Simheuristics to support efficient and sustainable freight transportation in smart city logistics

By

ALJOSCHA CLAUDIO GRULER

Department of Computer Science, Multimedia and Telecommunications
OPEN UNIVERSITY OF CATALONIA

A thesis submitted in fulfillment of the requirements for the degree of DOCTOR OF PHILOSOPHY IN NETWORK & INFORMATION TECHNOLOGIES

DECEMBER 2018

Thesis committee
Prof. Dr. Angel A. Juan
Prof. Dr. Antoni Pérez Navarro
Prof. Dr. Markus Rabe

"George," said Fred, *"I think we've outgrown full-time education."*
"Yeah, I've been feeling that way myself," said George lightly.
"Time to test our talents in the real world, d'you reckon?" asked Fred.
"Definitely," said George.

— J.K. Rowling, Harry Potter and the Order of the Phoenix (2003)

Abstract

Smart city logistics are a crucial factor in the creation of efficient and sustainable urban transportation systems. Among other factors, they focus on the incorporation of real-time data and the creation of collaborative business models in urban freight transportation concepts, whilst considering rising urban population numbers, increasingly complex customer demands, and highly competitive markets. This allows transportation planners to minimize the monetary and environmental costs of freight transportation in metropolitan areas. Many decision-making problems faced in this context can be formulated as combinatorial optimization problems. While different exact solving approaches exist to find optimal solutions to such problem settings, their complexity and size in addition to the need for instantaneous decision-making regarding vehicle routing, scheduling, or facility location, make such methodologies inapplicable in practice. Due to their ability to find pseudo-optimal solutions in almost real-time, metaheuristic algorithms have received increasing attention from researchers and practitioners as efficient and reliable alternatives in solving numerous optimization problems in the creation of smart city logistics.

Despite their success, traditional metaheuristic techniques fail to fully represent the complexity of most realistic systems. By assuming deterministic problem inputs and constraints, the uncertainty and dynamism experienced in urban transportation scenarios are left unaccounted for. Simheuristic frameworks try to overcome these drawbacks by integrating any type of simulation into metaheuristic driven processes to account for the inherent uncertainty in most real-life applications. This thesis defines and investigates the use of simheuristics as a method of first resort for solving optimization problems arising in smart city logistics concepts. Simheuristic algorithms are applied to a range of complex problem settings including urban waste collection, integrated supply chain design problems, and innovative transportation models related to horizontal collaboration among supply chain partners. In addition to methodological discussions and the comparison of developed algorithms to state-of-the-art benchmarks found in the academic literature, the applicability and efficiency of simheuristic frameworks in different large-scaled case studies are shown.

Resumen

Las actividades de logística en ciudades inteligentes constituyen un factor crucial en la creación de sistemas de transporte urbano eficientes y sostenibles. Entre otros factores, estos sistemas se centran en la incorporación de datos en tiempo real y la creación de modelos empresariales colaborativos en transporte urbano de mercancías, al tiempo que considera el aumento del número de habitantes en las ciudades, la creciente complejidad de las demandas de los clientes y los mercados altamente competitivos. Esto permite minimizar los costes monetarios y ambientales del transporte de mercancías en las áreas metropolitanas. Muchos de los problemas de toma de decisiones en este contexto se pueden formular como problemas de optimización combinatoria. Si bien existen diferentes enfoques de resolución exacta para encontrar soluciones óptimas a tales problemas, su complejidad y tamaño, además de la necesidad de tomar decisiones instantáneas con respecto al enrutamiento, la programación o la ubicación de las instalaciones, hacen que dichas metodologías sean inaplicables en la práctica. Debido a su capacidad para encontrar soluciones pseudo-óptimas casi en tiempo real, los algoritmos metaheurísticos están recibiendo cada vez más atención por parte de investigadores y profesionales como alternativas eficientes y fiables para resolver numerosos problemas de optimización en la creación de la logística de ciudades inteligentes.

A pesar de su éxito, las técnicas metaheurísticas tradicionales no representan completamente la complejidad de los sistemas más realistas. Al asumir insumos y restricciones de problemas deterministas, se ignora la incertidumbre y el dinamismo experimentados en los escenarios de transporte urbano. Los algoritmos simheurísticos persiguen superar estos inconvenientes integrando cualquier tipo de simulación en procesos basados en metaheurísticas con el fin de considerar la incertidumbre inherente en las mayoría de las aplicaciones de la vida real. Esta tesis define e investiga el uso de las simheurísticas como método adecuado para resolver problemas de optimización que surgen en la logística de ciudades inteligentes. Se aplican algoritmos simheurísticos a una variedad de problemas complejos, incluyendo la recolección de residuos urbanos, problemas de diseño de la cadena de suministro integrada y modelos de transporte innovadores relacionados con la colaboración horizontal entre los socios de la cadena de suministro. Además de las discusiones metodológicas y la comparación de los algoritmos desarrollados con los de referencia de la literatura académica, se muestra la aplicabilidad y la eficiencia de los algoritmos simheurísticos en diferentes estudios de casos a gran escala.

Resum

La logística urbana intel·ligent constitueix un factor crucial en la creació de sistemes de transport urbà eficients i sostenibles. Entre altres factors, aquests sistemes es centren en la incorporació de dades en temps real i en la creació de models de negoci col·laboratius en el transport urbà de mercaderies, tot considerant l'augment dels habitants en les ciutats, la creixent complexitat de les demandes dels clients i els mercats altament competitius. Això permet als que planifiquen el transport minimitzar els costos monetaris i ambientals del transport de mercaderies a les àrees metropolitanes. Molts problemes de presa de decisions en aquest context es poden formular com a problemes d'optimització combinatòria. Tot i que existeixen diferents enfocaments de resolució exacta per trobar solucions òptimes a aquests problemes, la seva complexitat i grandària, a més de la necessitat de prendre decisions instantànies pel que fa a l'enrutament de vehicles, la programació o la ubicació d' instal·lacions, fan que aquestes metodologies no s'apliquin a la pràctica. A causa de la seva capacitat per trobar solucions pseudo-òptimes en gairebé temps real, els algorismes metaheurístics estan rebent una atenció creixent dels investigadors i professionals com alternatives eficients i fiables per la resolució de nombrosos problemes d'optimització en la creació de la logística de les ciutats intel·ligents.

Malgrat el seu èxit, les tècniques metaheurístiques tradicionals no representen plenament la complexitat dels sistemes més realistes. En assumir inputs i restriccions de problemes deterministes, la incertesa i el dinamisme experimentats en els escenaris de transport urbà queden sense explicar. Els algorismes simheurístics persegueixen superar aquests inconvenients mitjançant la integració de qualsevol tipus de simulació en processos metaheurístics per explicar la incertesa inherent a la majoria de les aplicacions de la vida real. Aquesta tesi defineix i investiga l'ús d'algorismes simheurístics com el mètode més adequat per resoldre problemes d'optimització derivats de la logística de les ciutats. Alguns algorismes simheurístics s'apliquen a una sèrie de problemes complexos, com ara la recollida de residus urbans, els problemes de disseny de la cadena de subministrament integrada i els models de transport innovadors relacionats amb la col·laboració horitzontal entre els socis de la cadena de subministrament. A més de les discussions metodològiques i la comparació d'algorismes desenvolupats amb els referents de la literatura acadèmica, es mostra l'aplicabilitat i l'eficiència dels algorismes simheurístics en diferents casos de gran escala.

Dedication and acknowledgements

I want to thank everyone who supported me in the creation of this dissertation. Especially my thesis supervisors Dr. Angel A. Juan, Dr. Antoni Pérez, and Dr. Markus Rabe have greatly contributed to this work through their guidance and support. Moreover, I want to express my gratitude to friends and colleagues I met in the Internet Computing & Systems Optimization (ICSO) research group at the IN3 center of the UOC: Adela, Alejandro, Carlos, Daniele, Enoc, Jana, Javi, Jesica, Laura, Manuel, Sara and Stephanie. I also want to thank Prof. Dr. Javier Faulin from the Public University of Navarra (Pamplona) and Prof. Dr. Carlos Hernández Ulloa from the Universidad Andrés Bello (Santiago de Chile) for their invitations to visit their research groups and universities. A special greeting goes out to Hamza, who became my good friend and companion by sharing similar experiences as PhD student at the UOC. Finally, I want to thank all my friends, my girlfriend Sara, and my family for their loving support during all this time.

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LIST OF ALGORITHMS

Nomenclature

2E-LRP Two-Echelon Location Routing Problem

ABM Agent Based Model

ABS Agent Based Simulation

ARP Arc Routing Problem

BKS Best Known Solution

BR Biased Randomization

CL City Logistics

COP Combinatorial Optimization Problem

CT Computational Time

CTM Collaborative Transportation Management

DES Discrete Event Simulation

FIFO first-in-first-out

GRASP Greedy Randomized Adaptive Search Procedure

HC Horizontal Collaboration

ICT Internet and Communication Technologies

ILS Iterated Local Search

IRP Inventory Routing Problem

LRP Location Routing Problem

MDVRP Multi Depot Vehicle Routing Problem

MDWCP Multi-Depot Waste Collection Problem

MILP Mixed Integer Linear Programming

MPIRP Multi-Period Inventory Routing Problem

OR Operations Research

PFSP Permutation Flow Shop Problem

PVRP Periodic Vehicle Routing Problem

RC Retail Center

RCL Restricted Candidate List

SA Simulated Annealing

SCM Supply Chain Management

T&L Transportation & Logistics

TDVRPTW Time-dependent VRP with time windows

UCC Urban Consolidation Center

UFLP Uncapacitated Facility Location Problem

VMI Vendor Managed Inventories

VNS Variable Neighborhood Search

VRP Vehicle Routing Problem

VRPTW Vehicle Routing Problem with Time Windows

WCP Waste Collection Problem

CHAPTER 1

INTRODUCTION

1.1 Motivation

The *Law of Caesar on Municipalities* —dating back to the year 44 B.C.— includes the first known urban freight transport regulation. It states that "on the roads which are in the city of Rome or will be within the area where will be lived joined tightly, no one is allowed after next January 1st to drive or lead a carriage during the day after sunrise and before the tenth hour of the day (...)" (Quak 2008).

While this shows that the creation of efficient urban transportation systems is not a recent phenomenon, the challenges faced by modern day city planners are unprecedented. More than ever, modern cities are the main global drivers of economic, social, and cultural development (Keivani 2010). This trend is undermined by growing population numbers in metropolitan areas around the world. As highlighted in Figure 1.1, urban population numbers are expected to double until 2050 (United Nations - Department of Economic and Social Affairs 2015). By that time, more than 80% of the world's population will live in urban conglomerates, accounting for over 90% of the global economic output (Dobbs et al. 2011).

