.5	981.5	673.6	-49.17	-62.39	-57.48	-55.79
A12	500	1559.1	2059.1	1325.9	500	719.9	1219.9	621.7	200	764.3	964.3	668.8	-40.76	-53.11	-53.17	-49.56
Average													**-42.07**	**-55.77**	**-55.37**	**-52.74**

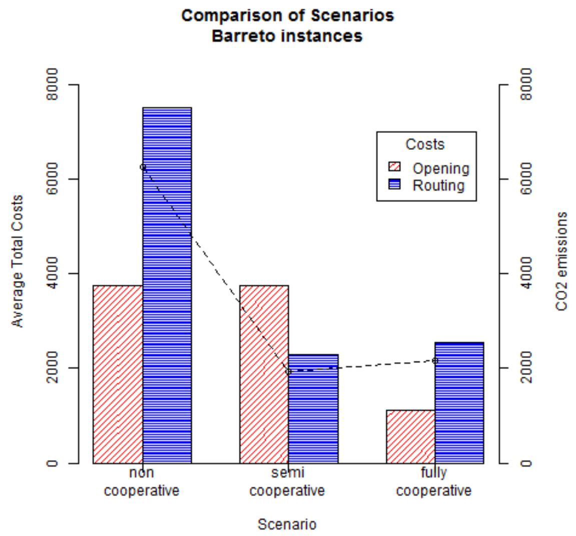


Figure 4.7 Summary average results of Barreto instances.

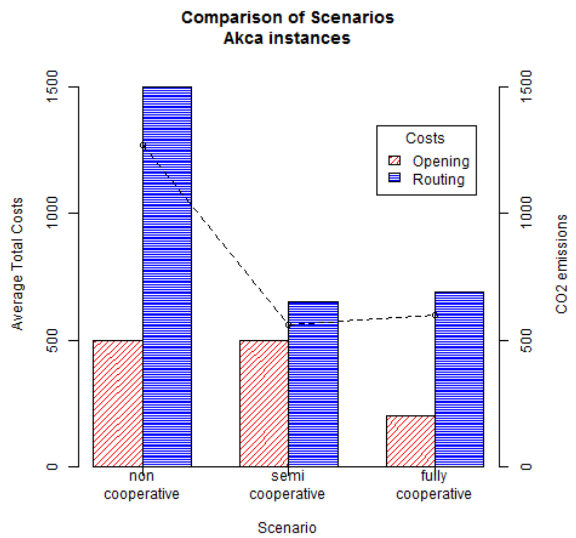


Figure 4.8 Summary average results of Akca instances.

Table 4.14 Result comparison VRP

Instance	Muñoz Villamizar et al. (2015) km	Depots	Our approach km	Depots	%-Gap
I1	289.05	3	279.79	3	-3.20
I2	310.02	3	282.94	3	-8.73
I3	283.8	3	279.81	3	-1.41
I4	295.51	3	282.94	3	-4.25
I5	323	3	277.61	3	-14.05
I6	307.22	3	287.34	3	-6.47
I7	284.17	3	279.21	3	-1.75
I8	297.32	3	316.35	3	6.40
I9	332.42	3	288.14	3	-13.32
I10	290.37	3	282.94	3	-2.56
Average					**-4.93**

Table 4.15 Result comparison MDVRP

Instance	Muñoz Villamizar et al. (2015) km	Depots	Our approach km	Depots	%-Gap
I1	215.13	3	210.91	3	-1.96
I2	227.51	3	215.83	3	-5.13
I3	229.81	3	214.76	3	-6.55
I4	228.01	3	212.04	3	-7.00
I5	215.01	3	210.04	3	-2.31
I6	258.43	3	215.21	3	-16.72
I7	216.56	3	211.78	3	-2.21
I8	223.93	3	215.53	3	-3.75
I9	220.08	3	217.58	3	-1.14
I10	222.76	3	219.86	3	-1.30
Average					**-4.81**

nario can be seen in Table 4.16. Significant distance savings in comparison to the non-cooperative case can be expected. While the route savings are not as large in comparison to the semi-cooperative scenario, high investment savings through a lower number of necessary logistics facilities can be observed.

4.3.4.3 Managerial Insights

In general terms, our results suggest that significant cost savings on a supply chain level can be achieved through HC strategies in routing and facility location decisions. A visual overview of the solution for each considered scenario of the P1 instance –consisting of 5 possible depot locations to serve a total of 20 customers– of Prodhon's set is drawn in Figure 4.9. Notice that the scattered nature of the customer/depot assignments in the non-cooperative case *(b)* lead to higher routing distances compared to the semi-cooperative scenario *(c)*. Moreover, only three depots are necessary to serve all customers in the fully-cooperative

Table 4.16 Results comparison LRP

	Our approach non-cooperative (1)		Our approach semi-cooperative (2)		Our approach fully-cooperative (3)		Distance %-Gap	Distance %-Gap
Instance	Distance	Depots	Distance	Depots	Distance	Depots	(2)-(1)	(3)-(2)
I1	279.79	3	210.91	3	210.91	2	-24.62	0.00
I2	282.94	3	215.83	3	215.83	3	-23.72	0.00
I3	279.81	3	214.76	3	210.04	2	-24.93	-2.20
I4	282.94	3	212.04	3	211.89	2	-25.11	-0.07
I5	277.61	3	210.04	3	210.04	2	-24.34	0.00
I6	287.34	3	215.21	3	215.21	3	-25.10	0.00
I7	279.21	3	211.78	3	209.09	2	-25.11	-1.27
I8	316.35	3	215.53	3	215.53	2	-31.87	0.00
I9	288.14	3	217.58	3	215.58	2	-25.18	-0.92
I10	282.94	3	219.86	3	211.58	2	-25.22	-3.77
Average							**-25.52**	**-0.82**

scenario *(d)*. However, minimizing total cost in the fully-cooperative scenario do not necessarily lead to a reduction in CO_2 emissions, since a reduction in facility costs might imply longer routes. In other words, since the goal is to minimize total distribution cost, the fully-cooperative scenario allows us to take into account the trade-off between the cost of using more facilities and the distance-based cost.

All tested instances are influenced by the topology of the problem setting. Customers can be geographically dispersed (*scattered*) or grouped (*clustered*). Typically, markets in which companies and their customers are in relative proximity favor non-cooperative supply chain planning. The problem instances described by Belenguer et al. (2011) and Akca et al. (2009) differ in their number of clusters. A closer analysis of the the results, as performed in Figures 4.10 and 4.11, shows that HC strategies reach their highest potential benefits (both in monetary and environmental terms) in more scattered customer/depot maps. This is often the case in the context of city logistics (Savelsbergh and Woensel, 2016).

4.4 Chapter Conclusions

This chapter has presented efficient and relatively simple approaches for solving the CLRP. The proposed methods combine BR techniques with perturbations of the allocation maps to generate good solutions for the CLRP. As the numerical experiments showed, our approaches are able to provide competitive results when compared to other state-of-the-art methods, both in terms of solution quality and computational times. One of the main advantages of our approaches is their relative simplicity: the methods are relatively easy to implement (only two phases) and understand. Moreover, they need little fine-tuning. In contrast, most state-of-the-art approaches introduce a high number of parameters that have to be adjusted, often

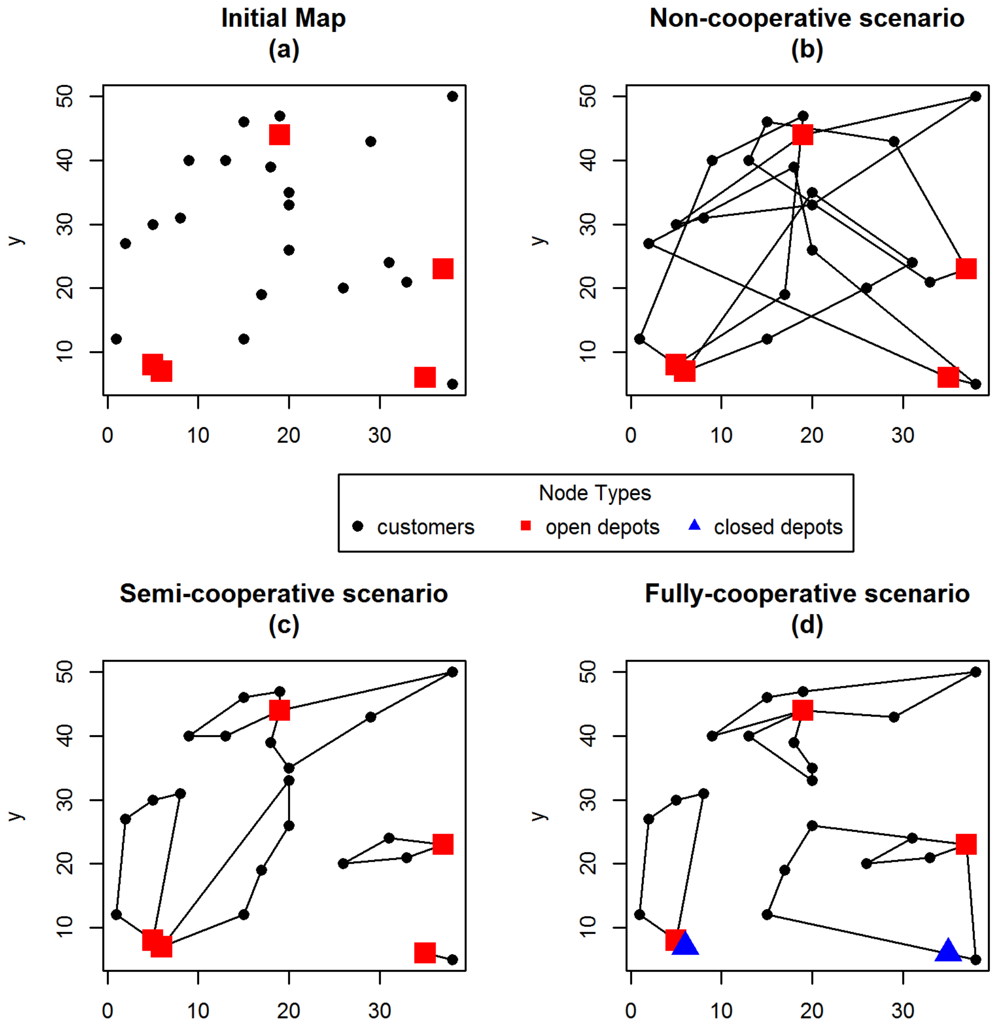


Figure 4.9 Routing map comparison of different scenarios for P1 instance (Prodhon's set).

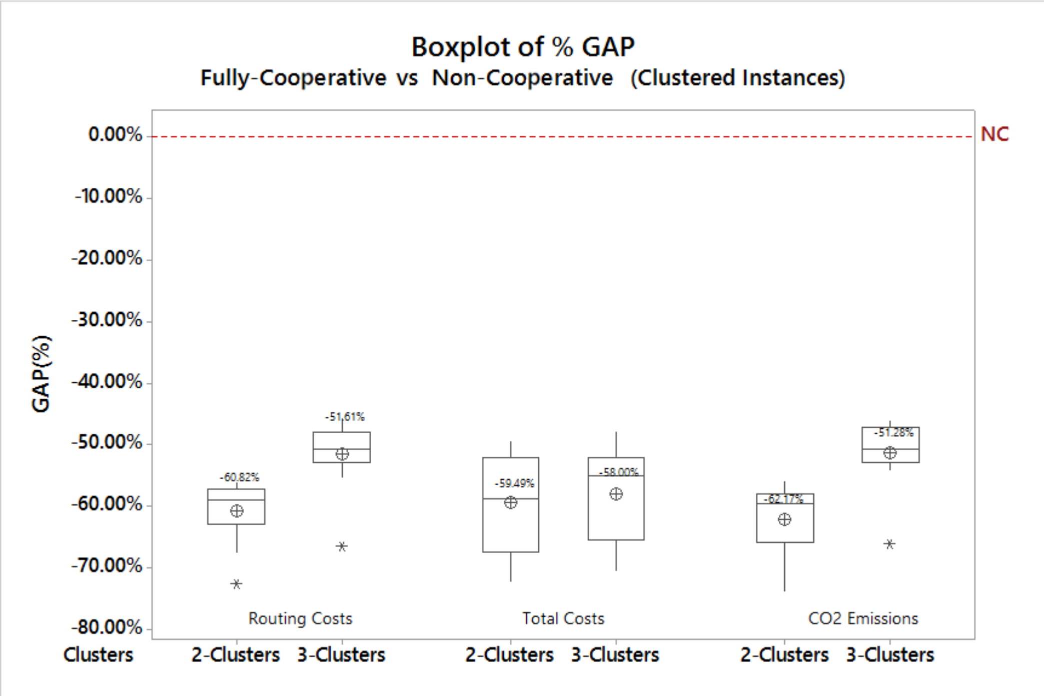


Figure 4.10 Clustered instances comparison of non- and fully cooperative scenarios.

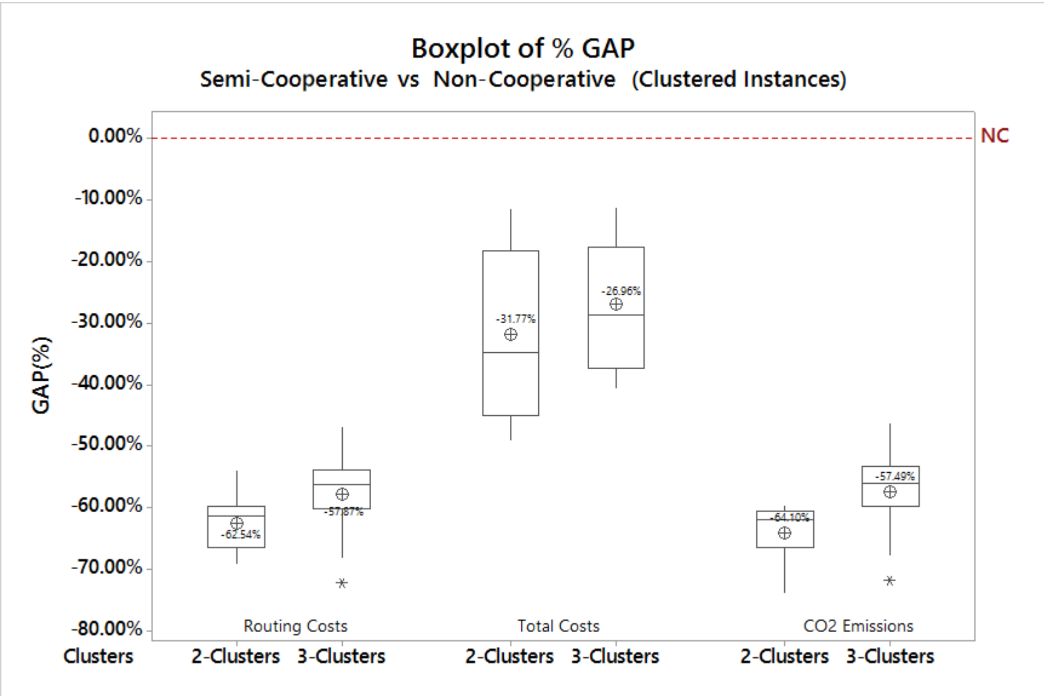


Figure 4.11 Clustered instances comparison of non- and semi cooperative scenarios.

requiring complex and time-consuming fine-tuning processes, as well as a high number of operators to be used.

This chapter also analyzed the CLRP with stochastic demands. This richer version has been solved by a simheuristic procedure in which three different simulation processes are combined with the two proposed metaheuristic approaches. Simulation is used not only to assess the quality of stochastic solutions but also to determine the safety stock strategy used to face demand uncertainty. Benchmarks from literature were adapted to the stochastic case with three different variability levels.

Furthermore, this chapter discusses different HC scenarios in integrated routing and location decisions. Three cases are considered: *(i)* the non-cooperative scenario, in which all decisions are taken decentralized by each company; *(ii)* the semi-cooperative scenario, based on operational cooperation in route planning through customer order exchanges as well as shared vehicle and depot capacities; and *(iii)* the fully-cooperative case, in which routing and facility location decisions are taken on an aggregated supply chain level. Each scenario is assessed concerning monetary and environmental costs by considering the associated optimization problem that can be deduced from each planing situation: the VRP, the MDVRP, and the LRP, respectively. All scenarios are compared through extensive experiments based on real-life and theoretical benchmark sets. Reported results suggest that significant overall costs savings (considering depot opening-, routing-, and vehicle usage costs) can be achieved when applying strategic HC in the integrated routing and location decision making process. This is specially the case in less-clustered problem settings. In some instances, the semi-cooperative (operative) supply chain planning approach yields the most promising results regarding CO_2 emissions due to lower routing distances when no facility location decisions (and associated costs) are considered. Moreover, the effects of clustered topologies are also analyzed in cooperative scenarios.

Chapter 5

Other RVRPs in City Logistics

The content of this chapter is based on the following publication:

- Gruler, A.; Quintero-Araujo, C.L.; Calvet, L.; Juan, A. (2017). "Waste Collection Under Uncertainty: A Simheuristic Based on Vairable Neighborhood Search". European Journal of Industrial Engineering, Vol. 11, No. 2, pp.228–255. ISSN: 1751-5254. (*JCR*)

- Quintero-Araujo, C.L.; Pages-Bernaus, A.; Juan, A.; Travesset, O.; Jozefowiez, N. (2016). "Planning Freight Delivery Routes in Mountainous Regions". Springer Lecture Notes in Business Information Processing, (254), 123-132. ISSN: 1865-1348. (*Scopus*)

In this chapter, two different problem settings in the context of city logistics are analyzed. On the one hand, the Waste Collection Problem (WCP) is becoming increasingly popular due to the growth of urban areas and smart cities around the world. Efficient waste management has relevant benefits for society, such as the reduction of environment pollution, hygiene problems, traffic jams, and direct costs (up to two thirds of operational waste management costs according to Malakahmad et al. (2014); Son (2014); Tavares et al. (2009)). Formulated as an optimization problem, the WCP can be seen as an extension of the Capacitated Vehicle Routing Problem. Special problem characteristics include the pick-up activities of waste and the inclusion of additional landfill trips. Despite the amount of works in the literature devoted to this problem, most works assume that waste levels are known when designing vehicle routes, which is not the case in real-life applications. On the other hand, the planning of routes for the delivery of goods in mountainous regions is addressed. Mountainous regions may have special characteristics related to the topography. Some of the customers may be accessible only by regional roads, or after crossing mountain passes which in winter times may require that vehicles are equipped adequately. City centers, which usually have particular characteristics such as narrow streets and limited parking areas, may have even harder driving conditions (such as streets with slopes). All these characteristics limit the type of vehicles that can access certain areas. In particular, large trucks may be unable to access downtown areas or may experience difficulties in driving up and down the mountains. In such situation smaller vehicles seem more appropriate to be used to serve the customers.

5.1 The Waste Collection Problem with Stochastic Demands

5.1.1 Problem Description

Extending the classical VRP formulation, the WCP consists of a set of waste containers (customers) with associated waste levels (demands) and a central depot in which a capacitated vehicle fleet is located. Furthermore, there is a set of landfills or disposal sites where vehicles are unloaded. The arcs (edges) connecting any two nodes are characterized by travel costs, e.g.: distance, time, or CO_2 emissions. Figure 5.1 illustrates an example of a WCP solution with two routes (blue and red, respectively). Vehicles start at the departure depot to visit a set of waste containers. A WCP specific problem constraint is that vehicles start and end their routes empty. For this reason, at least one additional landfill trip is included on every route before the collection vehicle goes to the arrival depot (in many cases, departure and arrival depots are the same). As can be seen in the blue route, multiple landfill visits during the same trip are allowed. Thus, a vehicle might visit a disposal site once its capacity is reached and then continue the same trip as long as no further route constraints (e.g., time windows, maximum number of stops, etc.) are violated. Additional constraints such as the inclusion of lunch breaks during the execution of the route can be considered.

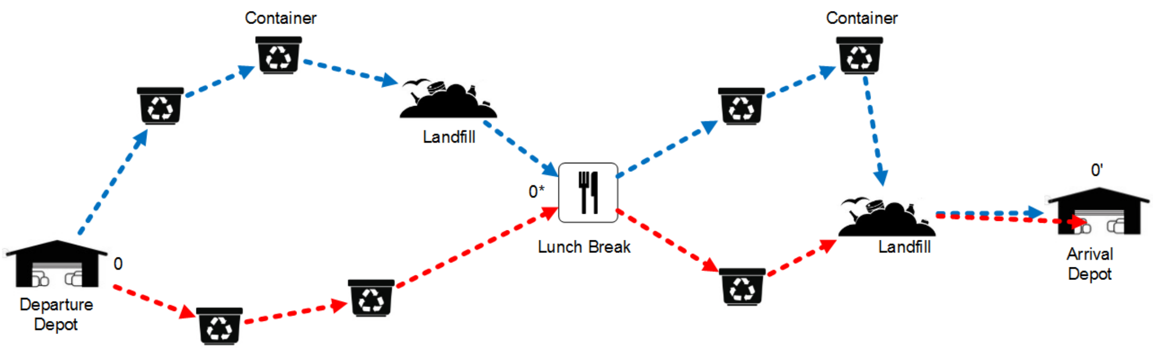


Figure 5.1 Representation of the WCP

In many real-world applications of routing problems, uncertainty is one of the major factors to be considered during operational planning because relevant information and input data is not perfectly available. A typical application area experiencing high levels of uncertainty is urban waste collection (Beliën et al., 2014). As waste generation and travel times of vehicles cannot be predicted with full certainty, there is a need for fast and risk-aware solutions of high quality which are able to take stochastic input variables into account.

5.1.1.1 Basic Version of the WCP

The WCP can be described on a graph $G = (V, A)$, where the set of nodes $V = V^d \cup V^f \cup V^c \cup V^b$ includes: *(i)* a set of starting and ending depots $V^d = \{0, 0'\}$ (in practice both depots could be the same), with the starting depot being the initial location of a fleet of homogeneous vehicles $K = \{1, 2, \ldots, k\}$, each of them having a capacity C; *(ii)* a set $V^f = \{1, 2, \ldots, m\}$ describing m landfills at which collected waste must be disposed at least once before visiting the ending depot (see Figure 5.1); *(iii)* a set of waste containers (customers) $V^c = \{m + 1, \ldots, m + n\}$ with associated waste levels $q_i > 0$ ($\forall i \in V^c$); and *(iv)* a set $V^b = \{0^*\}$ representing a virtual lunch-break node that has to be included in each route. Each node $i \in V \setminus V^d$ has an associated time window represented by $[a_i, b_i]$ (with $0 \leq a_i < b_i$). Necessary service times for emptying any container and the duration of the lunch break are formulated as $r_i > 0$ ($\forall i \in V^c \cup V^b$). Likewise, the set $A = \{(i, j)/i, j \in V, i \neq j\}$ describes the arcs connecting any pair of different nodes. Each pair is characterized by its respective travel costs, $c_{ij} = c_{ji} \geq 0$, and travel times, $t_{ij} = t_{ji} \geq 0$. The travel time associated with going from any node $i \in V \cup V^b$ to the virtual lunch-break node (and vice versa) is equal to zero, i.e.: $t_{i0^*} = t_{0^*i} = 0$. Notice, however, that the travel cost associated with 'crossing' the lunch-break virtual node is given by the travel cost of the origin and destination nodes, i.e.: $c_{i0^*} + c_{0^*j} = c_{ij}$. The decision variables x_{ijl} ($\forall (i, j) \in A$, $\forall l \in K$) equal 1 if arc (i, j) is employed by vehicle l and 0 otherwise. Our mathematical model is presented next. It extends the one proposed in Buhrkal et al. (2012) (e.g. by including the lunch break constraints) and the one proposed in Sahoo et al. (2005) (which only considers traveling times). In our model, d_{il} represents the accumulated load of vehicle l before serving node i, h_{il} represents the service starting time of vehicle l at node i, and M_1 is a large-enough constant that can be defined as $M_1 = \max\{b_i\}(\forall i \in V \setminus V^d) + \max\{s_i\}(\forall i \in V \setminus V^d) + \max\{t_{ij}\}$ ($\forall (i, j) \in A$).

$$\text{Min} \sum_{(i,j)\in A} c_{ij} \sum_{l\in K} x_{ijl} \tag{5.1}$$

Subject to:

$$\sum_{j \in V \setminus V^d} x_{0jl} = 1 \qquad \forall l \in K \tag{5.2}$$

$$\sum_{i \in V^f} x_{i0'l} = 1 \qquad \forall l \in K \tag{5.3}$$

$$\sum_{i \in V} \sum_{l \in K} x_{ijl} = 1 \qquad \forall j \in V^c \tag{5.4}$$

$$\sum_{\substack{i \in V \\ i \neq j}} x_{ijl} = \sum_{\substack{i \in V \\ i \neq j}} x_{jil} \qquad \forall j \in V \setminus V^d, \forall l \in K \tag{5.5}$$

$$a_i \leq h_{il} \leq b_i \qquad \forall i \in V \setminus V^d, \forall l \in K \tag{5.6}$$

$$h_{il} + r_i + t_{ij} \leq h_{jl} + (1 - x_{ijl})M_1 \qquad \forall (i,j) \in A, \forall l \in K \tag{5.7}$$

$$d_{il} = 0 \qquad \forall i \in V^d, \forall l \in K \tag{5.8}$$

$$\begin{aligned} &d_{jl} - C(1 - x_{ijl}) \leq d_{il} + q_i \leq \\ &d_{jl} + C(1 - x_{ijl}) \end{aligned} \qquad \forall i \in V^c \cup V^b \cup \{0\}, \forall j \in V \setminus V^d, \forall l \in K \tag{5.9}$$

$$d_{jl} \leq C(1 - x_{ijl}) \qquad \forall i \in V^f, \forall j \in V^c \cup V^b, \forall l \in K \tag{5.10}$$

$$\sum_{i \in V} x_{i0^*l} = 1 \qquad \forall l \in K \tag{5.11}$$

$$\sum_{j \in V} x_{0^*jl} = 1 \qquad \forall l \in K \tag{5.12}$$

$$\begin{aligned} &h_{il} + r_i + r_{0^*} + t_{ij} \leq \\ &h_{jl} + (2 - x_{i0^*l} - x_{0^*jl})(M_1 + r_{0^*}) \end{aligned} \qquad \forall (i,j) \in A, \forall l \in K \tag{5.13}$$

$$d_{il} \leq C \qquad \forall i \in V^f, \forall l \in K \tag{5.14}$$

$$c_{i0^*} + c_{0^*j} \geq c_{ij} \qquad \forall (i,j) \in A \tag{5.15}$$

$$d_{il} \geq 0 \qquad \forall i \in V, \forall l \in K \tag{5.16}$$

$$x_{ijl} \in \{0,1\} \qquad \forall (i,j) \in A, \forall l \in K \tag{5.17}$$

The objective function of minimizing total cost is formulated in Equation (5.1), which represents the costs of the traveled edges. Constraints (5.2) imply that each vehicle leaves exactly once the starting depot, while constraints (5.3) impose that each vehicle must visit a landfill right before reaching the ending depot. Constraints (5.4) ensure that each container is visited exactly once. Constraints (5.5) guarantee that we arrive to and leave from each non-depot node. Constraints (5.6) force to the compliance of time windows. Constraints (5.7) define the earliest possible starting time for the next customer taking into account service and travel times. Constraints (5.8) reset the vehicle load to zero when leaving from or arriving at a depot. Constraints (5.9) accumulate load levels after visiting each container. Constraints (5.10) are to empty vehicles after visiting a landfill. Constraints (5.11) and (5.12) introduce a lunch break during each route. Constraints (5.13) impose that travel times between the stops before and after the lunch break are taken into account to fix the earliest possible starting time of the next container. Constraints (5.14) limit the maximum waste a vehicle may carry at any time. Constraints (5.15) define the costs of crossing a virtual lunch-break node. Notice that these costs are calculated as the travel cost between the origin- and destination node, i.e.: $c_{i0^*} + c_{0^*j} = c_{ij}$. Thus, c_{i0^*} and c_{0^*j} are not inputs but decision variables satisfying the aforementioned constraint. Finally, constraints (5.16) and (5.17) define variable domains.