This increasing urbanization directly influences public and private freight transportation planners. On the one hand, municipalities need to efficiently reorganize public services such as waste collection in order to provide healthy and livable environments for its citizens (Lindhol 2014). On the other hand, private freight carriers need to incorporate the complexity of

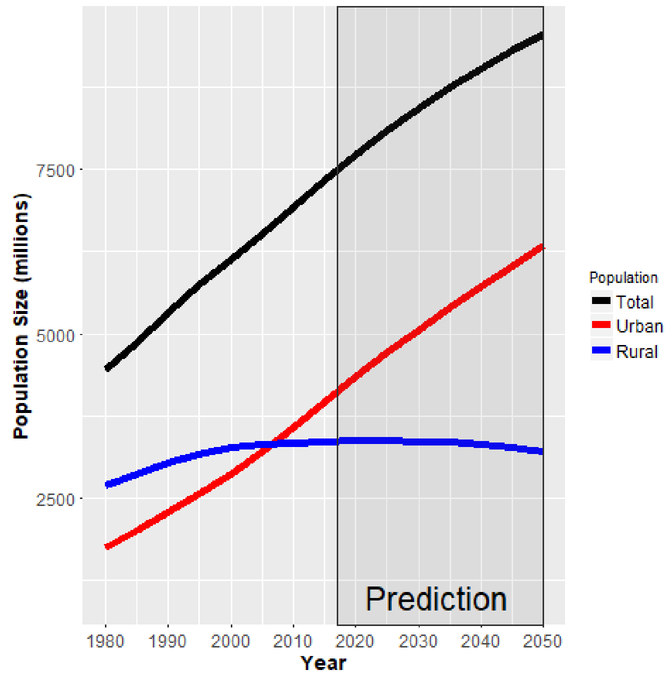

Figure 1.1: Past and expected world population development (1980-2050).

urban transportation systems in decision-taking processes to stay competitive and effectively respond to increasingly demanding customer requirements (Taniguchi 2014).

Apart from the economic aspects, cities and companies face the social responsibility to consider the negative externalities of the transportation of goods in their planning processes. Freight transportation vehicles are the source of excessive noise levels in urban areas affecting as much as 41 million Europeans (European Environment Agency 2009). At the same time, the Transportation & Logistics (T&L) sector is estimated to account for 27% in total greenhouse gas emissions in the USA (U.S. Environmental Protection Agency 2013).

The various challenges faced by urban freight distribution planners in the development of efficient and sustainable transportation systems are summarized in the concept of city logistics. City logistics are defined by Savelsbergh and van Woensel (2016) as "finding efficient and effective ways to transport goods in urban areas while taking into account the negative effects on congestion, safety, and environment". Some of the main challenges addressed by smart city logistic approaches in modern city planning initiatives include for example (DHL Trend Research 2014, Savelsbergh and van Woensel 2016, Taniguchi et al. 2016):

i the creation of last-mile logistic concepts.

ii the support of sustainable transportation operations.

iii the collection and use of vast amount of data provided by available Internet and Communication Technologies (ICT).

iv the rise of collaborative business models based on shared T&L assets between different supply chain actors.

In this context, many of the operational, tactical, and strategic decision-taking problems such as the vehicle routing between different delivery or pick-up points, customer clustering, or the location of cargo transportation hubs around city centers can be formulated as combinatorial optimization problems (COPs). Especially in realistic problem settings that are characterized by large problem sizes and numerous problem constraints, their complexity makes them extremely hard to solve. Even though a range of exact solving approaches exist that theoretically provide a guaranteed optimal solution to many COPs, their excessive calculation times make them impractical in many situations. Supported by the need for near instantaneous decision-taking, metaheuristic algorithms have established themselves as alternative in finding solutions to complex COPs. While these approximate methods cannot guarantee optimality, they are able to provide pseudo-optimal solutions in significantly reduced computation times (Talbi 2009).

Notwithstanding academic and practical advances in the field of Operations Research over the last few decades, a major drawback of traditional metaheuristics is their failure to fully represent the complexity of many real-life systems. By assuming deterministic inputs, objective functions, or problem constraints, many optimization techniques are only able to address oversimplified system representations. Especially in complex environments such as smart city logistics that are shaped by constant information flow and updates concerning traffic times, client demands, customers, etc., the inherent model uncertainty needs to be accounted for to provide valid and insightful solutions (Amaran et al. 2014).

The concept of *simheuristics* constitutes a possibility to include stochastic components in complex optimization settings. Simheuristics are based on the extension of classic metaheuristic solving techniques by guiding the solution search through feedback provided by different simulation paradigms. Apart from leading to more representative results to stochastic optimization problems, this also supports the introduction of different risk and reliability criteria during the assessment and analysis of alternative COP solutions (Juan et al. 2015*a*).

This thesis solidifies and extends the general methodology of simheuristics. Especially its use as a method of first resort for solving complex COPs in the context of efficient and sustainable smart city logistics planning concepts is supported.

1.2 Objectives and outline

The two central goals of this thesis and the derived research objectives are:

I **Solidification and extension of the general simheuristic framework**

- **Objective 1:**
  Development of new simulation-optimization algorithms according to the general simheuristic framework.
- **Objective 2:**
  Proposal of methodological extensions, definition of best-practices, and discussion of potential future applications of simheuristic paradigms.

II **Introduction of simheuristics as decision support tool for efficient and sustainable smart city logistics planning**

- **Objective 3:**
  Application of simheuristic algorithms to rich combinatorial optimization problems (of theoretical and practical nature) related to urban freight transportation on operational (e.g., daily product delivery), tactical (e.g., clustering), and strategic (e.g., warehouse location) planning levels.
- **Objective 4:**
  Analysis of simheuristics as a decision support tool to generate managerial insights in the development of smart city logistics.
- **Objective 5:**
  Comparison of developed optimization algorithms to state-of-the-art academic and real-life benchmarks.

Chapters 2-5 put forward the theoretical background of this thesis and highlight methodological advances proposed in this work. Chapter 2 introduces the concept of metaheuristics, which serve as underlying optimization engine of simheuristics. The main metaheuristic procedures that are applied in this work are outlined in more detail. This includes well-known optimization frameworks such as Variable Neighborhood Search (VNS), Simulated Annealing (SA), the Greedy Randomized Random Search Procedure (GRASP), and Biased Randomization (BR). Concerning the latter, a range of computational experiments are completed to underline the efficiency of Biased Randomization in different optimization settings.

The integration of metaheuristics with different forms of simulation according to the general simheuristic framework is outlined in chapter 3. A general introduction to the simheuristic paradigm is provided, including a review of recent applications in state-of-the-art literature and a discussion of the benefits and limitations of the simulation-optimization approach.

Chapter 4 presents generic simheuristic solving frameworks for combinatorial optimization problems under uncertainty. SimGRASP and SimVNS are introduced as simheuristic extensions of GRASP and VNS. In both cases the integration of simulation into the metaheuristic solving frameworks is proposed as possibility to consider stochastic inputs in a given optimization problem. While the elaborated algorithms are generic enough to be applied to any kind of stochastic COP, they form the central solving frameworks for the applications in the context of freight transportation in smart city logistics discussed in this dissertation.

To conclude the scientific background of this thesis, chapter 5 analyses the potential use of simheuristics to represent the inherent uncertainty of modeling human network behavior in complex systems such as manufacturing lines or city logistics. The analysis is based on a detailed literature review and concludes in the proposal of an agent-based simheuristic framework.

The main application areas of simheuristics in the context of efficient and sustainable freight transportation in smart city logistics discussed in this work are outlined in Figure 1.2. Chapter 6 introduces operational, tactical, and strategic optimization problems related to municipal waste management, integrated supply chain design, and horizontal collaboration concepts. The Waste Collection Problem (WCP), the time dependent Vehicle Routing Problem (VRP), the multi-depot VRP (MDVRP), the multi-period Inventory Routing Problem (IRP), and the two-echelon Location Routing Problem (2E-LRP) are formulated. Moreover, the relationship of these problem settings to different degrees of horizontal collaboration in supply chain management is outlined. For all problem settings, state-of-the-art solving frameworks presented in the literature for deterministic and stochastic problem extensions are reviewed.

The following chapters 7-10 present the application and analysis of developed simheuristic

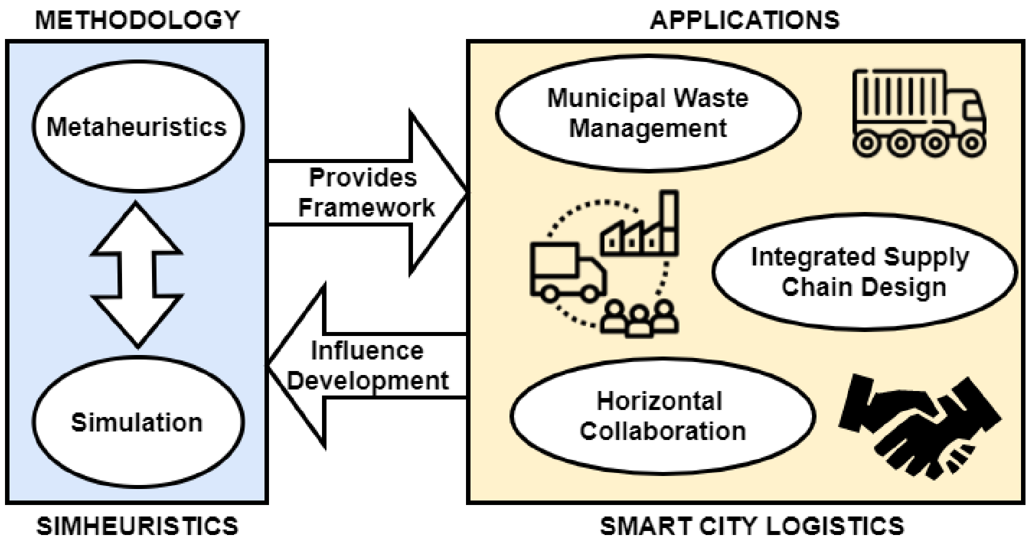

Figure 1.2: Main methodology and application areas discussed in this work.

frameworks in the environment of freight transportation in smart city logistics. Presented algorithms are compared to state-of-the-art benchmarks retrieved from the literature or derived from case studies completed in cooperation with private organizations. Obtained results are analyzed to highlight the potentials of simheuristics as method of first resort in urban freight transportation planning.

Chapter 7 focuses on stochastic optimization problems arising in smart urban waste management. This includes the development of efficient simheuristic approaches for different extensions of the Waste Collection Problem implemented as VRP adaptations. Computational experiments are based on theoretical benchmarks with up to 2100 collection points and a large scaled case-study completed with nearly 900 waste containers in the Catalan city of Sabadell. The obtained results show the competitiveness, scalability, and applicability of the presented algorithms in rich waste collection scenarios that incorporate time-windows, time dependency, capacity constraints, and stochastic inputs. Moreover, the potential of waste management collaboration in clustered urban areas is discussed. This includes the development of a simulation-optimization approach to integrate customer clustering and vehicle routing decisions, a problem setting formulated as multi-depot VRP.