5.1.1.2 A Richer and More Realistic Version of the WCP

The following restrictions, which significantly increase the difficulty of the problem, are added to the basic version described before: *(i)* the number of vehicles used is not predetermined, only the maximum number of available vehicles is given; *(ii)* the lunch break is automatically included in a route whenever a certain time window is reached; *(iii)* there is a maximum number of stops at containers and landfills per route; *(iv)* there is a maximum amount of waste that can be collected on a single vehicle route; and *(v)* the depot also has a time window.

5.1.2 Solving Approaches for the Deterministic WCP

5.1.2.1 Exact Methods

The previous model was implemented in the GAMS®language (Version 23.5.2). Then, the CPLEX®solver (Version 12.2.0.0) was used to try solving the smallest instance provided by Kim et al. (2006), which has 1 depot, 99 containers, and 2 landfills. However, the solver ran out of memory after 54 minutes of computation. Therefore, we generated three smaller instances with 20, 24, and 44 containers, respectively. The number of landfills used was 2, as in the original instances. The CPLEX®solver was allowed to run for a maximum time of 48 hours or until a gap lower than 1% was reached. Then, we also employed our VNS algorithm –described in subsection 5.1.2.2– to solve the same instances. Table 5.1 shows the comparison of results between CPLEX®and our VNS algorithm for the aforementioned instance. For each solving method, we include the best solution found (Z), the time consumed to find that solution ($TC\,Z$) and the maximum computing time allowed (TC). Notice that both methods provide optimal solutions for the first two instances, but the VNS clearly outperforms the exact method in computing times (less than 1 second compared to 126 and 854 seconds required by CPLEX®, respectively). Regarding the third instance, CPLEX®ran out of memory after 5864 seconds. The best solution found by the exact method –after 2306 seconds– has an objective value of 70.85 (relative gap of 65% with respect to the lower bound), while our VNS algorithm provides an objective value of 63.09 in 1.5 seconds. These results reveal how difficult it becomes for the CPLEX®solver to find optimal/near-optimal solutions in low computing times, even for small instances of the basic WCP version. For that reason, in the following we will focus on developing heuristic-based approaches, which allow us to deal with richer and more realistic versions of the problem.

Table 5.1 Comparison of results among CPLEX®and our VNS

	CPLEX®			**VNS**			**Gap**
Instances	*Z(1)*	*TC Z (sec.)*	*TC (sec.)*	*Z(2)*	*TC Z (sec.)*	*TC(sec.)*	*Z(2) - Z(1)*
Kim102(20)	38.19	126.31	8916	38.19	<1	300	0.00%
Kim102(24)	24.88	854.05	3641.51	24.88	<1	300	0.00%
Kim102(44)	70.85	2306.55	5864.28*	63.09	1.5	300	-10.95%
Average							*-3.65%*

5.1.2.2 A Variable Neighborhood Search (VNS) Algorithm for the Deterministic WCP

In order to solve the deterministic WCP a VNS metaheuristic is proposed. VNS is based on the construction of different solution neighborhoods and the following descent phase to define a local minimum in the corresponding neighborhood structure (Hansen et al., 2010). An initial solution is obtained by applying the well-known savings routing heuristic (Clarke and Wright, 1964) and its biased-randomized extension as described in Faulin et al. (2008) and in Juan et al. (2013a). This procedure is adapted to the special case of waste collection by changing the calculation of savings values used for merging two customers i and j, originally calculated as $s_{ij} = c_{i0} + s_{0j} - c_{ij}$ (Figure 5.2 - left). In the WCP, the costs of traveling between a customer and the depot are asymmetric due to the additional landfill visit. To address this new situation, we employ a simple transformation based on the average savings associated to each arc (Figure 5.2 - right).

Based on the initial solution $baseSol$, different neighborhood structures $N_k(k = 1, ..., k_{max})$ are created. The shaking procedures applied to create new solution structures are outlined in Table 5.2. Within each neighborhood $N_k(baseSol)$, different local descent heuristics described in Table 5.3 are randomly applied to find the local minimum of $N_k(baseSol)$. To conclude the local search phase, a quick solution improvement procedure based on a cache memory technique (Juan et al., 2013a) is implemented: the best-known order of traveling between a set of nodes establishing a sub-route –i.e., starting at the depot or a landfill and

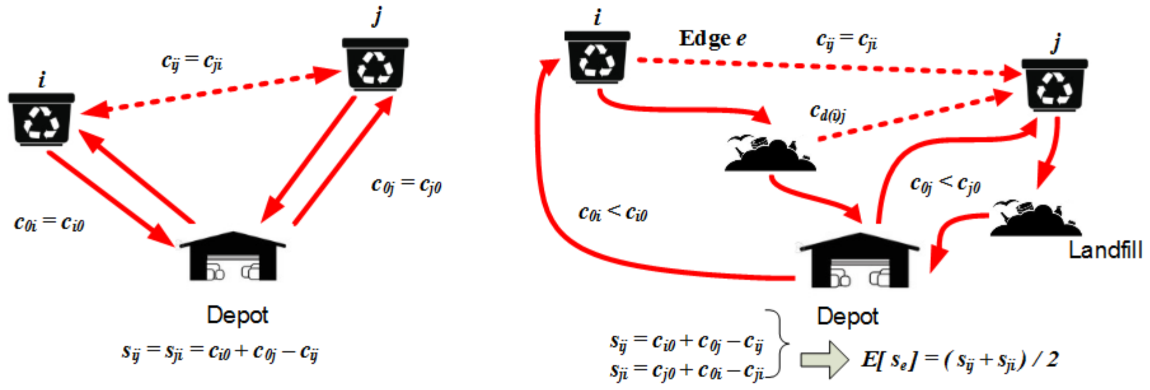


Figure 5.2 Savings of the original CWS heuristic (left) and expected savings proposed for the WCP (right)

ending at a disposal site– is stored in a hash-table data structure, thus allowing new solutions to benefit from previously constructed ones. Whenever the local search phase leads to a more competitive objective function value than that of $baseSol$, $baseSol$ is updated and k is returned to its initial value of 1. If $baseSol$ cannot be improved through the local minimum of N_k, k is incremented by 1 and the next shaking operator is applied. Once each neighborhood has been constructed ($k = k_{max}$), the process is repeated until a certain predefined stopping criterion (e.g.: time, iterations, etc.) has been reached. Note that we shuffle the list of neighborhood operators every time $k > k_{max}$. A description of the VNS procedure for the deterministic WCP can be seen in Algorithm 5.

Table 5.2 Shaking operators

Operator (k)	**Description**
Customer Swap Inter-Route	Swaps two randomly selected customers between different routes.
2-Opt Inter-Route	Interchanges two chains of randomly selected customers among different routes.
Reinsertion Inter-Route	Inserts a randomly selected customer in a different route.
Cross-Exchange	Interchanges positions of 2-4 random, non-consecutive customers from different routes.

Table 5.3 Local search operators

Operator (LS-Scheme)	**Description**
Best Position Insertion	Reinserts the container with the highest objective function increase into the best available position of any route.
Re-allocate all	Iteratively calculates the objective function increase of each container and reinserts it at the best possible position.
Random Swaps	Randomly selects and interchanges two nodes (from the same or different routes) if the objective function improves.

Algorithm 5: VNS for the WCP

```
baseSol ← solve biased randomized CWS for the WCP  // Juan et al. (2013a)
while stopping criteria not reached do
    shuffle(ListOfShakingOperators)
    k ← 1
    repeat
        newSol ← shake(baseSol, k)                      // see Table 5.2
        improving ← true                                // Start Local Search
        while improving do
            newSol* ← localDescent(newSol, randomLSoperator)   // see Table 5.3
            if costs(newSol*) ≤ costs(newSol) then
                newSol ← newSol*
            end
            else
                improving ← false
            end
        end
        cacheSubRoutes(newSol)                          // End Local Search
        if costs(newSol) < costs(baseSol) then
            baseSol ← newSol
            k ← 1
        end
        else
            k ← k+1
        end
    until k > k_max
end
bestSol ← baseSol
return bestSol
```

To test the competitiveness of our algorithm we use the benchmark instances provided by Kim et al. (2006). This benchmark set includes 10 realistic instances, ranging from 102-2100 nodes with time windows, multiple landfills, a single depot, a driver lunch break during each route, and a homogeneous vehicle fleet. Furthermore, we compare our approach to the clustered instances presented by Buhrkal et al. (2012). A clustering procedure is applied to nodes with the same location and time windows to change the total number of nodes. The algorithm was implemented as Java application and run on a personal computer with an Intel®Xeon™CPU E5-2630 v2 @ 2.60GHz processor. The initial solutions constructed with the biased randomized version of the savings heuristic are based on a distribution parameter randomly chosen within the range (0.4, 0.5) at each solution construction step.

Our results are summarized in Table 5.4. Column (1) reports the best known solution (BKS) for each instance (listed as Kim_numberOfNodes) as reported in the works of Benjamin and Beasley (2010); Kim et al. (2006) and Buhrkal et al. (2012). The computational times (CT) in seconds, to reach each solution can be seen in column (2), while column (3) lists the average results with 10 different random number seeds as presented in the benchmark papers. Notice that the benchmark papers use different computers, computational times, and programming languages to implement and execute their described algorithms, making a fair comparison difficult. For this reason, we have tested our VNS metaheuristic with two different stopping criteria. On the one hand, our best solution (achieved with 10 different random number seeds) when applying the CTs listed in column (2) is reported in column (4). Furthermore, we report our average solution with 10 different random number seeds (5) and our best solution (6) with a stopping criterion of 300 seconds per instance as suggested by Benjamin and Beasley (2010). It can be seen that our algorithm outperforms current BKS's by an average of -0.85% and -2.65%. Moreover, our algorithm reaches 9 new BKS's (11 with the extended algorithm running time). As can be observed, the percentage gap compared to the BKS extends to more than 10% in some cases. These differences are supported by results described in a technical report by Markov et al. (2015), in which the authors use the five smallest (non-clustered) instances of the applied benchmark set to test a heuristic for the WCP.

Some final remarks concerning the algorithm can be made. The initial solution for all instances is constructed in under 3 seconds (only a few milliseconds for the smaller problem cases). In comparison to the previous BKS's, the average gap of the initial solutions is 8.92%. A similar comparison to our best solution is done with the different local search operators. When only running the algorithm with the "best position insertion", the "re-allocate all", and the "random-swaps" local search, the average percentage gaps are -0.38%, 1.28%, and 2.34% respectively. While performance differences between the operators can be observed, these results suggest that the combination of various local search techniques is highly convenient in the solution of the WCP.

5.1.3 Solving the Stochastic Waste Collection Problem

5.1.3.1 A Simheuristic Approach Based on VNS

In realistic scenarios, waste levels cannot be predicted with certainty. The fact that real waste levels in containers are only known when reaching designated pick-up points can lead

Table 5.4 Computational results for the deterministic case and comparison with BKSs

Instance	**(1) BKS**	**(2) CT BKS (s)**	**(3) BKS average**	**(4) Our best sol**[1]	**(5) Our sol average**[2]	**(6) Our best sol**[2]	**(7) CT Our best sol (s)**	**%-Gap (1)-(4)**	**%-Gap (1)-(6)**
Kim102	174.5	3	176.03	158.61	158.64	154.62	5	-9.11	-11.39
Kim277	447.6	8	455.7	472.73	457.14	450.6	299	5.61	0.67
Kim335	182.1	10	196.49	189.79	187.36	184.22	298	4.22	1.16
Kim444	78.3	18	78.99	80.22	80.09	79.49	292	2.45	1.52
Kim804	604.1	72	650.65	603.17	601.14	593.2	300	-0.15	-1.80
Kim1051	2250.6	194	2387.7	2128.37	2119.50	2077.37	294	-5.43	-7.70
Kim1351	871.9	105	891.17	929.5	929.40	910.6	238	6.61	4.44
Kim1599	1337.5	252	1385.3	1184.67	1208.54	1182.58	292	-11.43	-11.58
Kim1932	1162.5	285	1192.2	1149.45	1169.95	1136.34	273	-1.12	-2.25
Kim2100	1749	356	1916.8	1595.48	1622.29	1603.93	293	-8.78	-8.29
Clustered Instances									
Kim86	174.5	3	176.6	155.68	158.35	155.68	10	-10.79	-10.79
Kim267	450.7	8	456.4	460.4	455.96	449.41	294	2.15	-0.29
Kim322	182.4	10	190.7	189.78	185.93	184.26	298	4.05	1.02
Kim444	78.6	18	79.2	80.22	80.09	79.49	292	2.06	1.13
Kim602	586.2	72	647.8	610.52	593.25	586.11	297	4.15	-0.02
Kim1011	2295.2	116	2370.5	2151.51	2131.00	2102.23	299	-6.26	-8.41
Kim536	850	105	850.9	885.83	877.69	850.46	292	4.22	0.05
Kim870	1170.2	252	1230.6	1156.15	1180.07	1145.83	286	-1.20	-2.08
Kim1860	1128.7	285	1180.9	1129.89	1154.48	1138.6	295	0.11	0.88
Kim1877	1594.2	266	1650.8	1620.89	1642.20	1604.33	186	1.67	0.64
Average	***868.44***	***122***	***908.27***	***846.64***	***849.65***	***833.47***	***257***	***-0.85***	***-2.65***

[1]computational times per instance equal to column (2)
[2]computational times per instance equal to column (7)

to route failures whenever collected garbage exceeds the planned collection amount. In these cases, the collection vehicle needs to add an additional and, usually, expensive landfill visit to its route. The proposed simheuristic methodology outlined in Algorithm 6 allows an estimation of the solution quality of previously created outputs using the VNS metaheuristic proposed in subsection 5.1.2.2 by integrating MCS into the solution procedure. Note that the simheuristic structure for the WCP can theoretically be combined with any metaheuristic approach addressing the problem setting. However, the quality of the stochastic solution is directly related to the results obtained in the deterministic metaheuristic process (Juan et al., 2015a). For this reason, the use of an efficient deterministic solution process such as the one outlined in subsection 5.1.2.2 is a clearly a real necessity.