Chapter 8 presents simheuristic solving frameworks for integrated supply chain design problems. In particular, stochastic versions of the multi-period Inventory Routing Problem and the two-echelon Location Routing Problem are addressed. The former optimization problem combines inventory replenishment with vehicle routing decisions, an integrated planning approach that often arises in vendor managed inventory concepts. The latter integrates operational vehicle routing and long-term (strategic) facility location decisions. This COP is especially important in the creation of urban consolidation centers (UCCs), which is a common city logistics concept to reduce monetary and environmental urban freight transportation costs. The simheuristic algorithms elaborated to solve both problem settings are tested and compared on theoretical and real-life benchmark instances.

All previously mentioned problem settings need to be solved in order to evaluate different supply chain collaboration scenarios. The use of simheuristics to quantify different horizontal collaboration (HC) cases that are based on cooperation agreements between stakeholders on the same supply chain level is put forward in chapter 10. A competitive solving framework based on Biased Randomization and VNS that is flexible enough to solve the optimization problems related with different collaboration degrees (non/semi/fully-collaborative) is presented. Moreover, the monetary and environmental benefits of HC concepts in deterministic and stochastic urban freight transportation cases are analyzed.

Finally, chapter 11 concludes this work. The main findings and research outcomes of this thesis are summarized, the potential managerial impact of simheuristics is analyzed, and potential future research lines steaming from the completed research are presented.

1.3 Main research outcomes

This document is based on research outcomes that are published in different ISI-JCR/Scopus indexed journals and the proceedings of international peer-reviewed conferences. Relevant publications by the author of this thesis are highlighted at the beginning of each chapter and cited where necessary. The cover pages of the articles that serve as basis of this work can be found in appendices A and B. The main research outcomes that are published or currently in the review process of ISI-JCR indexed journals are listed below. Additionally, detailed article information, the publication abstract, and the main contributions of the PhD-student (Aljoscha Gruler) during article development is provided for each document.

- **Gruler, A.**; Fikar, C.; Juan, A.; Hirsch, P.; Contreras, C. (**2017**): *Supporting multi-depot and stochastic waste collection management in clustered urban areas via simulation-optimization*. Journal of Simulation, 11(1): 11-19 (indexed in ISI SCI, 2017 IF = 1.218, Q3; 2017 SJR = 0.428, Q2). DOI: `https://doi.org/10.1057/s41273-016-0002-4`.

– **Abstract**

Waste collection is one of the most critical logistics activities in modern cities with considerable impact on the quality of life, urban environment, city attractiveness, traffic flows and municipal budgets. Despite the problem's relevance, most existing work addresses simplified versions where container loads are considered to be known in advance and served by a single vehicle depot. Waste levels, however, cannot be estimated with complete certainty as they are only revealed at collection. Furthermore, in large cities and clustered urban areas, multiple depots from which collection routes originate are common, although cooperation among vehicles from different depots is rarely considered. This paper analyses a rich version of the waste collection problem with multiple depots and stochastic demands by proposing a hybrid algorithm combining metaheuristics with simulation. This simheuristic approach allows for studying the effects of collaboration among different depots, thus quantifying the potential savings this horizontal supply chain collaboration could provide to city governments and waste collection companies.

– **Main contributions of PhD-candidate:**

This work was completed in cooperation with Prof. Dr. Angel A. Juan from the Universitat Oberta de Catalunya in Barcelona and Prof. Dr. Patrick Hirsch and Dr. Christian Fikar from the University of Natural Resources and Life Sciences in Vienna. As first and corresponding author of this publication, the PhD-student was strongly contributing to the research question definition, the review of relevant literature in the field, the design of the simulation-optimization algorithm, the implementation of procedure in Java, the analysis of obtained results, and the completion of the manuscript. Dr. Fikar developed major parts of the Java code, while Prof. Dr. Hirsch and Prof. Dr. Juan supported the article development with their expertise and guidance.

- **Gruler, A.**; Quintero, C.; Calvet, L.; Juan, A. (**2017**): *Waste Collection Under Uncertainty: a simheuristic based on variable neighborhood search*. European Journal of Industrial Engineering, 11(2): 228-255 (indexed in ISI SCI, 2017 IF = 1.085, Q3; 2017 SJR = 0.595, Q1). DOI: `https://doi.org/10.1504/EJIE.2017.083257`.

– **Abstract**

Ongoing population growth in cities and increasing waste production has made the optimization 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 characterized 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 neighborhood 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 the metaheuristic framework, which also allows a closer risk analysis of the best-found stochastic solutions. Different computational experiments illustrate the potential of this methodology.

– **Main contributions of PhD-candidate:**

This work was completed in cooperation with Prof. Dr. Angel A. Juan, Dr. Laura Calvet, and Dr. Carlos Quintero-Araujo from the Universitat Oberta de Catalunya in Barcelona. As first and corresponding author of this publication, the PhD-student was strongly contributing to the research question definition, the review of relevant literature in the field, the design of the simulation-optimization algorithm, the implementation of procedure in Java, the analysis of obtained results, and the completion of the manuscript. Dr. Calvet contributed by helping in the statistical analysis of obtained results. Dr. Quintero-Araujo was responsible of formulating the problem mathematically and implementing the model in the GAMS programming language. Prof. Dr. Juan supported the article development with his expertise and guidance.

- **Gruler, A.**; Panadero, J.; de Armas, J.; Moreno-Perez, J.; Juan, A. (**2018**): *Combining variable neighborhood search with simulation for the inventory routing problem with stochastic demands and stock-outs*. Computers and Industrial Engineering (indexed in ISI SCI, 2017 IF = 3.195, Q1; 2017 SJR = 1.463, Q1). DOI: `https://doi.org/10.1016/j.cie.2018.06.036`.

– **Abstract**

Vendor managed inventory aims at reducing supply chain costs by centralizing inventory management and vehicle routing decisions. This integrated supply chain approach results in a complex combinatorial optimization problem known as the inventory routing problem (IRP). This paper presents a variable neighborhood search metaheuristic hybridized with simulation to solve the IRP under demand uncertainty. This simheuristic approach is able to solve large sized instances for the single period IRP with stochastic demands and stock-outs in very short computing times. A range of experiments underline the algorithm's competitiveness compared to previously used heuristic approaches. The results are analyzed in order to provide closer managerial insights.

– **Main contributions of PhD-candidate:**

This work was completed in cooperation with Prof. Dr. Angel A. Juan and Dr. Javier Panadero from the Universitat Oberta de Catalunya in Barcelona, Dr. Jesica de Armas from the Universitat Pompeu Fabra in Barcelona, and Prof. Dr. José Moreno-Perez from the Universidad La Laguna in Teneriffe. As first and corresponding author of this publication, the PhD-student was strongly contributing to the research question definition, the review of relevant literature in the field, the design of the simulation-optimization algorithm, the implementation of procedure in Java, the analysis of obtained results, and the completion of the manuscript. Dr. Panadero completed major parts of the Java code. Dr. de Armas helped in defining the simheuristic algorithm. Prof. Dr. Juan and Prof. Dr. Moreno-Perez supported the article development with their expertise and guidance.

- **Gruler, A.**; Panadero, J.; de Armas, J.; Moreno-Perez, J.; Juan, A. (**2018**): *A Variable Neighborhood Search Simheuristic for the Multi-Period Inventory Routing Problem with Stochastic Demands*. Int. Transactions in Operational Research (indexed in ISI SCI, 2017 IF = 2.400, Q1; 2017 SJR = 1.071, Q1). DOI: `https://doi.org/10.1111/itor.12540`.

– **Abstract**

The inventory routing problem (IRP) combines inventory management and delivery route-planning decisions. This work presents a simheuristic approach that integrates Monte Carlo simulation within a variable neighborhood search (VNS) framework to solve the multiperiod IRP with stochastic customer demands. In this realistic variant of the problem, The goal is to establish the optimal refill policies for each customer–period combination, that is, those individual refill policies that minimize the total expected cost over the periods. This cost is the aggregation of both expected inventory and routing costs. The proposed simheuristic algorithm allows to consider the inventory changes between periods generated by the realization of the random demands in each period, which have an impact on the quantities to be delivered in the next period and, therefore, on the associated routing plans. A range of computational experiments are carried out in order to illustrate the potential of this simulation–optimization approach.

– **Main contributions of PhD-candidate:**

This work was completed in cooperation with Prof. Dr. Angel A. Juan and Dr. Javier Panadero from the Universitat Oberta de Catalunya in Barcelona, Dr. Jesica de Armas from the Universitat Pompeu Fabra in Barcelona, and Prof. Dr. José Moreno-Perez from the Universidad La Laguna in Teneriffe. As first and corresponding author of this publication, the PhD-student was strongly contributing to the research question definition, the review of relevant literature in the field, the design of the simulation-optimization algorithm, the implementation of procedure in Java, the analysis of obtained results, and the completion of the manuscript. Dr. Panadero completed major parts of the Java code. Dr. de Armas helped in defining the simheuristic algorithm. Prof. Dr. Juan and Prof. Dr. Moreno-Perez supported the article development with their expertise and guidance.

- Quintero, C.; **Gruler, A.**; Juan, A.; Faulin, J. (**2017**): *Using Horizontal Cooperation Concepts in Integrated Routing and Facility Location Decisions*. Int. Transactions in Operational Research (indexed in ISI SCI, 2017 IF = 2.400, Q1; 2017 SJR = 1.071, Q1). DOI: `https://doi.org/10.1111/itor.12479`.

- **Abstract**

In a global and competitive economy, efficient supply networks are essential for modern enterprises. Horizontal collaboration (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 collaboration scenarios concerning integrated routing and facility-location decisions in road transportation: (a) a non-collaborative scenario in which all decisions are individually taken (each enterprise addresses its own vehicle routing problem [VRP]); (b) a semi-collaborative scenario in which route-planning decisions are jointly taken (facilities and fleets are shared and enterprises face a joint multidepot VRP); and (c) a fully cooperative scenario in which route-planning and facility-location decisions are jointly taken (also customers are shared, and thus enterprises face a general location routing problem). The completed analysis explores how this increasing level of HC leads to a higher flexibility and, therefore, to a lower total distribution cost. A hybrid metaheuristic algorithm, combining biased randomization with a variable neighborhood search framework, is proposed to solve each scenario. This allows us to quantify the differences among these scenarios, both in terms of monetary and environmental costs. This solving approach is tested on a range of benchmark instances, outperforming previously reported results.

- **Main contributions of PhD-candidate:**

This work was completed in cooperation with Prof. Dr. Angel A. Juan and Dr. Carlos Quintero-Araujo from the Universitat Oberta de Catalunya in Barcelona, and Dr. Javier Faulin from the Universidad Pùblica de Navarra in Pamplona. As second author of this publication, the PhD-student was contributing to the review of relevant literature in the field, the design of the simulation-optimization algorithm, the analysis of obtained results, and the completion of the manuscript. Dr. Quintero-Araujo was leading this research effort and was involved in all steps of the article completion. Prof. Dr. Juan and Prof. Dr. Faulin supported the article development with their expertise and guidance.

- Ferone, D.; **Gruler, A.**; Festa, P.; Juan, A. (**2018**): *Enhancing and Extending the Classical GRASP Framework with Biased Randomization and Simulation*. Journal of the Operational Research Society (indexed in ISI SCI, 2017 IF = 1.396, Q3; 2017 SJR = 1.002, Q1). DOI: `https://doi.org/10.1080/01605682.2018.1494527`.

  – **Abstract**

  Greedy Randomized Adaptive Search Procedure (GRASP) is one of the best-known metaheuristics to solve complex combinatorial optimization problems (COPs). This paper proposes two extensions of the typical GRASP framework. On the one hand, applying biased randomization techniques during the solution construction phase enhances the efficiency of the GRASP solving approach compared to the traditional use of a restricted candidate list. On the other hand, the inclusion of simulation at certain points of the GRASP framework constitutes an efficient simulation-optimization approach that allows to solve stochastic versions of COPs. To show the effectiveness of these GRASP improvements and extensions, tests are run with both deterministic and stochastic problem settings related to flow shop scheduling, vehicle routing, and facility location.

  – **Main contributions of PhD-student:**

  This work was completed in cooperation with Prof. Dr. Angel A. Juan and Dr. Daniele Ferone from the Universitat Oberta de Catalunya in Barcelona, and Prof. Dr. Paola Festa from the Universidad de Nápoles Federico II in Napoli. As second author of this publication, the PhD-student was contributing to the the development of the simulation-optimization algorithms, the design of computational experiments, the analysis of obtained results, and the completion of the manuscript. Dr. Ferone was leading this research effort and was involved in all steps of the article completion. Prof. Dr. Juan and Prof. Dr. Festa supported the article development with their expertise and guidance.

- **Gruler, A.**; Perez, T.; Calvet, L.; Juan, A. (***under review***): *A Simheuristic Algorithm for Time-Dependent Waste Collection Management with Stochastic Travel Times*. Int. Transactions in Operational Research (indexed in ISI SCI, 2017 IF = 2.400, Q2; 2017 SJR = 1.071, Q1). ISSN: 0969-6016.

– **Abstract**

A major operational task in city logistics is related to waste collection, which can be formulated as a rich extension of the well-known vehicle routing problem. Due to large problem sizes and numerous constraints, the optimization of real-life waste collection problems (WCPs) on a daily basis requires the use of metaheuristic solving frameworks to generate near-optimal collection routes in low computation times. However, most existing optimization frameworks are based on simplifying assumptions regarding the time dependency and stochasticity of input variables. In order to overcome this drawback, this paper presents a simheuristic algorithm for the time dependent WCP with stochastic travel times (TDWCPST). By combining Monte Carlo simulation with a biased randomized iterated local search metaheuristic, time-varying and stochastic travel speeds between different network nodes are accounted for. The implementation and performance of the proposed solving methodology is shown in a case study involving the waste collection of several hundred garbage containers in Sabadell, a medium-sized city located in the autonomous Spanish region of Catalonia.

– **Main contributions of PhD-candidate:**

This work was completed in cooperation with Prof. Dr. Angel A. Juan, Dr. Laura Calvet, and Dr. Antoni Perez from the Universitat Oberta de Catalunya in Barcelona. The article is currently in the review process of the cited ISI-JCR indexed journal. As first and corresponding author of this publication, the PhD-student was strongly contributing to the research question definition, the review of relevant literature in the field, the design of the simulation-optimization algorithm, the implementation of procedure in Java, the analysis of obtained results, and the completion of the manuscript. Moreover, the student was in direct contact with the waste management service provider SMATSA to obtain data and define the completed case-study. Dr. Calvet was contributing to the development of the Java code. Prof. Dr. Juan and Prof. Dr. Perez supported the article development with their expertise and guidance. Especially Prof. Dr. Perez helped in the completion of the manuscript by guiding guiding the PhD-candidate in the necessary data processing with Geographic Information Systems.

- **Gruler, A.**; De Armas, J.; Juan, A.; Goldsman, D. (***under review***): *Modeling Human Behavior in Social Networks: a survey and the need for simheuristics*. Statistics and Operations Research Transactions (indexed in ISI SCI, 2017 IF = 1.344, Q2; 2017 SJR = 0.551, Q2). ISSN: 1696-2281.

  - **Abstract**

    The inclusion of stakeholder behavior in Operations Research / Industrial Engineering (OR/IE) models has gained much attention in recent years. Behavioral and cognitive traits of people and groups have been integrated in simulation models (mainly through agent based approaches) as well as in optimization algorithms. However, especially the influence of relations between different actors in social networks is a broad and interdisciplinary topic that has not yet been fully investigated. This paper analyzes, from an OR/IE point of view, the existing literature on behavior-related factors in social networks. This review covers different application fields, including: supply chain management, public policies in emergency situations, and Internet-based social networks. The review reveals that the methodological approach of choice (either simulation or optimization) is highly dependent on the application area. However, an integrated approach combining simulation and optimization is rarely used. Thus, the paper proposes the hybridization of simulation with optimization — and, in particular, the use of simheuristics — as one of the best strategies to incorporate human behavior in social networks and the resulting uncertainty, randomness, and dynamism in related OR/IE models.

  - **Main contributions of PhD-student:**

    This work was completed in cooperation with Prof. Dr. Angel A. Juan from the Universitat Oberta de Catalunya in Barcelona, Dr. Jesica de Armas of the Universitat Pompeu Fabra in Barcelona, and Prof. Dr. David Goldsman from the Georgia Institute of Technology in Atlanta. The article is currently in the review process of the cited ISI-JCR indexed journal. As first and corresponding author of this publication, the PhD-student was strongly contributing to the research question definition, the extensive review of related literature, and the development of the proposed agent-based simheuristic. Dr. de Armas was involved in finding related research papers and completing the manuscript. Prof. Dr. Juan and Prof. Dr. Goldman supported the article development with their expertise and guidance.

(I) METHODOLOGY

CHAPTER 2

METAHEURISTICS IN COMBINATORIAL OPTIMIZATION

This chapter describes the theoretical background of metaheuristic algorithms in combinatorial optimization. The highlights of this chapter include:

- a short introduction to metaheuristic optimization.
- a detailed description of the main metaheuristic concepts applied in this work, including Variable Neighborhood Search (VNS), Simulated Annealing (SA) Greedy Randomized Adaptive Search Procedure (GRASP), and Biased Randomization (BR).
- a computational analysis of extending the traditional GRASP framework with Biased Randomization. Results suggest significant improvements for the Permutation Flow Shop Problem (PFSP), the Vehicle Routing Problem (VRP), and the uncapacitated Facility Location Problem (UFLP) with no additional computational effort or parameters in comparison to basic GRASP implementations (Ferone et al. 2016, 2018).[1]

[1] The work put forward by Ferone et al. (2016) is published in the SCOPUS indexed conference proceedings of the Winter Simulation Conference 2016 in Washington D.C., USA. Its findings were presented by the PhD-candidate Aljoscha Gruler. As co-author of this publication, the student was mainly responsible for the algorithm design, literature review, and analysis of results.

2.1 General overview

A wide range of decision-taking processes related to transportation, supply chain management, engineering, finance, or smart cities can be formulated as optimization problems. Mathematically speaking, optimization problems are defined through a couple (S, f), where the solution search space S defines a set of feasible solutions, while $f : S \to \mathbf{R}$ represents the objective function to optimize. A representative solution search space with the corresponding objective function values can be seen in Figure 2.1. The figure highlights different extrema of the plotted function. On the one hand, local minima and maxima define different extreme points within a specific neighborhood of the solution space. On the other hand, the global minimum and maximum correspond to the lowest and largest values of the complete function domain. The main goal of solving an optimization problem is to find a global optimal solution $s^* \in S$ in such a way that $f(s^*) \le f(s)$ for any solution $s \in S$ (and vice versa in the case of maximization) (Talbi 2009).

One subset of mathematical optimization with high relevance in applied operations research and theoretical computer science is that of combinatorial optimization problems

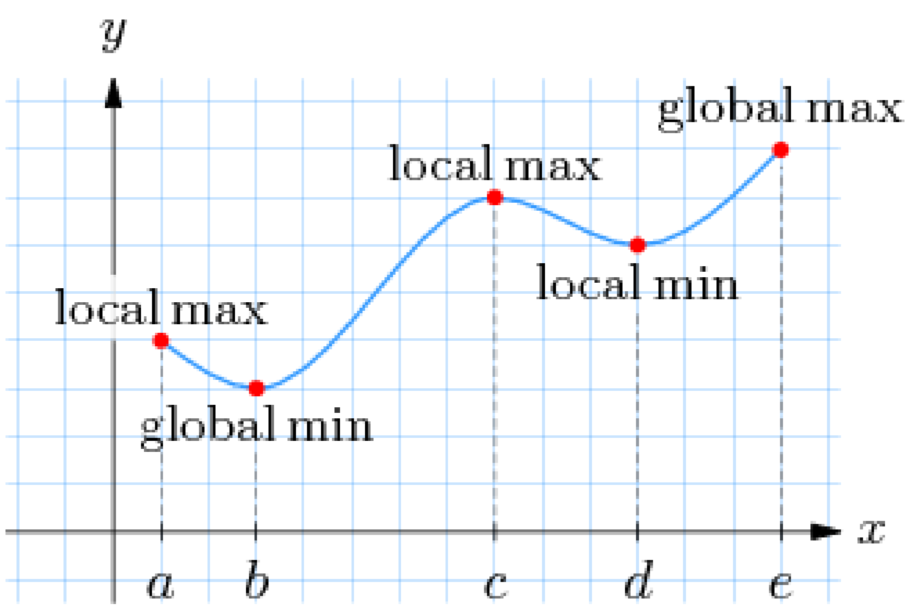

Figure 2.1: Global and local minima and maxima in a solution search space. Retrieved from Sveriges Universitets Matematikportal (2017)

(COPs). These problems are characterized by solutions that are encoded with discrete variables within a finite solution search space, while their objective function and problem constraints can take any form (Papadimitriou and Steiglitz 1982, Pardalos and Resende 2002).

Among possible solving frameworks for COPs, exact (complete) algorithms based on methods from the branch-and-X family, dynamic programming, Bayesian search algorithms, or successive approximation guarantee to find an optimal solution to a given problem. However, many COPs are NP-hard in nature, which means that no algorithm exists that can solve these problem settings within polynomial time (Festa 2014, Garey and Johnson 1990). The risk of running into exponential computing times makes the use of exact algorithms impractical in many real-life applications, which are often characterized by large-scaled problem instances, hard constraints, and complex mathematical functions. This has supported the rising theoretical and practical interest in metaheuristic solving approaches over the last few decades (Boussaïd et al. 2013, Gogna and Tayal 2013, Nesmachnow 2014).