Before simulating waste levels, our methodology starts by transforming the stochastic input variables into their deterministic counterpart, which is used to establish initial WCP solutions. Even though waste levels (especially in urban settings) face different levels of stochasticity, their behavior can typically be modeled according to some kind of theoretical or empirical distribution (e.g., based on historical data). This allows the (stochastic) waste levels w_i at each container i to be replaced with expected values $E[w_i]$. Using these deterministic values, an initial solution $baseSol$ is constructed. In the following, the solution quality in a stochastic environment is tested by randomly simulating the waste levels of each container i for a certain number of iterations (or simulation runs) using the predefined probability distribution. During each run the occurring route failure costs are estimated by penalizing situations in which vehicle capacities are reached before a scheduled landfill trip. More specifically, route failure costs are calculated as corrective actions to the predefined routes –i.e., the necessary additional landfill trip starting and ending at the container at which the vehicle capacities are reached. Finally, the sum of all route failure costs of all simulation runs are divided by the number of simulation runs. Thus, the expected total costs of $baseSol$ now consist not only of the deterministic routing costs, but rather in the addition of the deterministic routing costs with the expected route failure costs. At this stage we propose the application of a small number of iterations $shortSimIter$. On the one hand, a larger number of simulation runs lead to more reliable estimates of the stochastic route costs. On the other hand, at this stage a shorter simulation procedure can be used to keep the computational effort through the simulation reasonable.

Once $detCosts(baseSol)$, $stochCosts(baseSol)$, and $totalCosts(baseSol)$ have been defined, new deterministic solution neighborhoods are constructed and locally improved as described previously. A newly constructed solution $newSol$ is considered as promising whenever it yields lower deterministic costs than the current base solution. The behavior of each promising solution under waste level uncertainty is then evaluated by applying

Algorithm 6: Simheuristic for the WCP

```
replace stochastic waste levels by expected values  // Creation of det. inputs
baseSol ← solve biased randomized CWS for the WCP
shortSimulation(baseSol)                                                // MCS
while stopping criteria not reached do
    k ← 1
    repeat
        newSol ← shake(baseSol, k)                          // see Algorithm 5
        localSearch(newSol)                                 // see Algorithm 5
        if detCosts(newSol) < detCosts(baseSol)       // Solution is promising
         then
            shortSimulation(newSol)                                     // MCS
            if totalCosts(newSol) < totalCosts(baseSol) then
                update(eliteSols)
                baseSol ← newSol
                k ← 1
            end
            else
                k ← k+1
            end
        end
    until k > k_max
end
foreach eliteSol do
    longSimulation(eliteSol)
    estimateReliability(eliteSol)
end
return Pareto non-dominated eliteSols
```

a short simulation run, leading to a first estimation of the total solution costs. Whenever $totalCosts(newSol) < totalCosts(baseSol)$, the current base solution is updated and k is returned to its initial value. Furthermore, the solution is stored as elite stochastic solution. With each elite solution, a more extensive simulation run is started for $longSimIter$ iterations once the metaheuristic stopping criteria has been reached. As discussed in Juan et al. (2015a), it is recommendable to use a restricted number of solutions for the more extensive simulation run at this stage. For this reason, we limit the number of stored $eliteSols$ to a maximum of 10. While some changes in the stochastic objective function of single solutions can be observed through the more detailed simulation, an augmented elite solution list does not yield to significant changes in the final ranking of the best stochastic solutions.

In addition to calculating the stochastic objective function value of promising deterministic solutions, our methodology allows the estimation of a solution reliability by considering the proportion of runs where the solution plan can be implemented without any route failure (a route failure occurs whenever the actual demand at any container exceeds the vehicle capacity, which forces the vehicle to visit a disposal site before resuming the original route). Thus, the reliability $reliab_r$ of each route r of any solution S is computed as the quotient of the number of runs in which a route failure occurs divided by the total number of simulation runs, i.e. $reliab_r = simRunsWithRouteFailure/simRuns$. Notice that each route in a solution can be seen as an independent component of a series system (i.e., the proposed solution will fail if, and only if, a failure occurs in any of its routes). Therefore, the overall reliability of a solution with R routes can be computed as $\prod_{r=1}^{R} reliab_r$. This leads to another valuable decision variable for waste collection route planners, especially due to the fact that more than one solution is evaluated in the same manner when applying the described reliability calculation to each elite solution. Furthermore, it allows for a closer risk and sensitivity analysis of the considered solutions, as explained in the following subsection.

5.1.3.2 Computational Experiments for the Stochastic Waste Collection Problem

Similar to the deterministic case, a set of computational experiments have been performed for the WCP under uncertainty, which are described in this subsection. Furthermore, the obtained results are discussed and analyzed.

As there are not benchmarks for the stochastic case, we use the non-clustered instances of Kim et al. (2006) as reference. The deterministic instances are transformed into stochastic ones by using random waste levels following a log-normal distribution with expected values equal to the original deterministic value. This probability distribution has been chosen because it is quite flexible and among the most popular ones when modeling non-negative random variables. Other probability distributions, like the normal one, are rarely employed to model non-negative random variables. Nevertheless, our approach could be used with any other probability distribution (e.g., Weibull, gamma, etc.). Note that any probability distribution will allow the easy construction of the deterministic case by putting the variance level $Var[w_i]$ of any container equal to 0, considering that the deterministic values provided by the instances are used as the distribution mean.

We test our approach using low ($Var[w_i] = 0.05w_i$), medium ($Var[w_i] = 0.15w_i$), and high variance levels ($Var[w_i] = 0.25w_i$) concerning the waste level distribution at any container. The number of short simulation runs is set to 500, while a more extensive simulation with 5000 runs is applied only to the elite solutions. Moreover, we propose the inclusion of vehicle safety stocks k to better deal with unexpected demands, as discussed in more detail by Juan et al. (2011a). Instead of considering the complete available vehicle capacity C in the construction of the deterministic solution, a decreased capacity $C^* = C * (1 - k)$ is applied. On the one hand, high levels of k will, on average, lead to higher deterministic costs (and increased solution reliabilites), as the considered vehicle capacity during the route construction is reduced. On the other hand, it can be expected that the stochastic route failure costs will decrease. For the following analysis and discussion of results, 6 different safety stock levels k: 0, 0.02, 0.04, 0.06, 0.08, and 0.1 are considered. Combined with the three variance levels, this leads to a total of 18 different scenarios for each instance. Tables 5.5-5.7 show the deterministic costs (1), the total costs including the expected route failure penalties (2), and the related reliability calculated as described in the previous Section (3) of each tested scenario, where listed results refer to the best obtained solution according to the overall costs. The average calculation time (to complete the VNS procedure and the subsequent extensive simulation for the elite solutions) of all scenarios was 351.92 seconds.

5.1.3.3 Discussion and Analysis of Results

Figure 5.3 shows the expected total costs and reliabilities for the average of all tested instances for each variance level/safety capacity factor combination. As can be observed, the highest total costs for each waste variance level is obtained when no safety capacity factor is considered as a result of high expected route failure costs. Furthermore, it can be seen that the lowest total costs over all instances for a low variance level are obtained with a safety capacity factor of 2%. For medium and high waste variance, a safety capacity factor of 4% seems to yield the most promising results concerning total costs. As expected however, the reliability levels (also calculated as an average of all instances) increase for all variance levels as the vehicle safety capacity is increased. It can also be concluded that the inclusion of only a small safety capacity already significantly increases reliability levels (up to around 60% in the most extreme case). In contrast to the stochastic case, safety capacity levels negatively impact the deterministic results as vehicle capacity levels are reduced. This can be clearly seen in Figure 5.4, showing the average deterministic costs of all instances and variance levels with different safety stock levels.

A more detailed risk analysis is done in Figure 5.5, which shows a boxplot of the long simulation outputs for the three most competitive elite solutions of the Kim277 instance. In this specific case the first solution seems to be the most promising one, as it has the lowest mean and the lowest quartiles. However, this is not necessarily always the case.

Table 5.5 Computational results for the stochastic case with a low variance level

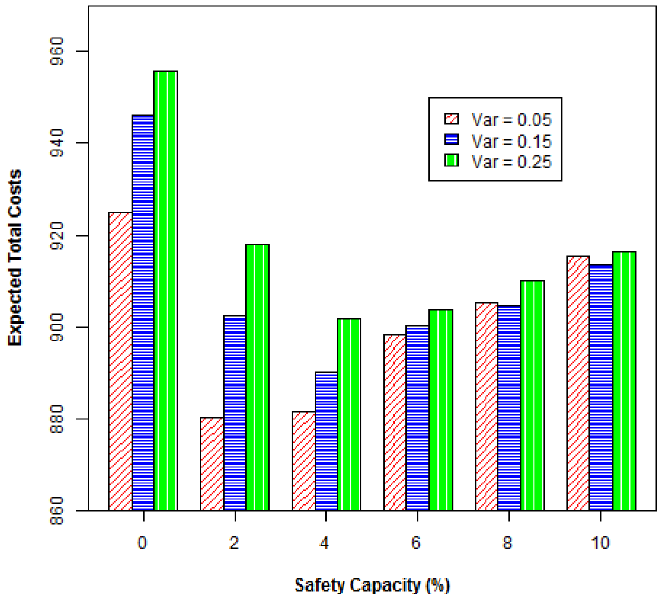
Safety Capacity	**0%**			**2%**			**4%**			**6%**			**8%**			**10%**		
Instance	**(1) Det Costs**	**(2) Total Costs**	**(3) Reliab.**	**(1) Det Costs**	**(2) Total Costs**	**(3) Reliab.**	**(1) Det Costs**	**(2) Total Costs**	**(3) Reliab.**	**(1) Det Costs**	**(2) Total Costs**	**(3) Reliab.**	**(1) Det Costs**	**(2) Total Costs**	**(3) Reliab.**	**(1) Det Costs**	**(2) Total Costs**	**(3) Reliab.**
Kim102	158.78	158.78	1	158.55	158.55	1	156.14	156.15	0.9996	157.67	157.67	1	158.56	158.56	1	158.18	158.18	1
Kim277	471.48	512.35	0.2052	462.46	478.32	0.6274	486.71	487.16	0.9864	491.45	491.45	0.9998	493.89	493.89	1	494.7	494.7	1
Kim335	189.19	189.97	0.3142	187.83	188.06	0.8563	187.09	187.11	0.9944	187.65	187.65	1	189.72	189.72	1	189.66	189.66	1
Kim444	80.48	83.23	0.15	84.68	85.1	0.8476	84.52	84.55	0.9886	86.37	86.37	1	88.43	88.43	1	91.06	91.06	1
Kim804	606.48	645.04	0.0323	621.8	627.4	0.7031	624.94	625.03	0.9952	631.61	631.61	1	642.98	642.98	1	638.02	638.02	1
Kim1051	2200.05	2402.75	0	2216.32	2251.19	0.1883	2229.97	2231.21	0.9497	2313.75	2313.75	0.9996	2319.08	2319.08	1	2333.96	2333.96	1
Kim1351	924.17	1014.92	0.0158	954.2	961.61	0.756	978.95	979.31	0.9871	990.21	990.21	1	996.45	996.45	1	1021.53	1021.53	1
Kim1599	1205.23	1296.8	0.002	1209.95	1217.99	0.6641	1242.46	1242.54	0.9934	1270.23	1270.23	1	1276.18	1276.18	1	1283.12	1283.12	1
Kim1932	1144.16	1237.23	0.0008	1149.68	1152.5	0.7698	1182.4	1182.4	1	1197.76	1197.76	1	1209.53	1209.53	1	1243.92	1243.92	1
Kim2100	1599.38	1707.03	0.0002	1679.76	1683.14	0.8555	1640.45	1640.46	0.9996	1655.24	1655.24	1	1678.34	1678.34	1	1699.23	1699.23	1

Table 5.6 Computational results for the stochastic case with a medium variance level

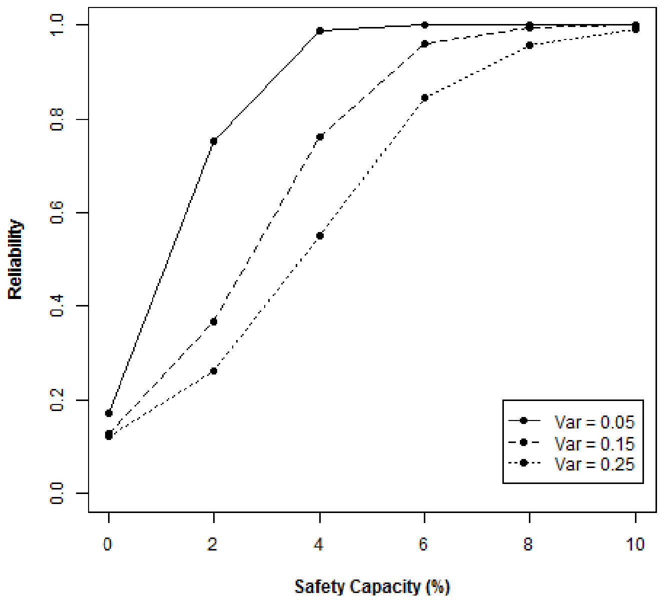
Safety Capacity	**0%**			**2%**			**4%**			**6%**			**8%**			**10%**		
Instance	**(1) Det Costs**	**(2) Total Costs**	**(3) Reliab.**	**(1) Det Costs**	**(2) Total Costs**	**(3) Reliab.**	**(1) Det Costs**	**(2) Total Costs**	**(3) Reliab.**	**(1) Det Costs**	**(2) Total Costs**	**(3) Reliab.**	**(1) Det Costs**	**(2) Total Costs**	**(3) Reliab.**	**(1) Det Costs**	**(2) Total Costs**	**(3) Reliab.**
Kim102	153.27	153.56	0.7681	154.7	154.9	0.9665	158.27	158.37	0.9968	157.67	157.73	0.9982	158.56	158.56	1	158.18	158.18	1
Kim277	462.58	524.87	0.1087	490.06	500.8	0.7097	492.65	498.32	0.8493	496.76	497.48	0.9809	494.29	494.58	0.9922	495.68	495.69	0.9998
Kim335	189.5	190.84	0.3456	187.2	187.71	0.5508	186.21	186.7	0.8249	187.17	187.19	0.9892	189.72	189.72	0.999	189.59	189.59	1
Kim444	80.43	85.53	0.034	84.69	86.8	0.3972	85.16	85.86	0.6948	86.37	86.47	0.9517	87.58	87.59	0.9966	90.84	90.84	0.999
Kim804	607.75	663.12	0.0117	623.64	643.96	0.3229	629.78	633.32	0.8274	630.59	630.79	0.9833	637.11	637.12	0.999	630.04	630.04	1
Kim1051	2201.89	2481.65	0	2215.63	2335.24	0.0026	2251.3	2278.71	0.2778	2309.16	2314.82	0.7669	2319.08	2319.78	0.9712	2333.96	2333.99	0.9988
Kim1351	925.63	1060.93	0.0019	950.02	988.05	0.2058	972.84	982.14	0.6875	1002.1	1002.87	0.9715	996.46	996.51	0.9978	1021.53	1021.53	0.9998
Kim1599	1202.08	1317.4	0.0006	1209.99	1248.56	0.123	1245.18	1251.18	0.6799	1270.23	1271.02	0.9613	1276.18	1276.2	0.9974	1283.12	1283.12	1
Kim1932	1144.16	1248.28	0.0003	1150.33	1171.73	0.1891	1182.4	1184.55	0.8934	1197.76	1197.83	0.9966	1209.53	1209.53	0.9996	1243.92	1243.92	1
Kim2100	1604.81	1735.66	0	1682.09	1707.87	0.1904	1640.79	1642.26	0.901	1655.24	1655.29	0.9962	1678.34	1678.34	1	1687.77	1687.77	1