Whereas early approximate methods for optimization problems were already discussed in the 1940s (Polya 1945), the term metaheuristics was first coined by Glover (1986). It refers to higher-level strategies to guide the solution search process to any given COP, regardless of the specific problem type. Metaheuristics — if properly designed — have shown to be promising alternatives to exact solving approaches in many situations by efficiently scanning large solution spaces in the search for new solutions. Even though metaheuristics cannot guarantee solving any given COP to optimality, they are able to find pseudo-optimal solutions in very short calculation times in comparison to their exact counterparts (Blum and Roli 2003). Some of the pioneering contributions and widely-used metaheuristics include for example Simulated Annealing (Kirkpatrick 1984), Tabu Search (Glover and Laguna 1998), Genetic Algorithms (Goldberg 1989), Ant Colony Optimization (Dorigo 1992), or Variable Neighborhood Search (Mladenović and Hansen 1997).

Within the design of metaheuristic algorithms, a general trade-off exists between intensification (or exploitation) and diversification (or exploration) within the solution search space. As visualized in Figure 2.2, the main focus of different metaheuristic procedures can be characterized as (Blum and Roli 2003, Nesmachnow 2014, Talbi 2009):

i Intensification focused metaheuristics investigate the direct solution neighborhood of promising COP solutions. Popular members of this class of algorithms include for example Simulated Annealing (SA), Variable Neighborhood Search (VNS), or Iterated Local Search (ILS). These approaches are also called single-solution (or trajectory) based methods, as they focus on creating and modifying a single candidate solution.

ii Diversification focused metaheuristics try to visit numerous solution neighborhoods within the solution space to improve the current incumbent solution. These kind of procedures are also known as population-based approaches and include algorithms such as Ant Colony Optimization or Genetic Algorithms, which maintain a pool of promising solutions with the aim of using population information to optimize a given objective function.

iii Multi-start method are typically based on two altering phases to strategically scan the solution space of a given COP: a randomized solution construction and the subsequent local search. The solution construction in most multi-start methods — in contrast to deterministic approaches — is typically based on some kind of randomized procedure to ensure that a different solution is found every time a new solution is created. In combination with some problem-specific local search procedure to find the local minimum within the neighborhood of a constructed solution, multi-start methods such as the Greedy Randomized Adaptive Search Procedure (GRASP) try to find a balance between diversification and intensification of systematic solution space sampling (Martí et al. 2013).

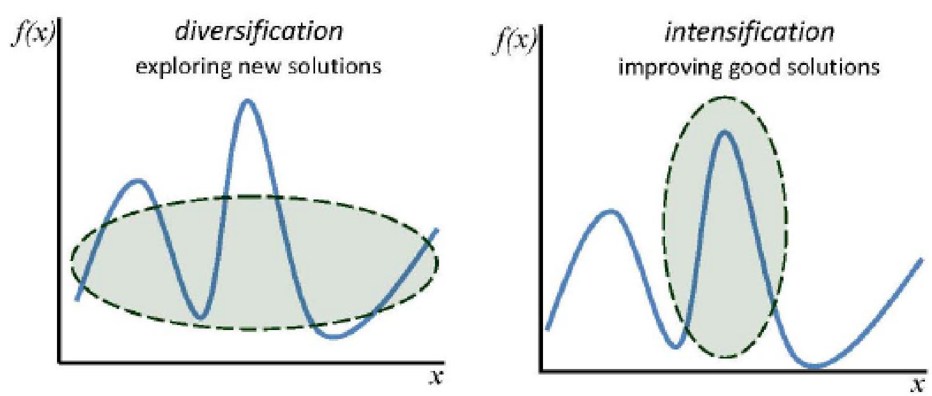

Figure 2.2: Diversification vs. intensification in metaheuristic solution search. Retrieved from Nesmachnow (2014).

2.2 Selected metaheuristic frameworks

The following subsections describe the main metaheuristic paradigms that are applied in this work. This includes Variable Neighborhood Search, Simulated Annealing, GRASP, and Biased Randomization. Especially the latter technique is applied at different points of this work. For this reason, its potentials in the context of transportation & logistics optimization are shown through a range of numerical experiments.

2.2.1 Variable Neighborhood Search

Variable Neighborhood Search (VNS) is a single-solution-based metaheuristic first presented by Mladenović and Hansen (1997). It is based on systematic neighborhood changes to find increasingly distant solution structures with reference to the current incumbent solution. Within each solution neighborhood, problem-specific local search methods are applied to find local optima. This combination of diversification-focused neighborhood changes with local search methods during the intensification phase makes VNS an efficient metaheuristic that has been applied to a wide range of theoretical and practical problem settings including routing, scheduling, or artificial intelligence (Duarte et al. 2017, Moreno-Vega and Melián 2008).

The basic VNS procedure is outlined in Algorithm 1. An initial solution is constructed and set as current incumbent $baseSol$ (line 1). In the following, the solution structure of $baseSol$ is altered by applying a problem-specific shaking operator and creating a new neighborhood structure $N_k(k = 1, 2, ..., k_{max})$. The neighborhood structure of k is locally optimized through some kind of problem-specific local descent procedure (line 8). If the locally optimized solution is more competitive than $baseSol$, $newSol$ is set as current incumbent solution and k is set to 1. If $newSol$ does not outperform $baseSol$, a new neighborhood structure is created by incrementing k ($k = 1$ if $k = k_{max}$). In any case, this process is repeated until the stopping criterion is reached. Apart from problem-specific decisions that need to be established in the definition of a VNS algorithm — including the defined stopping criterion, the neighborhood change (shaking) strategies, or the local search operators —, different VNS extensions have been investigated over the years that extend the basic VNS outlined in this description. They include concepts such as variable neighborhood descent, the skewed VNS, or the reduced VNS (Hansen et al. 2010).

Algorithm 1: General VNS framework

```
baseSol ← construct initial solution
while stopping criteria not reached do
    k ← 1
    repeat
        newSol ← shake(baseSol, k)
        improving ← true
        while improving do
            newSol* ← localDescent(newSol, randomLSoperator)
            if costs(newSol*) ≤ costs(newSol) then
                newSol ← newSol*
            end
            else
                improving ← false
            end
        end
        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
```

2.2.2 Simulated Annealing

Simulated Annealing (SA) in the context of combinatorial optimization was first presented over three decades ago (Kirkpatrick 1984). Its name is based on the algorithms' characteristic of miming the process undergone by misplaced atoms during the cooling process of heated metals, which strive towards minimum lattice energy state. With the goal of finding a global optimal solution, the algorithm applies different hill-climbing moves to escape local solution space extrema. As outlined in Algorithm 2, the procedure starts by creating an initial solution that is set as current incumbent solution $currentBest$. In the following, new solutions are created within a predefined stopping criterion (e.g., number of iterations or a maximum running time). Each new solution $newSol$ is accepted as new current best solution if its objective function value outperforms that of $currentBest$. Moreover, $newSol$ is also accepted as new current best solution according to a certain probability $P(t, newSol, currentBest) = e^{(quality_{newSol} - quality_{currentBest})/t}$ that is compared to a random uniform number within the range $[0, 1]$.

On the one hand, the probability of selecting $newSol$ is close to 0 if $newSol$ is significantly worse than $currentBest$. On the other hand, if both solutions are of similar quality, the probability of selecting $newSol$ as new incumbent solution is relatively high. Furthermore, the probability is directly affected by temperature parameter t $(0 < t)$. If t is close to 0, the fraction will also be a large number and thus decrease the probability of accepting worse solutions, and vice versa for higher values of t. Typically, SA algorithms start by setting a high value of t, focusing on the exploitation of the solution space. With each newly created solution, the value of t is reduced, thus intensifying the focus on the current best solution (Luke 2011, Nikolaev and Jacobson 2010).

Algorithm 2: General Simulated Annealing framework

```
currentBest ← construct initial solution
while stopping criteria not reached do
    newSol ← localSearch(currentBest)
    t ← temperature, initially a high number
    if quality(newSol) > costs(baseSol) or randomUniform(0,1) > P(t, newSol,
      currentBest) then
        currentBest ← newSol
    end
    decrease t
end
bestSol ← currentBest
return bestSol
```

2.2.3 Greedy Randomized Adaptive Search Procedure

The Greedy Randomized Adaptive Search Procedure (GRASP) is a well-studied constructive and randomized metaheuristic which has been successfully applied to a wide range of complex COPs in different environments (Festa and Resende 2009*a*,*b*, Resende and Ribeiro 2003). Its iterative procedure is based on two stages: a construction phase and a local search phase.

The general multi-start GRASP framework can be seen in Algorithm 3. During the solution construction (lines 1 and 4), a feasible COP solution is generated. All solution elements are hereby added to a candidate list CL that is sorted according to the incremental costs $c(\cdot)$ of including element $e \in CL$ in the solution (Algorithm 4). Then, the solution is iteratively built (lines 4–12). At each iteration, an element is chosen from a restricted candidate list (RCL) according to a uniformly distributed probability function. The size of the RCL is defined by a threshold value thr, which defines the quality of including an element in the currently constructed solution within the highest and lowest incremental costs of any element $e \in CL$. Threshold parameter α defines the size of the RCL, with $\alpha = 0$ equal to a completely greedy algorithm and $\alpha = 1$ leading to a completely randomized approach in which any element might be chosen. After including an element in the current solution, the incremental costs of the remaining CL elements are recalculated and the CL is reordered accordingly.

Algorithm 3: General GRASP framework

1 $\mathrm{s}_0 \leftarrow$ GenerateSolution
2 $\mathrm{s}^* \leftarrow$ LocalSearch(s_0)
3 **while** *stopping criterion not reached* **do**
4     $\mathrm{s}^{**} \leftarrow$ GenerateSolution
5     $\mathrm{s}^{**} \leftarrow$ LocalSearch(s^{**})
6   **if** $f(s^{**}) < f(s^*)$ **then**
7         $\mathrm{s}^* \leftarrow \mathrm{s}^{**}$
    end
end
8 **return** Best solution s^*

Any generated feasible solution s^{**} is not guaranteed to be locally optimal. For this reason, it is beneficial to apply a problem-specific local search procedure to the newly constructed solution. Solution s^{**} is locally improved within a suitable neighborhood structure $N(\mathrm{s}^{**})$ until no better solution can be found. Generally, the quality of the final solution directly depends on the neighborhood definition, the local search technique, and the starting solution applied for the specific problem (Festa and Resende 2009*a*).