Table 5.7 Computational results for the stochastic case with a high variance level

Safety Capacity	**0%**			**2%**			**4%**			**6%**			**8%**			**10%**		
Instance	**(1) Det Costs**	**(2) Total Costs**	**(3) Reliab.**	**(1) Det Costs**	**(2) Total Costs**	**(3) Reliab.**	**(1) Det Costs**	**(2) Total Costs**	**(3) Reliab.**	**(1) Det Costs**	**(2) Total Costs**	**(3) Reliab.**	**(1) Det Costs**	**(2) Total Costs**	**(3) Reliab.**	**(1) Det Costs**	**(2) Total Costs**	**(3) Reliab.**
Kim102	158.56	158.57	0.9996	158.27	158.74	0.9842	158.27	158.65	0.9874	156.58	157.02	0.9821	157.21	157.26	0.9984	158.18	158.18	1
Kim277	461.1	537.7	0.0678	487.9	515.37	0.4067	500.22	509.25	0.75	499.31	500.78	0.9588	500.28	502.17	0.9507	498.1	498.7	0.9833
Kim335	189.61	192.76	0.142	186.4	187.86	0.3888	190.09	191.22	0.6926	189.13	189.35	0.8959	189.05	189.08	0.9821	192.09	192.09	0.9982
Kim444	80.43	86.86	0.0154	85.52	87.57	0.3537	85.14	86.83	0.4329	85.92	86.2	0.857	87.88	87.97	0.9524	90.27	90.31	0.9782
Kim804	606.33	670.43	0.0069	624.63	646.11	0.2675	630.17	639.85	0.5774	630.63	632.15	0.8855	643.52	643.93	0.9788	642.68	642.75	0.9968
Kim1051	2204.77	2518.54	0	2215.87	2387.04	0.0001	2247.29	2325.05	0.0238	2311.87	2334.32	0.3647	2319.08	2324.99	0.7783	2333.96	2334.86	0.9627
Kim1351	919.79	1060.65	0.001	950.02	1011.85	0.0728	984.52	1003.82	0.4638	1002.2	1006.84	0.8436	1013.53	1014.49	0.964	1021.53	1021.59	0.9978
Kim1599	1202.08	1329.94	0.0003	1209.99	1268.65	0.0384	1246.46	1263.17	0.3251	1270.81	1275.48	0.7911	1290.52	1291.06	0.9725	1294	1294.1	0.9926
Kim1932	1144.16	1255.11	0.0002	1150.33	1187.7	0.0572	1182.4	1191.29	0.6235	1197.76	1198.99	0.9375	1209.53	1209.59	0.996	1243.55	1243.55	0.9998
Kim2100	1604.81	1746.22	0	1682.09	1728.19	0.0461	1640.79	1647.58	0.6153	1655.24	1656.45	0.9279	1678.34	1678.4	0.9976	1687.77	1687.77	1



(a)



(b)

Figure 5.3 Expected total costs (a) and reliabilities (b) over all instances

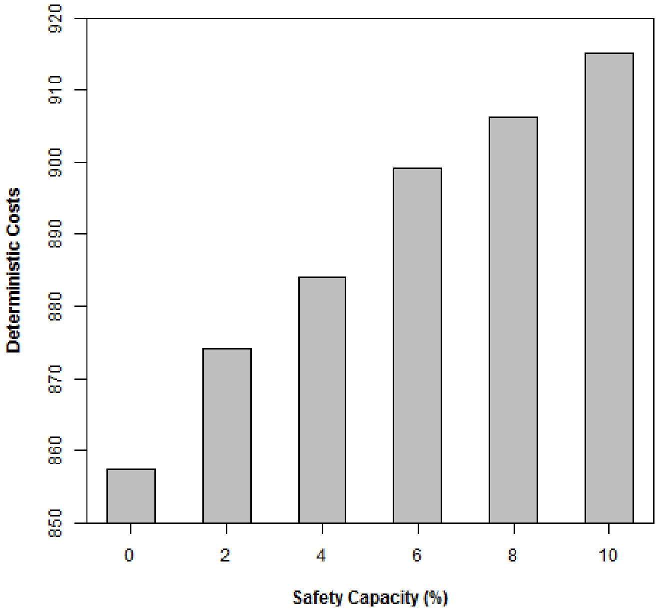


Figure 5.4 Deterministic costs over all instances and variance levels

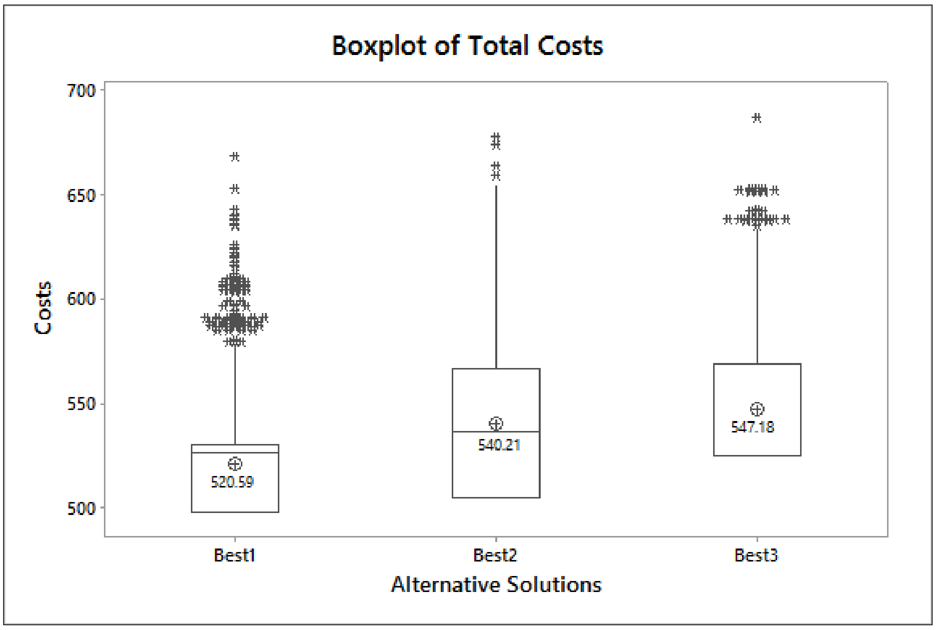


Figure 5.5 Boxplot of the total costs of each long simulation run of the Kim277 instance for the best three solutions considering a high waste variance level and a 2% safety capacity level

In Table 5.8, the mean and standard deviation of the results from the long simulation concerning total costs of the three best solutions of each instance (obtained with a single random-number seed) are listed. From the aforementioned table, it can be concluded that the solution with the lowest mean does not always has the lowest standard deviation (see for example Kim444). Thus, this information can be used by decision-makers to select the solution that he/she prefers according to his/her risk preference. In a similar manner, our solution approach allows the consideration of different risk-aversion levels of decision makers by comparing solutions with different safety capacity levels. A more risk-averse route planner will choose to construct routes with higher safety capacity levels, which typically lead to higher routing costs while experiencing lower route failure, and vice versa.

Table 5.8 Comparison of different elite solutions in terms of the mean and standard deviation of total costs

Elite Solutions	**Best 1**		**Best 2**		**Best 3**	
Instance Name	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Kim102	157.05	3.54	157.14	3.38	157.22	3.65
Kim277	498.66	4.53	499.07	4.45	499.12	4.59
Kim335	187.84	1.81	187.96	1.84	188.25	1.85
Kim444	87.79	0.84	87.80	0.79	91.35	0.82
Kim804	633.97	5.93	634.34	5.74	635.00	5.90
Kim1051	2342.85	16.67	2343.58	15.48	2345.62	16.29
Kim1351	1009.88	26.48	1012.78	26.57	1025.50	26.54
Kim1599	1290.02	24.34	1291.67	23.40	1292.07	23.83
Kim1932	1199.85	29.77	1202.21	30.50	1245.03	30.14
Kim2100	1742.47	13.97	1742.81	14.62	1748.34	13.83

5.2 The Site-Dependent Asymmetric VRP with Heterogeneous Fleet

5.2.1 Problem Description

The HSDAVRP is a natural extension of the classical capacitated VRP. Formally, the HSDAVRP is defined over a complete graph $G = (N, A)$ where $N = 0, 1, \ldots, n$ is the set of nodes where node 0 is assumed to be the depot and the rest represent the customers that need to be visited. Each customer has a (deterministic) demand d_i. The set $A = \{(i, j) : i, j \in (N), i \neq j\}$ contains the arcs that represent the road network. The set A considers that any pair of nodes is connected, and if this differs from the reality a large cost will be associated to it. The cost of traveling on the arc (i, j) is represented by c_{ij}. In the heterogeneous version, the cost of going from i to j is different from the cost of going from j to i. This cost can be related to distance, traveling time, fuel costs or any other measure depending on the case under study. Customer demands are carried by one of the vehicles available in the fleet. The set F includes all available vehicles. Each vehicle k will have particular characteristics. It is to note that the total cost of traveling from i to j will not only depend on the cost associated to the arc but also depends on the type of vehicle used. The cost of the arc is multiplied by a factor that depends on the vehicle type, v_k, (larger vehicles have higher variable cost than smaller ones), being the total cost of the arc a three-index parameter, $c_{ij}^k = v^k \times c_{ij}$. Moreover, each route includes a fixed cost for using a vehicle, f_k. Therefore, the cost of a route corresponds to the sum of the fixed and variable costs of the arcs belonging to the route. Parameter Q_k denotes the maximum load that vehicle k can carry. Vehicles can serve only compatible customers, C_k, where $C_k \subset (N \setminus \{0\})$ is the set of nodes that vehicle k can reach. The aim of the HSDAVRP is to find the routes, covered by a heterogeneous fleet of vehicles, to serve all customers demands while minimizing total traveling costs. This problem represents the main characteristics of route planning for freight transportation in mountainous regions: some type of vehicles might not be able to serve a subset of particular clients (thus requiring a fleet with multiple types of vehicles) and traveling costs depend on the direction of the route and type of vehicle. For a complete mathematical formulation of this problem, the reader should refer to Juan et al. (2014b).

5.2.2 Solving Approach

The proposed solving approach is based on the Successive Approximation Method (SAM) presented in Juan et al. (2014b). The SAM algorithm is a multi-round process in which the number of rounds is limited by the number of vehicle types. At each round a vehicle type is selected among the non-used ones. Then, a new VRP is solved for the non-served nodes by assuming unlimited vehicles of the selected type. When the number of resulting routes is higher than the number of available vehicles of the corresponding vehicle type, a subset of routes is randomly discarded in order to ensure that no more vehicles than the available ones are used. The feasible routes are saved as a partial solution, while the nodes belonging to the discarded routes are added to the subset of non-served nodes. Next, a new round of the process is executed. The process stops when all nodes are visited or when all vehicle types are considered. Site conditions (such as banning vehicles from visiting incompatible customers or the vehicle capacity) are ensured within the SAM algorithm.

Figure 5.6 shows the logic used to solve the HSDAVRP. It starts by defining the set of nodes that needs to be routed. The saving cost for each link in the network is calculated. At this initial stage, the network is reduced to a non-oriented symmetric network. A weighted saving associated to the link that connects node i and j is computed as defined in Herrero et al. (2014) to deal with asymmetric costs:

$$\hat{S}_{ij} = \beta \times max\ (S_{ij}, S_{ji}) + (1 - \beta) \times min\ (S_{ij}, S_{ji}), \beta \in [0.5, 1] \tag{5.18}$$

In equation (5.18), S_{ij} is the saving associated to the arc (i, j) and S_{ji} is the saving associated to the arc (j, i). Then, an available vehicle type is chosen and the set of nodes to be routed is modified by excluding those nodes which are incompatible with the current vehicle type. At each round, routes are created using the biased randomized version of the Clarke and Wright savings (CWS) heuristic proposed by Juan et al. (2010). In this version, edges from the saving list are randomly selected following a biased probability distribution such in a way that the edges with higher savings are more likely to be selected at each construction step. In this case, we use the single-parameter geometric distribution. Then, several runs of the same procedure come up with different proposals. The best solution is chosen as a partial solution. In this partial solution, it is likely that the number of vehicles used is higher than the available ones. In this case, leftover routes are randomly selected and removed from the partial solution. In the next round, those nodes that remain unrouted plus any other nodes left out because of vehicle incompatibility compound the subset of nodes to be routed. When all nodes have been assigned to a proper vehicle, a local search procedure is applied to improve the visiting order within each route. At this point asymmetric costs are employed. A first approach is to check a given route in both directions and take that with lowest value. More advanced techniques can be used such as those presented in Herrero et al. (2014). The scheme presented so far constitutes a basic local search heuristic that determines a set of routes ensuring that vehicles capacity is satisfied (CWS take care of the capacity constraint), customers are served with adequate vehicles (incompatible nodes are removed from the set of unrouted nodes) and routes are measured with asymmetric costs (using a specific local search). To generate new solutions, a base solution is partially destroyed (by removing a random number of routes) and the procedure is repeated.