2.2.4 Biased Randomization

The randomized construction of COP solutions in most multi-start metaheuristics is guided by information about the quality of solution elements. For example, the general GRASP frame-

Algorithm 4: Solution construction phase in GRASP algorithms

Input: $\alpha \in [0,1]$

$s \leftarrow \emptyset$

initialize candidate set: CL $\leftarrow$ E

order the Candidate List (CL) elements according to $c(\cdot)$

while *solution s is not complete* **do**

    $c_{\min} \leftarrow \min_{x \in CL}\{c(x)\}$

    $c_{\max} \leftarrow \max_{x \in CL}\{c(x)\}$

    $thr \leftarrow c_{\min} + \alpha(c_{\max} - c_{\min})$

    $RCLsize \leftarrow |\{x \in CL : c(x) \leq thr\}|$

    $pos \leftarrow \texttt{UniformRand}(1, 2, \ldots, RCLsize)$

    $s \leftarrow s \cup \{CL[pos]\}$

    $CL \leftarrow CL \setminus \{CL[pos]\}$

    Reorder CL

end

return s

work includes a restricted candidate list of ranked solution elements, which are chosen at each algorithm construction step according to a uniform distribution. Biased Randomization techniques extend this 'common sense' heuristic by attributing higher selection probabilities to more promising solution elements. This concept can be applied at different algorithm stages, e.g. during solution construction processes or local search procedures.

Instead of relying on a restricted candidate list, a bias function assigns non-negative weights to all elements that are potentially eligible. The bias function can hereby follow any kind of skewed probability function. An example of sorted solution elements can be seen in Figure 2.3. Each potentially eligible element of the candidate list — e.g., edges of a routing problem, machine jobs, replenishment levels in inventory management, etc. — is represented on the x-axis. They are ranked according to some criteria (e.g., priority rule, heuristic value), which defines the selection probability according to some theoretical skewed probability function. In the outlined example, the left figure corresponds to a geometric distribution (with a geometric distribution parameter of 0.2), while the right figure depicts the selection probabilities of a decreasing triangular probability function. Generally, the use of skewed probabilities offers two main advantages over using empirical distributions: *(i)* they contain at most one simple parameter, and *(ii)* they can be sampled using well-known analytical expressions, which from a computational perspective is typically faster than other sampling techniques involving the use of loops (Grasas et al. 2017, Juan et al. 2013a). A constructive procedure to create COP solutions based on Biased Randomization is described in Algorithm 5.

To show the benefits of using skewed probabilities during the solution construction phase, a biased randomized version of GRASP (BR-GRASP) is compared to the performance of a general GRASP implementation. Both algorithms have been applied to well-known problem settings in the field of transportation and logistics, namely the PFSP, the VRP, and the UFLP.

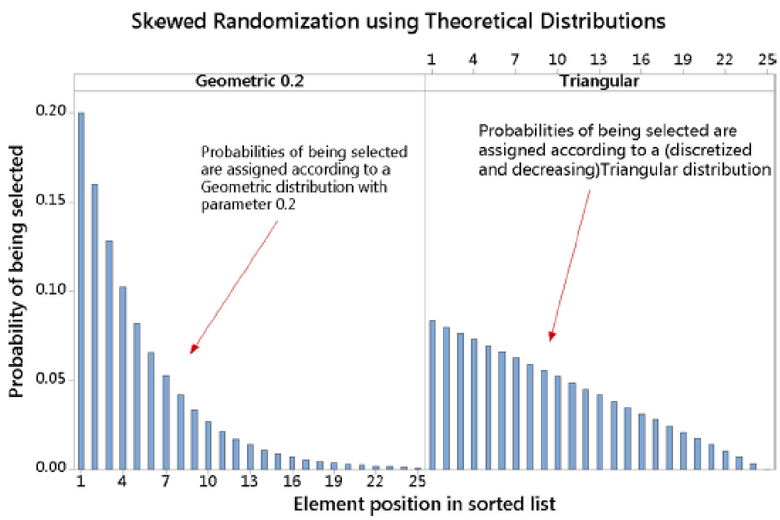

Figure 2.3: Use of skewed distributions in Biased Randomization. Retrieved from Grasas et al. (2017).

Algorithm 5: Solution construction phase with Biased Randomization

---

Input: Non-symmetric distribution function D; Distribution parameter β

$s \leftarrow \emptyset$

initialize candidate set: CL ← E

order the Candidate List (CL) elements according to $c(\cdot)$

while *solution s is not complete* **do**

  Randomly select $pos \in \{1,\ldots,|CL|\}$ according to distribution $D(\beta)$

  $s \leftarrow s \cup \{CL[pos]\}$

  $CL \leftarrow CL \setminus \{CL[pos]\}$

  Reorder CL

end

return s

Figure 2.4 depicts multiple boxplots showing the percentage differences of the traditional GRASP solution construction in comparison to BR-GRASP with reference to the best-known solutions (BKSs) of various problem instances. The detailed results and the experiment settings are listed in Appendices C-E.

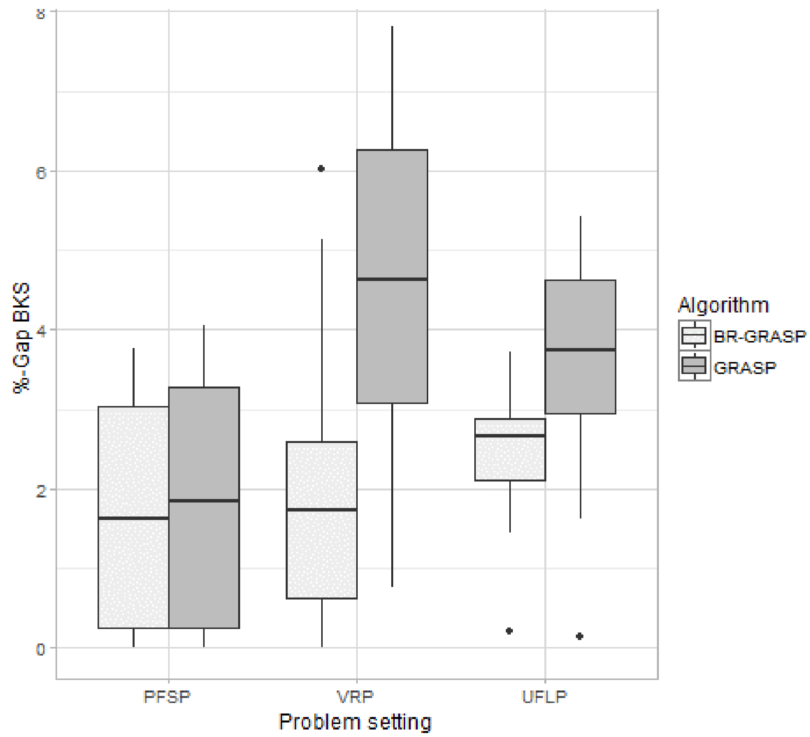

Figure 2.4: Comparison of %-gaps of traditional GRASP and BR-GRASP to BKSs of different COPs.

It can be concluded that the use of skewed probability functions outperforms the a uniform selection strategy in all cases. However, the significance of the improvements differs between the problem settings. In order to evaluate the statistical differences between both algorithm implementations, the nonparametric Mann-Whitney-U test with regards to the percentage differences to the BKS for all tested instances of each problem setting was completed. Significant differences can be observed for the VRP ($p-value = 1.567 \times 10^{-7}$) and the UFLP ($p-value = 0.0009862$). For the PFSP however, no significant differences can be deducted from the obtained results ($p-value = 0.6037$).

CHAPTER 3

Simheuristics for complex decision making problems under uncertainty

As shown in chapter 2, metaheuristics are able to solve complex decision-taking problems in short calculation times. However, one major drawback of traditional metaheuristic techniques is their disability to consider stochastic inputs in the solution search procedure. This chapter outlines simheuristics as general simulation-optimization approach to solve complex COPs under uncertainty in different application areas. The highlights of this chapter include:

- an introduction to the general simheuristic framework based on recent methodological advances and best practices defined by research completed within this dissertation.
- a comparison of simheuristics to other optimization and simulation techniques.
- a literature review of relevant publications presenting simheuristic algorithms to address different COPs under uncertainty.

3.1 General framework of simheuristic algorithms

Traditional metaheuristic frameworks are based on simplifying assumptions, which can lead to questionable optimization outcomes. By assuming deterministic optimization problem inputs and constraints, they fail to fully represent the inherent uncertainty and dynamism experienced in complex real-life systems such as smart city logistics (Chica et al. 2017).

As outlined in Figure 3.1, the concept of *simheuristics* is based on the integration of simulation in any of its forms into metaheuristic optimization methodologies to account for stochasticity in different COPs. It focuses on so called *a priori* stochastic optimization. In contrast to dynamic or reactive optimization approaches that reveal problem information during the execution of a predefined process, a priori optimization methodologies assume that some information (e.g., based on historical data) about the stochastic variable is already available during the planning phase. This information is incorporated during the optimization process by modeling random variables through some kind of probability distribution. Such simulation-optimization techniques are able to establish competitive solutions under the consideration of uncertainty experienced in the represented system. Apart from an estimated objective function value, the stochastic COP solution also provides information on its 'robustness' (i.e., risk-level) in stochastic environments (Bianchi et al. 2009, Juan et al. 2015*a*, Ritzinger et al. 2016).

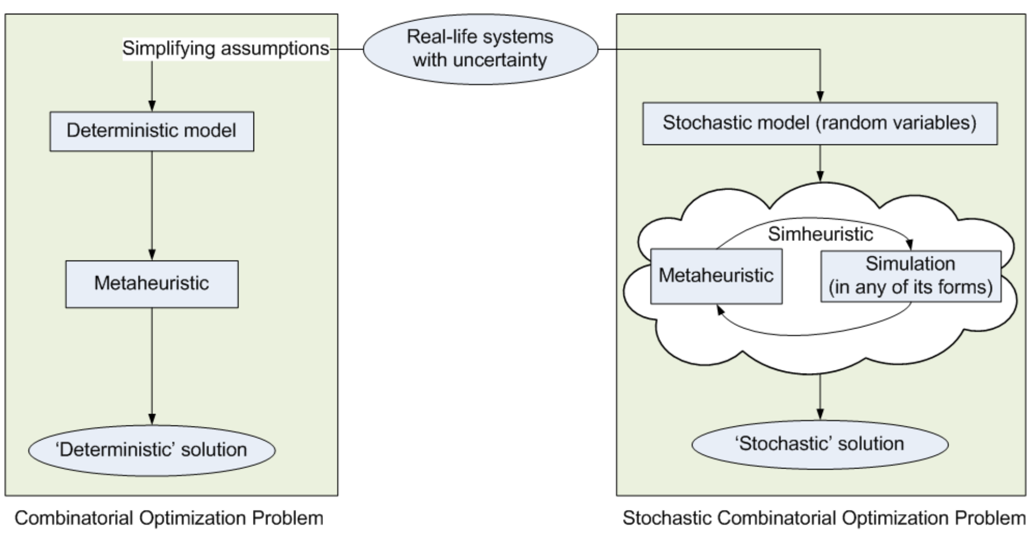

Figure 3.1: General difference between metaheuristics and simheuristics in solving COPs.

Early works on the combination of simulation and optimization include, for example, Glover et al. (1996, 1999) and April et al. (2003). The discussed methodologies are mostly simulation-focused, and have led to "black-box" optimization engines such as OptQuest, which are now distributed with well-known commercial simulation software such as Simio or Arena (OptTek 2018). From an optimization-focused point of view, the early integration with simulation to evaluate different stochastic COP solutions was mainly done in the context of engineering (Talbi 2009).

Properly implemented simheuristic frameworks extend earlier simulation-optimization procedures. On the one hand, the metaheuristic solution search is guided by feedback obtained through the simulation engine. On the other hand, an important feature of simheuristics is the inclusion of a risk and reliability analysis to assess different high-quality solutions to stochastic problem settings. As will be shown throughout this thesis, this information can lead to valuable managerial insights in complex decision-taking environments such as city logistic systems.

Simheuristics are able to extend any kind of metaheuristic framework through the integration of simulation to account for input uncertainty. Hereby, the quality of the stochastic solution is directly correlated to the efficiency of the underlying optimization methodology, which supports the use of high-quality metaheuristics as underlying solution search engine. Regarding the integrated simulation paradigm, any of the four most significant simulation approaches can be used. This includes Monte Carlo simulation (MCS), system dynamics, discrete event simulation (DES), and agent based simulation (ABS). On the one hand, MCS is used to model risk in an uncertain environment where the outcome is subject to chance through repeated random sampling. On the other hand, system dynamics intents to represent reality through continuous stocks and flows. Finally, DES and ABS are closely related simulation approaches which aim to model a given system as a discrete event of sequences in time. While DES takes a (top down) process oriented approach, ABS focuses on modeling different discrete entities and the interactions between them (bottom up). A closer comparison of both modeling frameworks is provided in chapter 5 (Gutenschwager et al. 2017, Raychaudhuri 2008, Robinson 2004, Siebers et al. 2010).

The selection of a suitable simulation approach strongly depends on the questions to be answered by the model. A general guideline to select the right simulation paradigm is provided by Kleijnen et al. (2005). The authors stress that the main goals of the simulation technique are:

i the facilitation of a basic understanding of the modeled system.

ii the definition of robust policies and decisions.

iii the comparison and analysis of different policies and decisions.

Well-designed simheuristic algorithms are generally defined by the stages depicted in Figure 3.2. The first stage regarding the preparation of input data is of special importance when solving real-life problem settings. Depending on the specific optimization case, this step directly affects the applicability and quality of the results (the importance and challenges of data preparation are closer discussed in the large-scaled case study described in chapter 5). Once the input data are of the required quality, the first simulation-optimization stage is started. Hereby an initial set of simheuristic solutions is defined by applying a fast simulation procedure. This enables a first rough estimate of 'promising' COP solutions and their behavior in uncertain environments. The simulation component of the simheuristic does not only provide a natural way to model the real system, but it also provides valuable information to the metaheuristic component (i.e., the search process is simulation-driven). Thus, it can be used as a first quick filter of low quality solutions during this stage of the simheuristic. The fast simulation with a reduced number of simulation runs is applied to avoid overloading the process with simulation, which might jeopardize computing times allocated to the search of high-quality metaheuristic solutions. During the second simulation-optimization stage, a more thorough simulation stage is used to closer analyze the performance of promising solutions in a stochastic environment. This allows for creating different 'elite' solutions. Finally, the last step in the general simheuristic paradigm includes a detailed risk or robustness analysis of the set of elite solutions (Chica et al. 2017).

The risk analysis completed within the simheuristic process involves the use of statistical methods to create additional decision-taking dimensions and closer managerial insights which go beyond the sole consideration of cost optimization. Especially in complex decision-taking environments such as city logistics, the objective function might not be the only variable of interest. For example, solutions with a promising expected objective function value might experience higher variability than alternative solutions. Consequently, decision-takers can rely on information provided by the simheuristic to decide which solution to choose based on her or his utility function and risk aversion. Even more advanced optimization methods such as multi-objective optimization algorithms could be applied at this point, to have a set

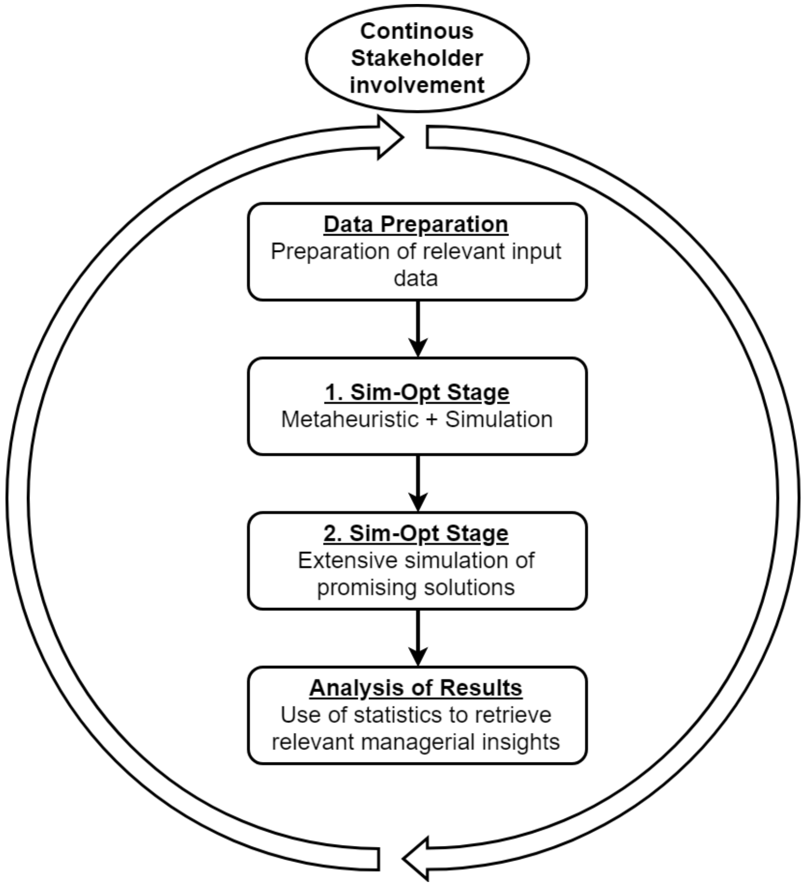

Figure 3.2: Typical stages of a simheuristic algorithm.

of solutions with different trade-offs between expected cost value and robust environment behavior (Juan et al. 2015*a*).

The simheuristic paradigm is not a purely sequential process. Rather, the stages should be repeated when necessary. Moreover, a participatory modeling process between all involved stakeholders is preferable to ensure a clear understanding and knowledge sharing between the simulation-optimization modeler and final decision-takers (Voinov and Bousquet 2010).

3.2 State-of-the-art simheuristic approaches in the literature

Various applications of simheuristics have been presented — mainly in the context of transportation and logistics — in recent years. A strong focus of research efforts has been put on the field of routing optimization in different environments. Initial applications still had a limited integration of the simulation into metaheuristic optimization frameworks, as computational issues were neglected and the feedback provided through simulation was not yet fully investigated.

One of the early simheuristic proposals was put forward by Juan et al. (2011). To reduce the probabilities of route failures, the authors propose the use of safety capacities in the Vehicle Routing Problem with stochastic demands. Through a two-stage algorithm, vehicle routes are first established through a routing heuristic and then evaluated through Monte Carlo simulation. This allows a performance evaluation of proposed vehicle routes in different uncertainty and safety capacity scenarios. While reduced vehicle capacities during the route planning phase might lead to higher initial routing costs, the reliability and associated route failure costs through vehicle stock-outs can be reduced (and vice versa if safety capacities are reduced). Similarly, Juan et al. (2014*d*) propose a simheuristic with a reduced integration of simulation and metaheuristics for the single period Inventory Routing Problem under demand uncertainty. In this problem setting, vehicle routing and inventory replenishment decisions are centralized. As customer demands are modeled as random variables, inventory holding costs and inventory stock-out costs are considered in the evaluation of different solutions.

More recent applications extend these initial simheuristic approaches. On the one hand, a higher simulation-optimization integration is outlined in these works by using feedback from the simulation component to drive the metaheuristic solution search. Typically, this is achieved by using a stochastic cost-driven base solution from which new solutions are generated. On the other hand, the latest simheuristic algorithms reduce the risk of excessive computational times by applying the concept of short and long simulation runs. Moreover, the potentials of a risk analysis as additional decision taking dimension to extend purely monetary objectives are highlighted.

Gruler et al. (2017*c*) develop an efficient simheuristic for the Waste Collection Problem with stochastic demands formulated as Vehicle Routing Problem extension. The algorithm is tested on a large-scaled benchmark with several thousand garbage containers, showing the trade-off between costs and reliabilities through a detailed risk analysis of created solutions. Gruler et al. (2017*a*) propose a simheuristic approach for the stochastic multi-depot Waste Collection Problem. The authors argue that this problem setting supports the creation of horizontal collaboration techniques between waste management service providers in clustered metropolitan areas and large cities. The Arc Routing Problem with stochastic demands is addressed in the work of Gonzalez-Martin et al. (2018), who use Monte Carlo simulation techniques to extend the RandSHARP algorithm elaborated in the work of González-Martín et al. (2012). In contrast to the Vehicle Routing Problem in which demands are modeled on customer nodes, this problem setting represents client demands along the edges between different network points. The simheuristic approach for the Inventory Routing Problem with stochastic demands put forward by Juan et al. (2014*c*) is extended in the work of Gruler et al. (2018*b*) and Gruler et al. (2018*c*), who consider the single and multi-period problem extension, propose an efficient Variable Neighborhood Search based simulation-optimization algorithm, and achieve a close integration between the metaheuristic and the simulation component. Stochastic versions of the uncapacitated and capacitated Facility Location Problem are addressed through simheuristic procedures by de Armas et al. (2017) and Pagès-Bernaus et al. (2017). On the one hand, the former integrate simulation into an efficient Iterated Local Search Procedure for the uncapacitated case of facility location. On the other hand, the latter put forward a simheuristic for the capacitated version of the Facility Location Problem. Their model represents alternative distribution policies in e-commerce environments. Also addressing a routing related topic, Fikar et al. (2016) discuss the use of discrete-event simulation in a simheuristic process for dynamic home service routing with synchronized trip-sharing.

Concerning flow shop scheduling, Juan et al. (2014*e*) present a simheuristic procedure for the permutation flow-shop problem with stochastic processing times. The distributed assembly permutation flow shop problem, in which different parts of a product are completed in a first stage by a set of distributed flow shop lines and then assembled in a second stage is analyzed by González-Neira et al. (2017). This work considers a stochastic version of the problem, where both processing and assembly times are modeled as random variables. Some publications have applied simheuristics in application areas outside the logistics and transportation context, A simulation-optimization approach to deploy Internet services in large-scale systems with user-provided resources is presented by Cabrera et al. (2014). Concerning the area of finance, Panadero et al. (2018) recently presented a SimVNS algorithm for project portfolio selection under uncertainty. Methodological discussions on simheuristics showing the potential applications with a strong focus on problem settings related to logistics and transportation include the presentation of SimILS (Grasas et al. 2016) and SimGRASP (Ferone et al. 2016, 2018).