5.2.3 Numerical Experiments

The aforementioned procedure was coded as a Java application. In order to test the potential of our method we carried out three different experiments: *(i)* homogeneous VRP with asymmetric instances, *(ii)* heterogeneous VRP with asymmetric distances and, *(iii)* hetero-

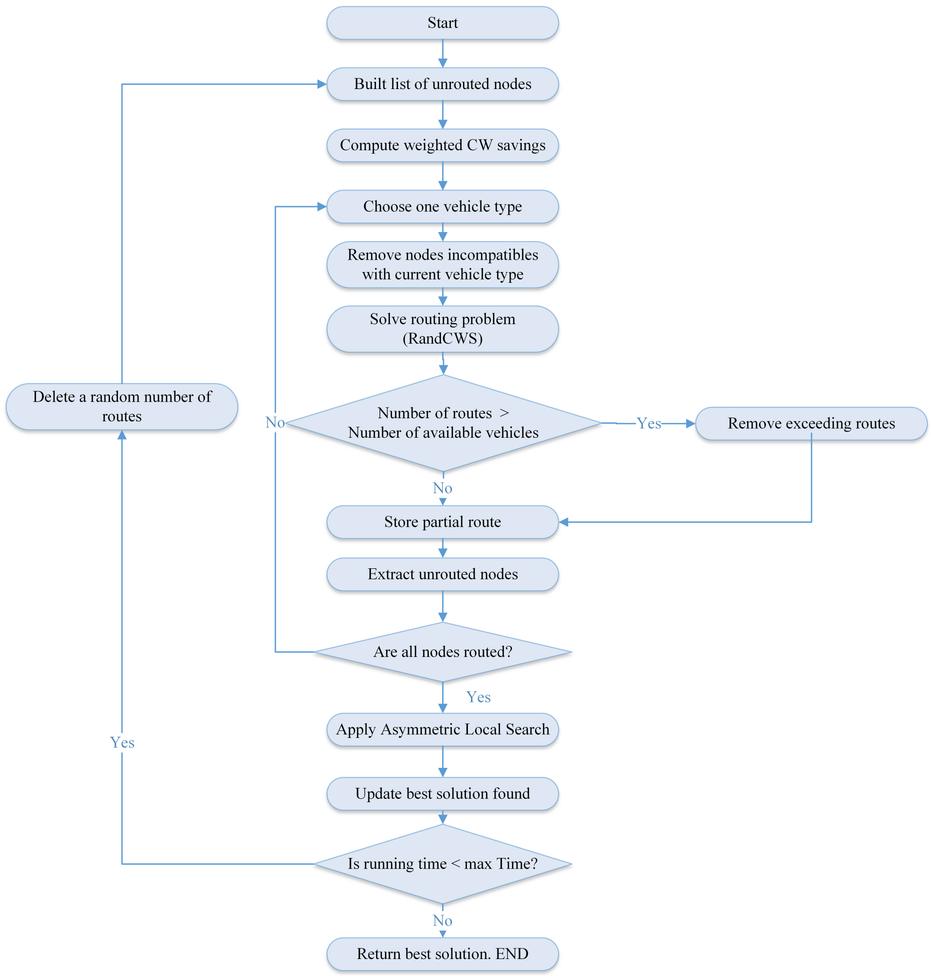


Figure 5.6 Flowchart of the solving method

geneous VRP with asymmetric distances and site-dependency (i.e. some customers can not be served by the vehicles with the largest capacity). Each experiment was carried over all selected instances using 5 different random seeds and was executed using a 2.4 GHz core i5 personal computer with 8Gb RAM. The execution time was established in 120 seconds per run.

5.2.3.1 Test Instances

In order to perform the tests described above, we have randomly selected 4 instances with Euclidean distances from classical Homogeneous VRP instances (NEO, 2013). These instances have been modified using the following procedure:

- For each pair of nodes (a, b), if the y-coordinate of b is greater than y-coordinate of a we multiply the distance of the arc by 1.1, otherwise the distance remains unmodified.

This allows us to generate asymmetric instances that can be easily replicated in further research projects.

- Next we generate two new vehicle capacities corresponding to the 75% and 50% of the original (T1) vehicle capacity. The number of available vehicles of the original capacity is chosen to be lower than the number of vehicles needed in the best known solution (BKS) for the homogeneous case with asymmetric distances.
- In order to have site-dependency, for each instance we randomly select a sub-region of the whole x-y space and we restrict the nodes belonging to that area of being visited by T1-capacity vehicles.
- The number of available vehicles for each of the new capacities is established to ensure the demand satisfaction constraints, considering a reduced fleet of T1-capacity trucks and the demand of the restricted nodes

5.2.3.2 Results and Analysis

Table 5.9 summarizes, for each instance, the results obtained during the experiments. For each instance we report the best solution obtained in terms of total costs (vehicle fixed cost + vehicle variable cost) and its corresponding distance-based cost. Note that our objective function is the minimization of the total costs, but we used the distance-based cost only for comparison purposes with respect to the best known solutions for the symmetric case. The left side of the table allows the comparison of the asymmetric and symmetric versions of the homogeneous VRP. In this case, since we have only one type of vehicles, the optimization of the total costs has the same solution than the optimization of routing distances. Our mean gap in terms of distance cost is 0.20% which shows the competitiveness of our approach. The right side of the table shows the results obtained for the heterogeneous VRP without and with site-dependency, which corresponds to experiments *(ii)* and *(iii)* respectively. In the case of non-site dependency, we can see that, in average, the heterogeneous version outperforms the homogeneous version in terms of total costs (average gap of -1.47%) while the distance cost is 8.89% higher, in average. Since there are less available vehicles with larger capacities, solutions are forced to use smaller vehicles (with lower fixed and variable costs) and to perform more trips. In the case of site-dependency, which restricts even more the usage of larger trucks, the total costs increases (average gap of 6.64%) with respect to the homogeneous case, while the distance costs increase, on average 19.71%.

Table 5.9 Summary of Results

Instances	Distance Costs (Symmetric)	Homogeneous Case					Instance Information			Heterogeneous Case													
							Available Trucks / Capacity			Non-Site Dependency				Used Trucks			Site Dependency				Used Trucks		
	BKS	Available Trucks	OBS Total Cost (2)	OBS Distance Cost (3)	Used Trucks	GAP% (3) - (1)	T1	T2	T3	OBS Total Cost (4)	OBS Distance Cost (5)	GAP% (4) - (2)	GAP% (5) - (3)	T1	T2	T3	OBS Total Cost (6)	OBS Distance Cost (7)	GAP% (6) - (2)	GAP% (7) - (3)	T1	T2	T3
P-n40-k5	461.73	8	2115.45	471.82	5	2.18	4/140	2/105	3/70	2045.87	475.62	-3.29	0.81	4	1	0	2275.93	575.89	7.58	22.06	3	2	1
B-n41-k6	834.92	13	3089.90	829.97	6	-0.59	5/100	6/75	6/50	3095.45	975.26	0.17	17.51	3	4	0	3513.71	1072.76	13.72	29.25	4	4	0
B-n45-k5	754.22	8	2729.91	743.30	5	-1.44	4/100	3/75	3/50	2579.33	791.69	-5.51	6.51	3	3	0	2748.16	829.38	0.67	11.58	3	3	0
A-n80-k10	1766.50	16	6334.66	1778.22	10	0.66	8/100	6/75	6/50	6508.37	1969.47	2.74	10.76	8	3	0	6627.54	2062.12	4.62	15.97	6	5	0
		AVERAGE GAP				0.20						-1.47	8.89						2.89	20.71			

5.3 Chapter Conclusions

We have proposed a competitive Variable Neighborhood Search metaheuristic for the deterministic WCP. Moreover, this chapter presented an efficient approach to solve the WCP under uncertainty by modeling waste levels as random variables following an empirical or theoretical probability distribution. The algorithm was tested using a large-scaled benchmark set for the WCP with several realistic constraints. The proposed methodology for the WCP with stochastic waste levels is based on a simheuristic algorithm in which a VNS metaheuristic is combined with simulation techniques. Initially, a stochastic problem instance is transformed into a deterministic one by replacing random variables with their means. In the following the metaheuristic explores the search space to find a set of promising solutions, which are then assessed in a stochastic environment by using Monte Carlo simulation. Apart from finding different solutions in only a few minutes (even for stochastic WCP cases with over 2000 nodes solutions are found in under 400 seconds), the results allow a risk analysis considering waste level variances and vehicle safety capacities. A further advantage of our approach is its easiness to be understood and implemented. In addition, no strong assumptions are made related to the probability distribution of the random variables. As the results of our computational experiment show, our algorithm yields competitive solutions in a relatively small amount of time.

A number of possible future research lines stem from this work. The most natural extension would be the inclusion of stochastic travel and/or service times. Especially in urban settings, these variables may experience high uncertainty levels due to the unpredictability of traffic jams, road works, adverse weather, etc. A second research line extends the stochastic problem by considering on-line optimization techniques. In the development of smart cities for example, total waste collection costs could be reduced by using real-time waste level information obtained through volumetric sensors in containers. Another interesting topic would be the introduction of routing externalities (pollution, benefits for society, etc.) in the objective function. Finally, a multi-stage version of our problem (e.g., daily waste collection over a weekly or monthly planning horizon) could be addressed.

We have introduced an efficient, fast and easy to implement multi-round algorithm for planning goods delivery in mountainous regions with heterogeneous fleet. This situation was represented by the so-called Heterogeneous Site-Dependent with Asymmetric Costs Vehicle Routing Problem (HSDAVRP). The proposed algorithm is based on a randomized version of the CWS heuristic which assigns a higher probability of being chosen to the most promising movements. Preliminary tests carried out show that our approach seems promising in order to solve this new RVRP. Further research efforts could be oriented to include real-life data or conditions (i.e. customer locations, real distance-based costs, other vehicle types and associated costs, uncertain demand, uncertain travel times, etc.)

Chapter 6

Conclusions and Future Research Lines

This thesis integrates three important topics related to the optimization of transportation and logistics activities: *(i)* the consideration of new RVRP in order to study more realistic cases; *(ii)* the implementation of horizontal cooperation strategies to generate higher benefits to firms and; *(iii)* the development of efficient solving approaches to deal with such complex problems and support related decision-making processes. Thus, it includes both methodological and practical contributions to the research community in T&L.

First of all, in chapter 2, we have reviewed the main theoretical concepts and developments regarding the RVRP studied in this thesis, the different solving methodologies and HC. As the analyzed problems are known to be richer versions of well-known NP-Hard problems, approximated algorithms seem to be more suitable to tackle them. Taking into consideration the main trends in the design of approximated algorithms, we have decided to develop easy to implement and, at the same time, efficient metaheuristics based on biased randomization techniques to deal with the deterministic RVRP proposed in this thesis. Furthermore, we have combined them with Monte Carlo simulation to efficiently solve more realistic problem settings in which uncertainty is involved.

Next, in chapter 3, horizontal cooperation has been analyzed in the context of urban distribution of goods under uncertainty. This situation has been represented by the MDVRPSD, which has been solved by means of a simheuristic algorithm combining Iterated Local Search with MCS. We have compared the cooperative scenario against a non-cooperative one using both theoretical and real-life instances available in literature. The benefits of implementing HC have been quantified in terms of distance costs (for each individual company as well as at an aggregated level) and reliability of the solutions. Then, we have moved towards a mid-term planning horizon in which we have considered a multi-objective approach considering both distance and CO_2 emissions optimization by including electrical vehicles.

Then, the Capacitated Location Routing Problem has been studied in both deterministic and stochastic settings. The deterministic version has been solved by means of a two-stage biased randomized ILS algorithm whose competitiveness has been tested using three sets of benchmarks. Furthermore, it has been enhanced through the incorporation of: *(i)* three different local search operators; *(ii)* the usage of two different acceptance criteria for non-improving solutions and; *(iii)* the hybridization with MCS to determine the right safety stock policy to face demand uncertainty and to estimate both solution quality and reliability. In addition, the flexibility of the proposed algorithm has allowed us to compare three cooperative scenarios for integrated routing and facility location decisions in terms of economic and environmental costs. The important effects of implementing fully cooperative strategies are validated by average savings of, at least, 55% and 52%, respectively.

Finally, two RVRP concerning city logistics have been addressed. The waste collection problem with stochastic demands has been solved by means of a simheuristic based on a VNS algorithm. The efficiency of the proposed VNS has been compared to both exact and approximated approaches, providing in several cases new BKS for the deterministic WCP. In addition, it has been shown how the proposed simheuristic can be used to suit different decision-maker profiles by providing alternative solutions. On the other hand, the distribution of goods in mountainous regions has been represented by the HSDAVRP. This problem has been solved by means of a biased randomized multi-round process in which, at each round, we consider a different vehicle type to create a partial solution. Then, partial solutions are merged to obtain a feasible solution for the problem. As there are no benchmark instances for this problem, existing VRP instances have been adapted. The variations in costs when adding the different constraints of this problem have been compared to the classical VRP.

6.1 Future Research Work

A broad set of research lines stem from this thesis. Some of them are summarized in the following:

- From a theoretical perspective, the consideration of other key concepts of HC, such as social concerns and equity in terms of workload. Moreover, the integration with other logistic activities such as inventory management, procurement, forecasting, etc., could be of interest.

- From a methodological point of view, the development of different metaheuristics, such as GRASP, TS or SA, as underlying optimization methods to enhance the body of knowledge on simheuristics. In addition, a modified version of simheuristics in which the approach could be simulation-driven instead of optimization-driven.

- The hybridization of simheuristics with other analytical tools, e.g. machine learning to deal with dynamic inputs or real-time optimization problems to tackle more realistic versions than the ones proposed in this thesis.
- Regarding RVRP literature, the incorporation of multi-objective approaches to consider sustainability in its broad sense (economic, environmental and social).

6.2 Outcomes Derived from this Thesis

One of the objectives of this thesis is related to the dissemination of the outcomes in several international indexed journals as well as in international conferences. In the following, we include the list of publications, conference papers and talks generated during the development of this project.

6.2.1 JCR Indexed Papers

- Quintero-Araujo, C.L.; Caballero-Villalobos, J.P.; Juan, A.; Montoya-Torres, J.R. (2017) "A Biased-Randomized Metaheuristic for the Capacitated Location Routing Problem". International Transactions in Operational Research, 24: 1079–1098. ISSN: 0969-6016. doi:10.1111/itor.12322
- Gruler, A.; Quintero-Araujo, C.L.; Calvet, L.; Juan, A. (2017). "Waste Collection Under Uncertainty: A Simheuristic Based on Vairable Neighborhood Search". European Journal of Industrial Engineering, Vol. 11, No. 2, pp.228–255. ISSN: 1751-5254. (indexed in ISI SCI, 2014 IF = 0.736, Q3; 2014 SJR = 0.898, Q1).
- Quintero-Araujo, C.L.; Gruler, A.; Juan, A.; Faulin, J. (*Under Review*) "Using Horizontal Cooperation Concepts in Integrated Routing and Facility Location Decisions". Int. Transactions in Operational Research. ISSN: 0969-6016. (indexed in ISI SCI, 2015 IF = 1.255, Q2; 2015 SJR = 1.179, Q1).
- Muñoz-Villamizar, A.F.; Quintero-Araujo, C.L.; Montoya-Torres, J.R.; Faulin, J. (*Under Review*): "Short- and Mid-term Evaluation of the Use of Electric Vehicles in Urban Freight Transport Collaborative Networks: A Case Study". Transportation Research Part D: Transport and Environment. ISSN: 1361-9209. (indexed in ISI Web of Science and Scopus, 2015 JCR = 1.864, Q2, 2015 SJR = 1.144, Q1).

- Quintero-Araujo, C.L.; Guimarans, D.; Juan, A. (*Under Review*): "A SimILS algorithm for the Capacitated Location Routing Problem with Stochastic Demands". Journal of the Operational Research Society (indexed in ISI SCI, 2015 IF = 1.225, Q2; 2015 SJR = 1.026, Q1). ISSN: 0160-5682. .

6.2.2 Scopus Indexed Papers

- Quintero-Araujo C.L., Gruler A., Juan A.A. (2016). "Quantifying Potential Benefits of Horizontal Cooperation in Urban Transportation Under Uncertainty: A Simheuristic Approach". In: Luaces O. et al. (eds) Advances in Artificial Intelligence. CAEPIA 2016. *Lecture Notes in Computer Science*, vol 9868, 280-289. Springer, Cham. ISSN: 1611-3349. (indexed in Scopus, 2014 SJR = 0.339, Q2).

- Quintero-Araujo, C.L.; Pages-Bernaus, A.; Juan, A.; Travesset, O.; Jozefowiez, N. (2016). "Planning freight delivery routes in mountainous regions". Springer Lecture Notes in Business Information Processing, (254), 123-132. ISSN: 1865-1348. (indexed in Scopus, 2014 SJR = 0.244, Q3).

- Quintero-Araujo, C.L; Gruler, A.; Juan, A.; De Armas, J.; Ramalhinho, H. (2017) "Using Simheuristics to promote Horizontal Collaboration in Stochastic City Logistics". Progress in Artificial Intelligence. ISSN: 2192-6352. DOI: 10.1007/s13748-017-0122-8 *Accepted for Publication*.

6.2.3 Conference Papers Indexed in ISI-WOS or Scopus

- Quintero-Araujo, C.L.; Juan, A.; Montoya-Torres, J.R.; Muñoz-Villamizar, A.F. (2016): "A simheuristic algorithm for horizontal cooperation in urban distribution". *Proceedings of the 2016 Winter Simulation Conference*, 2193-2204. Washington D.C., USA. December 11-14. ISBN: 978-1-5090-4485-6. (indexed in ISI Proceedings and Scopus, 2014 SJR = 0.131).

6.2.4 Conference Papers/Abstracts with Peer-reviewing Process

- Quintero, C.; Juan, A. (2016): "Enhancing Metaheuristics through Simulation to solve real-life problems under uncertainty. An application to the Single Depot Location Routing Problem with Stochastic Demands". Escuela Latinoamericana de Verano de Investigación de Operaciones, ELAVIO 2016. May 9-13. Cali, Colombia.

- Quintero, C.; Juan, A.; Caballero, J.; Montoya, J. (2015):"A New Randomized Procedure To Solve The Location-Routing Problem". Proceedings of the 2015 Int. Conf. of the Forum for Interdisciplinary Mathematics (FIM2015). November 18-20. Barcelona, Spain.

- Quintero, C.; Juan, A. (2015): "Solving the Integrated Location Routing Problem considering Uncertainty and Risk factors". Proceedings of the ICRA6/Risk 2015 Int. Conference, 655-662. ISBN: 978-84-9844-496-4. May 26-29. Barcelona, Spain.

- Quintero, C.; Juan, A.; Montoya, J.; Faulin, J. (2015): "Simheurísticas: una herramienta para resolver problemas de optimización combinatoria". ASOCIO 2015. July 15-16. Chia, Colombia.

- Juan, A.; Faulin, J.; Calvet, L.; Pages, A.; Quintero, C. (2015): "Applications of Simheuristics in Transportation and Logistics". EURO 2015. July 12-15. Glasgow, UK.

- Quintero, C.; Torres, A.; Alfonso, E.; Reyes, L.; Juan, A. (2015): "Uso combinado de métodos exactos con heurística aleatorizada para el HHRCSP". In: Proceedings of the X Congreso Español de Metaheurísticas, Algoritmos Evolutivos y Bioinspirados, 441-446. ISBN: 978-84-697-2150-6. Feb 4-6. Mérida, Spain.

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Appendix A

GAMS®Model for the Waste Collection Problem

```
*Model WCP
sets
nodes /i0*i102, j0/
i(nodes) set of container nodes /i3*i101/
d(nodes) set of depot nodes /i0, j0/
l(nodes) set of landfill nodes /i1*i2/
n(nodes) lunch break node /i102/
k set of vehicles /v1*v2/
allnodes(nodes)
cont_depot(nodes)
depot_landfills(nodes)
cont_landfills(nodes)
cont_lb(nodes)
cont_depot_lb(nodes)
landfills_lb(nodes)
cont_depot_landfills(nodes)
cont_landfills_lb(nodes);
allnodes(nodes) = i(nodes)+d(nodes)+l(nodes)+n(nodes);
cont_depot(nodes) = i(nodes)+d(nodes);
depot_landfills(nodes) = d(nodes)+l(nodes);
cont_depot_landfills(nodes) = i(nodes)+d(nodes)+l(nodes);
cont_landfills(nodes) = i(nodes)+l(nodes);
```

```
cont_lb (nodes) = i(nodes)+n(nodes);
cont_depot_lb(nodes) = i(nodes)+d(nodes)+n(nodes);
landfills_lb(nodes) = l(nodes)+n(nodes);
cont_landfills_lb(nodes) = i(nodes)+l(nodes)+n(nodes);
alias (i,j)
alias (allnodes, allnodes2)
alias (nodes, nodes2)
alias (cont_landfills_lb, cont_landfills_lb2)


parameters
vcap capacity of each vehicle /280/
yardage max amount of waste that a vehicle can collect /400/
speed vehicle speed in mph /40/
secondsinhour /3600/
convfactor /5280/
maxstops /500/
bigM /1400000/
lunch_break duration in seconds /3600/
demand(nodes) demand of each node /Load demands of each node/
stime(nodes) service time at node i seconds /Load service time at each node/
ew(nodes) early time window for node i HHMM /Load early time windows for each
node/
lw(nodes) late time window for node i HHMM /Load late time windows for each
node/
coordx(nodes) x-coordinate of each node /Load x-Coord/
coordy(nodes) y-coordinate of each node /Load y-Coord/;

parameter
mat_dist(nodes,nodes2) distance matrix between nodes
travel_times(nodes,nodes2) travel times between nodes
maximal;
mat_dist(nodes,nodes2)= (abs(coordx(nodes)-coordx(nodes2))+abs(coordy
(nodes)  -coordy(nodes2)))/convfactor;
mat_dist('i102',nodes2)= 0;
mat_dist(nodes, 'i102') = 0;
```

```
travel_times(nodes,nodes2) =(mat_dist(nodes,nodes2))*(secondsinhour/
speed);
maximal = (smax(nodes,stime(nodes))+(smax(nodes,lw(nodes))/100*
secondsinhour)  +smax((nodes,nodes2),travel_times(nodes,nodes2)));

variables
x(nodes,nodes2,k) 1 if vehicle k goes from node i to j - 0 otherwise
w(nodes,k) cumulative waste loaded in vehicle k before serving node i
r(nodes,k) starting time at node i for vehicle k
g(nodes,k) waiting time at node
y(nodes, nodes2, k) 1 if vehicle k goes from nodes to lunch break and then
to nodes2 - 0 otherwise
max_time
NT(k) number of landfill trips in route k
free variable z variable for the objective function
binary variable x,y;
integer variable NT;
positive variables g,w,r;

equations
fobj objective function
eq2(k) one single depart from depot
eq3(k) all vehicles must arrive to depot coming from one landfill.
eq4(j) arriving once at each container node
eq5(nodes,k) inflow and outflow equal for all nodes except for the depot
eq6(nodes,k) early time windows for each container
eq7(nodes, nodes2, k) starting time at each node
eq7b(nodes, nodes2, k) starting time after visiting lunch break
eq8(nodes,k) vehicles must be empty at the start of the routes
eq8b(nodes, nodes2,k) vehicles must be empty after visiting a landfill
eq9(nodes, nodes2, k) cumulative demand for each container
eq9b(nodes,nodes2,k)
eq11(k) lunch break- each route arrives once at lunch break node
eq12(k) lunch break- each route departs once from lunch break node
eq13(k) initialize starting time at depot
eq1d(k) no trips leaving from finishing depot
```

```
eq6b(nodes,k) late time windows for each container
eq3c(k,nodes,nodes2) no trips allowed between one node and itself
eq3f(nodes,nodes,k) no subtours are allowed
eq3g(nodes,k) no subtours are allowed
eq3h(nodes,k) no subtours are allowed
eq14(nodes, nodes2, k) relationship among x and y
eq14b(nodes, nodes2, k) relationship among x and y
eq14c(nodes, nodes2, k) value of y
;

fobj..  z=e= sum((nodes,nodes2,k)$(ord(nodes) ne ord(nodes2)),
mat_dist(nodes,nodes2)*x(nodes,nodes2,k))+sum((nodes, nodes2,k)$(ord
(nodes) ne ord(nodes2)),mat_dist(nodes,nodes2)*y(nodes,nodes2,k));
eq2(k).. sum(cont_landfills_lb,x('i0',cont_landfills_lb,k))=e= 1;
eq3(k)..sum(l, x(l,'j0',k))=e=1;
eq4(i).. sum((allnodes,k),x(allnodes,i,k)) =e= 1;
eq5(cont_landfills_lb,k).. sum(allnodes,x(allnodes,cont_landfills_lb,
k)) =e= sum(allnodes,x(cont_landfills_lb,allnodes,k));
eq6(cont_landfills_lb,k).. ((ew(cont_landfills_lb)/100))*secondsinhour
=l= r(cont_landfills_lb,k);
eq7(nodes,nodes2,k)$(ord(nodes) ne ord(nodes2)).. r(nodes,k)+stime(nodes)
+travel_times(nodes,nodes2) =l= r(nodes2,k)+(1-x(nodes,nodes2,k))*maximal;
eq7b(nodes,nodes2,k)$(ord(nodes) ne ord(nodes2)).. r(nodes,k)+stime(nodes)
+stime('i102')+travel_times(nodes,nodes2) =l= r(nodes2,k)+(2-x(nodes,'i102',
k) -x('i102',nodes2,k))*(maximal+stime('i102'));
eq8(d,k).. w(d,k) =e= 0;
eq8b(l, cont_lb,k).. w(cont_lb,k) =l= (1-x(l,cont_lb,k))*vcap;
eq9(cont_lb,cont_landfills_lb,k)$((coordx(cont_landfills_lb) ne coordx(cont_
lb))  and (coordy(cont_landfills_lb) ne coordy(cont_lb))).. w(cont_lb,
k) + demand(cont_lb) =l= w(cont_landfills_lb,k)+(1-x(cont_lb,cont_landfills_
lb,k)) *vcap;
eq9b(cont_lb,cont_landfills_lb,k)$((coordx(cont_landfills_lb) ne coordx(cont_
lb))  and (coordy(cont_landfills_lb) ne coordy(cont_lb))).. w(cont_lb,k)
+demand(cont_lb) =g= w(cont_landfills_lb,k)+(1-x(cont_lb,cont_landfills_lb,
k))*  ((-1)*vcap);
eq11(k).. sum(cont_depot_landfills,x(cont_depot_landfills,'i102',k)) =e= 1;
```

```
eq12(k).. sum(cont_depot_landfills,x('i102',cont_depot_landfills,k)) =e=
1;
eq13(k)..r('i0',k) =e= ew('i0')*(secondsinhour/100);
eq1d(k).. sum(cont_landfills_lb,x('j0',cont_landfills_lb,k))=e= 0;
eq6b(cont_landfills_lb,k).. r(cont_landfills_lb,k)=l= lw(cont_landfills_
lb)*(secondsinhour/100);
eq3c(k,nodes,nodes2)$(ord(nodes) eq ord(nodes2)).. x(nodes,nodes2,k) =e=
0;
eq3f(cont_landfills_lb,cont_landfills_lb2,k).. w(cont_landfills_lb,k)
+demand(cont_landfills_lb) - (w(cont_landfills_lb2,k)+demand(cont_
landfills_lb2)) + vcap*X(cont_landfills_lb,cont_landfills_lb2,k)  =l=
vcap - demand(cont_landfills_lb2);
eq3g(cont_landfills_lb,k).. demand(cont_landfills_lb) =l=  w(cont_
landfills_lb,k)+demand(cont_landfills_lb);
eq3h(cont_landfills_lb,k).. w(cont_landfills_lb,k)+demand(cont_
landfills_lb) =l= vcap;
eq14(nodes,nodes2,k).. y(nodes,nodes2,k) =l= x(nodes,'i102',k);
eq14b(nodes, nodes2,k).. y(nodes,nodes2,k) =l= x('i102',nodes2,k);
eq14c(nodes, nodes2, k).. y(nodes,nodes2,k)+1 =g= x(nodes,'i102',k)
+x('i102',nodes2,k);


model wcp /all/;
wcp.reslim=172800;
solve wcp using mip minimizing z;
display x.l, x.m, w.l, travel_times, mat_dist, r.l;
```

Appendix B

Cover Page of Peer-Reviewed Accepted Publications

INTERNATIONAL TRANSACTIONS IN OPERATIONAL RESEARCH

IFORS

WILEY

INTERNATIONAL TRANSACTIONS IN OPERATIONAL RESEARCH

Intl. Trans. in Op. Res. 00 (2016) 1–20
DOI: 10.1111/itor.12322

A biased-randomized metaheuristic for the capacitated location routing problem

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Abstract

The location routing problem (LRP) involves the three key decision levels in supply chain design, that is, strategic, tactical, and operational levels. It deals with the simultaneous decisions of (a) locating facilities (e.g., depots or warehouses), (b) assigning customers to facilities, and (c) defining routes of vehicles departing from and finishing at each facility to serve the associated customers' demands. In this paper, a two-phase metaheuristic procedure is proposed to deal with the capacitated version of the LRP (CLRP). Here, decisions must be made taking into account limited capacities of both facilities and vehicles. In the first phase (selection of promising solutions), we determine the depots to be opened, perform a fast allocation of customers to open depots, and generate a complete CLRP solution using a fast routing heuristic. This phase is executed several times in order to keep the most promising solutions. In the second phase (solution refinement), for each of the selected solutions we apply a perturbation procedure to the customer allocation followed by a more intensive routing heuristic. Computational experiments are carried out using well-known instances from the literature. Results show that our approach is quite competitive since it offers average gaps below 0.4% with respect to the best-known solutions (BKSs) for all tested sets in short computational times.

Keywords: biased randomization; location routing problem; metaheuristics; supply chain design

1. Introduction

The location routing problem (LRP) is one of the most complete problems in logistics and transportation because it involves all decision levels in supply chain design and management, that

Figure B.1 Paper accepted in International Transactions in Operational Research

228 European J. Industrial Engineering, Vol. 11, No. 2, 2017

Waste collection under uncertainty: a simheuristic based on variable neighbourhood search

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Abstract: Ongoing population growth in cities and increasing waste production has made the optimisation of urban waste management a critical task for local governments. Route planning in waste collection can be formulated as an extended version of the well-known vehicle routing problem, for which a wide range of solution methods already exist. Despite the fact that real-life applications are characterised by high uncertainty levels, most works on waste collection assume deterministic inputs. In order to partially close this literature gap, this paper first proposes a competitive metaheuristic algorithm based on a variable neighbourhood search framework for the deterministic waste collection problem. Then, this metaheuristic is extended to a simheuristic algorithm in order to deal with the stochastic problem version. This extension is achieved by integrating simulation into

Figure B.2 Paper accepted in European Journal of Industrial Engineering

Quantifying Potential Benefits of Horizontal Cooperation in Urban Transportation Under Uncertainty: A Simheuristic Approach

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Abstract. Horizontal Cooperation (HC) in transportation activities has the potential to decrease supply chain costs and the environmental impact of delivery vehicles related to greenhouse gas emissions and noise. Especially in urban areas the sharing of information and facilities among members of the same supply chain level promises to be an innovative transportation concept. This paper discusses the potential benefits of HC in supply chains with stochastic demands by applying a simheuristic approach. For this, we integrate Monte Carlo Simulation into a metaheuristic process based on Iterated Local Search and Biased Randomization. A non-cooperative scenario is compared to its cooperative counterpart which is formulated as multi-depot Vehicle Routing Problem with stochastic demands (MDVRPSD).

Keywords: Horizontal cooperation · Simheuristics · MDVRPSD · Biased randomization · Iterated local search

1 Introduction

Driven by fierce competition, rapidly changing customer demands, and the need for high service levels, efficient transportation activities are of major importance for companies [5]. However, transportation activities should not only be viewed from a cost- and customer satisfaction point of view. Especially in urban areas freight transportation yields consequences related to the environment, society, and economy that impact a range of different stakeholders. As such, transportation accounts for over a quarter of total greenhouse gas emissions in the USA [27], while 41 % of Europeans are affected by extensive noise levels through freight transportation vehicles in cites [7]. Furthermore, urban areas account for 85 % of total Gross Domestic Product (GDP) in the European Union (EU), leading to increased interest of municipalities in efficient transportation systems to fortify their cities economic attractiveness [6].

O. Luaces et al. (Eds.): CAEPIA 2016, LNAI 9868, pp. 280–289, 2016.
DOI: 10.1007/978-3-319-44636-3_26

Figure B.3 Publication in Lecture Notes in Computer Science

Planning Freight Delivery Routes in Mountainous Regions

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Abstract. The planning of delivery routes in mountainous areas should pay attention to the fact that certain types of vehicles (such as large trucks) may be unable to reach some customers. The use of heterogeneous fleet is then a must. Moreover, the costs of a given route may be very different depending on the sense taken. The site-dependent capacitated vehicle routing problem with heterogeneous fleet and asymmetric costs is solved with the successive approximations method. The solution methodology proposed is tested on a set of benchmark instances. Preliminary tests carried out show the benefits, in terms of total costs, when using a heterogeneous fleet. In both cases, with and without site dependency, the increase in distance-based costs is mitigated by the use of heterogeneous fleet.

Keywords: Heterogeneous Site-Dependent VRP · Successive approximations method · Clarke-and-Wright Savings algorithm

1 Introduction

The delivery of goods plays an important role within the logistics and transportation sector. With the increase of demand, promoted by the growth of e-commerce or the development of new logistic strategies such as just-in-time, the number of batches to deliver also grows. Therefore, an accurate planning of the delivery routes is extremely important.

Road transport constitutes a major activity especially in urban areas, but also in many regions with limited access to other modes of transport. Globally, road transport is responsible for around a quarter of the EU's energy consumption and about a fifth of its CO_2 emissions. Moreover, freight delivery within cities is seen as a disturbing factor by its inhabitants. Freight related activities increase traffic congestion and impact on the

R. León et al. (Eds.): MS 2016, LNBIP 254, pp. 123–132, 2016.
DOI: 10.1007/978-3-319-40506-3_13

Figure B.4 Publication in Lecture Notes in Business Information Processing

Proceedings of the 2016 Winter Simulation Conference
T. M. K. Roeder, P. I. Frazier, R. Szechtman, E. Zhou, T. Huschka, and S. E. Chick, eds.

A SIMHEURISTIC ALGORITHM FOR HORIZONTAL COOPERATION IN URBAN DISTRIBUTION: APPLICATION TO A CASE STUDY IN COLOMBIA

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ABSTRACT

The challenge in last-mile supply chains deliveries is to maintain and improve the operational cost-effectiveness by the implementation of efficient procedures while facing increased levels of congestion in cities. One competitive alternative is Horizontal Cooperation (HC). City distribution problems under HC conditions can be modeled as multi-depot vehicle routing problems, which are NP-hard problems meaning that exact methods provide optimal solutions only for small datasets. This complexity increases when considering stochastic demand. Therefore, real-life situations must be solved using heuristic algorithms. This paper proposes the implementation of a simheuristic (i.e., an algorithm combining heuristics with simulation). Experiments are carried out using realistic data from the city of Bogotá, Colombia, regarding the distribution of goods to the whole network of the three major chains of convenience stores currently operating in the city. Results show the power of the proposed simheuristic in comparison with traditional solution approaches based on mathematical programming.

1 INTRODUCTION

The complexities of current supply chains and the increased requirements from customers require logistics systems with more efficient and cost-effective delivery tours (Ehmke 2012). In supply chain management (SCM), the term last mile delivery refers to the distribution of goods to customers (either at home or via a retail store), usually located in cities. Efficient methods for transport planning have become increasingly important (Álvarez et al. 2010). However, congestion in cities is continuously rising due to increasing levels of traffic demand, and most large cities are confronted with problems regarding air and noise pollution and congestion caused by motorized road traffic (Geroliminis and Daganzo 2006). The evolution of urban logistics in the past decades worsened that situation due to an increasing use of heavier goods vehicles in city centers (Benjelloum et al. 2010). Because of the increase in mobility patterns in cities (both in the case of people and freight), new services based on resource sharing have appeared

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Figure B.5 Publication in Proceedings of the 2016 Winter Simulation Conference

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CrossMark

REGULAR PAPER

Using simheuristics to promote horizontal collaboration in stochastic city logistics

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Abstract This paper analyzes the role of horizontal collaboration (HC) concepts in urban freight transportation under uncertainty scenarios. The paper employs different stochastic variants of the well-known vehicle routing problem (VRP) in order to contrast a non-collaborative scenario with a collaborative one. This comparison allows us to illustrate the benefits of using HC strategies in realistic urban environments characterized by uncertainty in factors such as customers' demands or traveling times. In order to deal with these stochastic variants of the VRP, a simheuristic algorithm is proposed. Our approach integrates Monte Carlo simulation inside a metaheuristic framework. Some computational experiments contribute to quantify the potential gains that can be obtained by the use of HC practices in modern city logistics.

Keywords City logistics · Horizontal collaboration · Stochastic optimization · Vehicle routing problems · Simheuristics

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1 Introduction

Freight transportation activities in modern cities are characterized by the need of high-quality service levels as well as by uncertainty environments generated by stochastic customers' demands and traveling times. Thus, companies in the city logistics sector must ensure the efficiency of their operations in order to survive in such a competitive environment [12]. However, transportation activities should not only be viewed from an economic cost- and customer satisfaction point of view. Especially in urban areas, freight transportation yields consequences related to the environment, society, and economy that have an impact on a range of different stakeholders [28]. According to some studies, transportation accounts for over a quarter of total greenhouse gas emissions in the USA [43], while 41% of Europeans are affected by extensive noise levels through freight transportation vehicles in cities [14]. Moreover, urban areas account for 85% of total gross domestic product in the European Union. These facts have lead to an increasing interest among municipalities in developing efficient transportation systems as a way to promote both economical and environmental sustainability [13].

Horizontal collaboration (HC) is defined by some authors as "a business agreement between two or more companies at the same level in the supply chain or network in order to allow ease of work and co-operation toward achieving a common objective" [1]. In recent years, HC has been increasingly discussed in theory and practice as a way of decreasing the negative impacts of transportation. In HC scenarios, companies on the same level of different supply chains—e.g., suppliers, manufacturers, and retailers—collaborate by sharing information and/or resources. Thus, some HC practices include sharing warehouses or transportation vehicles as a way of increasing efficiency in their logistics activities.

Springer

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Figure B.6 Paper accepted in Progress in Artificial Intelligence

Appendix C

Cover Page of Under Review Publications

INTERNATIONAL TRANSACTIONS IN OPERATIONAL RESEARCH

Intl. Trans. in Op. Res. XX (20XX) 1–24
DOI: xx.xxxx/itor.xxxxx

Using Horizontal Cooperation Concepts in Integrated Routing and Facility Location Decisions

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Abstract

In a global and competitive economy, efficient supply networks are essential for modern enterprises. Horizontal cooperation (HC) concepts represent a promising strategy to increase the performance of supply chains. HC is based on sharing resources and making joint decisions among different agents at the same level of the supply chain. This paper analyzes different cooperation scenarios concerning integrated routing and facility location decisions in road transportation: *(i)* the non-cooperative case, in which all decisions are decentralized –i.e. each enterprise solves its own vehicle routing problem; *(ii)* the semi-cooperative case, based on centralized route planning decisions –i.e., facilities and fleets are shared and enterprises solve a common multi-depot vehicle routing problem; and *(iii)* the fully-cooperative case, in which route planning and facility location decisions are jointly made by different agents –i.e., enterprises need to solve a common location-routing problem. Our analysis explores how the increasing centralization of transportation and logistics planning leads to higher freedom degrees concerning aggregated supply chain decisions. A metaheuristic algorithm, combining biased randomization with variable neighborhood search, is proposed to solve each scenario and quantify the differences among them, both in terms terms of monetary and environmental costs. Our solving approach is tested on a range of real-life and theoretic benchmark instances, outperforming previously reported results.

Keywords: horizontal cooperation; variable neighborhood search; environmental impact; biased randomization; location routing problem

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Figure C.1 Paper submitted to International Transactions in Operational Research

A SimILS algorithm for the Capacitated Location Routing Problem with Stochastic Demands

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Abstract

In this paper, a simheuristic algorithm combining Monte Carlo simulation with iterated local search (SimILS) is proposed to solve the capacitated location routing problem with stochastic demands (CLRPSD). Our algorithm employs simulation to: *(i)* propose a safety stock policy to face demand uncertainty; and *(ii)* estimate both the expected value and the reliability index of the stochastic solutions. In order to show the competitiveness of our approach, computational experiments were carried out using three sets of benchmark instances for the capacitated location routing problem which were transformed appropriately in order to be suitable for the CLRPSD. Different variability levels for the random demands have been considered. An analysis of the effects of the safety stock policy on the solution quality (cost) and reliability index is also performed. Finally, our simheuristic provides alternative solutions –with different characteristics– allowing the decision makers to choose the one that fits better their utility function.

Keywords: location routing problem, stochastic demand, simheuristic, iterated local search, biased randomization

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Preprint submitted to Journal of the Operational Research Society *May 16, 2017*

Figure C.2 Paper submitted to the Journal of the Operational Research Society

Short- and Mid-term Evaluation of the Use of Electric Vehicles in Urban Freight Transport Collaborative Networks: A Case Study

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Abstract

Freight transportation is a primary component of all supply chain and logistics systems. However, this process has many negative effects including congestion, noise and environmental pollution, which affect life quality, particularly, in urban areas. Decision makers have considered diverse strategies, such as Horizontal Collaboration (HC), to reduce the overall cost and the environmental and social impact of the freight transportation. This paper assesses the implementation of an electric fleet of vehicles in urban distribution of goods under Horizontal Collaboration strategy between carriers, in order to reduce

1

Figure C.3 Paper submitted to Transportation Research Part D: Transport and Environment