3.3 Benefits and limitations

A visual comparison of simheuristics, exact approaches, metaheuristics, and simulation along different dimensions can be seen in Figure 3.3. The methodologies are ranked from 1 (→ lowest score) to 3 (→ best score). The considered dimensions include:

- The **optimality** dimension refers to the quality of obtained solutions with reference to the global optimal of the modeled problem setting.
- The **modeling** dimension compares the capability of accurately modeling and representing real-life systems.
- The **scalability** dimension rates the behavior of solution methods with increasing problem sizes.
- The **computing time** dimension compares the computational times that are needed to reach a solution.
- The **uncertainty** dimension refers to the ability to cope with stochastic input variables that are inherent to most real-life problem settings.

Exact solving approaches stand out regarding the optimality dimension of modeled COPs, as these purely analytical methods guarantee finding optimal solutions in a given solution search space. In comparison to simheuristics, however, they show clear limitations regarding their scalability, modeling capacity, and uncertainty. On the one hand, their scalability is reduced through exponentially rising computing times with increasing problem sizes (Blum and Roli 2003). On the other hand, the modeling capacity is constrained through necessary oversimplifications. Especially simulation techniques show clear advantages in fully representing complex systems (Lucas et al. 2015).

As discussed in the previous chapter, the main advantages of metaheuristics lie in their scalability and computational times. Even though they are not able to guarantee finding optimal solutions, they can find pseudo-optimal solutions in reasonable computing times. However, metaheuristics are unable to address the stochasticity inherent to most real-life systems (Talbi 2009).

One of the main advantages of simulation techniques can be found in their modeling flexibility, which makes them a powerful tool to realistically represent real-life models and

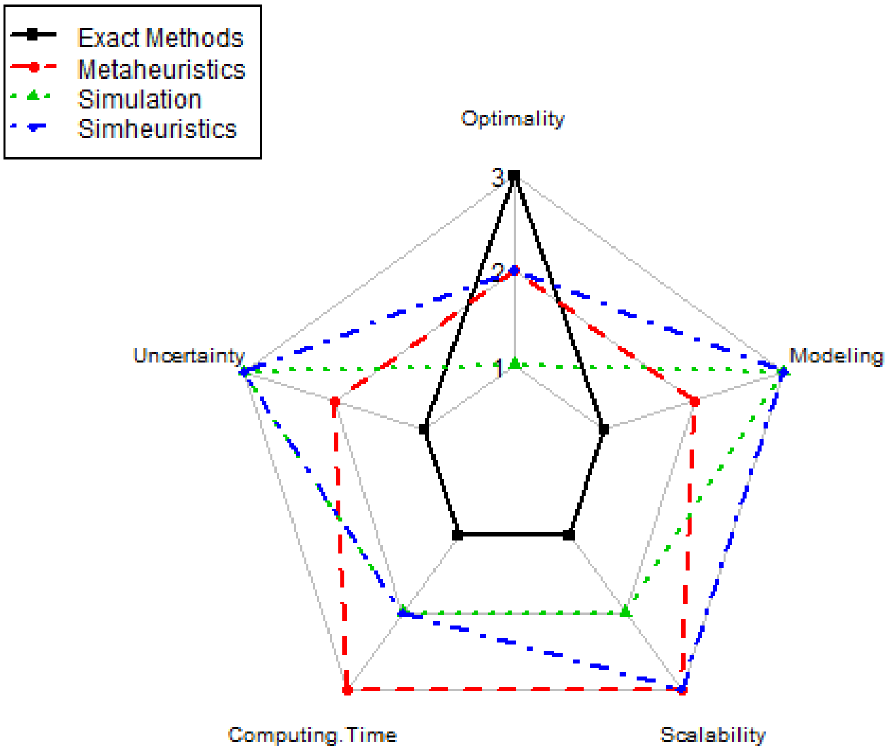

Figure 3.3: Multi-dimensional comparison of simheuristics to other solving approaches for COPs.

system uncertainty. Nonetheless, simulation in itself is not an optimization tool, as it focuses on the evaluation of pre-defined scenarios (Robinson 2004).

Well-implemented simheuristics leverage the advantages of both simulation and optimization methodologies. By using the modeling capabilities of simulation to guide the metaheuristic optimization, system uncertainty in different environments can be accounted for. At the same time, a suitable trade-off between short and long simulation runs supports reasonable computational times for problem instances of different sizes. Another major advantage of simheuristics lies in the risk/reliability analysis of obtained outputs. This information can be used to create additional decision-taking dimensions and improve the system understanding of involved stakeholders. One of the drawbacks of simheuristic frameworks in comparison to other methodologies is that results are not expected to be truly optimal. Rather, they directly depend on the quality of the underlying metaheuristic optimization procedure. For this reason, it is recommended to use an efficient metaheuristic algorithm to scan the solutions search space. Moreover, the use of simheuristic algorithms requires additional stakeholder involvement compared to "black-box" solvers of stochastic COPs. This additional effort is necessary to properly define the system and available inputs, including, for example, the modeling of stochastic behavior or data preparation to fully represent real-life systems (Juan et al. 2015*a*).

CHAPTER 4

GENERIC SIMHEURISTIC SOLVING FRAMEWORKS FOR COMBINATORIAL OPTIMIZATION PROBLEMS UNDER UNCERTAINTY

As discussed in the previous chapters, one of the main drawbacks of well-studied metaheuristics such as the Greedy Adaptive Randomized Search Procedure (GRASP) or Variable Neighborhood Search (VNS) is their inability to incorporate stochastic input variables. This chapter outlines two simheuristic extensions to the these solving approaches, namely SimGRASP and SimVNS. While this dissertation exclusively tests these frameworks on problem settings related to logistics and transportation with special focus on an city logistics environment, the elaborated algorithms are generic enough to be applied to any combinatorial optimization problem (COP) under uncertainty. The main research contributions of this section include:

- the introduction of SimGRASP as generic solving framework for stochastic COPs. Apart from outlining the integration of simulation in the GRASP metaheuristic, the application and performance of the algorithm is tested on a range of problem settings in the field of logistics and transportation, including vehicle routing, flow shop scheduling, and facility location (Ferone et al. 2016, 2018)[1].

[1]The work put forward by Ferone et al. (2016) is published in the SCOPUS indexed conference proceedings

- the presentation of the generic SimVNS algorithm, which is based on the combination of the VNS metaheuristic with simulation. SimVNS serves as the central solving framework for stochastic COPs in the context of urban freight distribution addressed in the application focused chapters 7-9 of this dissertation (Gruler et al. 2017*c*, 2018*b*,*c*).

4.1 Extending the GRASP metaheuristic with simulation

The general SimGRASP framework is outlined in Algorithm 6. Given a stochastic COP, the problem setting is transformed into its deterministic counterpart (line 1). Based on a set X of stochastic variables, each variable $x \in X$ is transformed into a deterministic value x^* by considering the expected values $E[x] = x^*$. Using the deterministic values, an initial solution $baseSol$ is constructed using the GRASP metaheuristic (lines 2-3) and set as current incumbent solution. As the algorithm performance is directly related to the underlying optimization procedure, the use of the BR-GRASP framework discussed in chapter 2.2.4 is proposed.

In order to evaluate $baseSol$ in an uncertainty environment, a first 'short' simulation run is completed (line 4). The term 'short simulation' refers to a reduced number of simulation iterations, which generates just rough estimates but does not require an excessive computing time in this exploratory stage. Thus, during $nIter_{short}$ simulation runs, all stochastic variables are simulated from any suitable empirical or theoretical probability distribution, using the expected values x^* as distribution mean. Different variance levels can be considered for the random variables. Note that as variance levels converge to zero, the deterministic case is approached. The output of this simulation procedure is a first estimation of the stochastic objective function value $sf(baseSol)$ in combination with key system performance statistics (e.g.: mean, variance, quartiles, etc.).

In the following, new BR-GRASP solutions are generated within a predefined stopping criterion (such as number of iterations or maximum running time). Each created solution $newSol$ is evaluated using the short simulation procedure. If the stochastic objective function estimate $sf(newSol)$ outperforms that of the current best solution $baseSol$, $newSol$ is set as current incumbent solution and added to a set of elite solutions (lines 10-11). Once the multi-start GRASP has reached its stopping criterion, all elite solutions undergo a more

of the Winter Simulation Conference 2016 in Washington D.C., USA. Its findings were presented by the PhD-candidate Aljoscha Gruler. As co-author of this publication, the student was mainly responsible for the algorithm design, literature review, and analysis of results.

detailed simulation procedure (lines 12-13). At this stage, the number of simulation iterations is increased to $nIter_{long}$. This second simulation phase allows a more detailed analysis of the most promising solutions with regards to the robustness and reliability of different stochastic COP solutions.

Algorithm 6: General SimGRASP framework

```
1  Transform stochastic COP into deterministic counterpart
2  baseSol ← GenerateSolution
3  baseSol ← LocalSearch(baseSol)
4  (baseSol, sf(baseSol), statistics) ← Simulation (baseSol, short)
5  while GRASP stopping criterion not reached do
6      newSol ← GenerateSolution
7      newSol ← LocalSearch(s**)
8      (newSol, sf(newSol), statistics) ← Simulation (newSol, short)
9      if sf(newSol) < sf(baseSol) then
10         EliteSolutions ← add(newSol)
11         baseSol ← newSol
       end
   end
12 foreach solution eliteSol ∈ EliteSolutions do
13     (eliteSol, sf(eliteSol), statistics) ← Simulation (eliteSol, long)
   end
14 return Set of stochastic solutions
```

The results of applying SimGRASP to the PFSP, the VRP, and the UFLP are outlined in Appendices C-E. In all cases, SimGRASP is implemented with a uniform and a skewed (Biased Randomization) element selection strategy and compared to other simheuristic approaches. It can be seen that the tested SimILS algorithms reach the most competitive results for the PFSP and the UFLP, while Biased Randomization in the solution construction of SimGRASP outperforms a traditional GRASP implementation in all cases. This underlines one of the best practices in constructing simheuristic algorithms outlined in the previous chapter, stating that the performance of any simheuristic algorithm will depend on the quality of the applied metaheuristic for the underlying deterministic problem setting. When comparing SimGRASP with a multi-start based simheuristic for the stochastic VRP, SimGRASP with Biased Randomization yields the most competitive results.

4.2 Extending the VNS metaheuristic with simulation

A closer integration of the simulation output into the metaheuristic optimization procedure is achieved in the SimVNS framework depicted in Algorithm 7. As can be observed in lines 1-3, the creation of an initial solution $baseSol$ is similar to the process described for the SimGRASP algorithm. After turning the random variables of interest into their deterministic counterparts, the initial solution is constructed with any suitable problem-specific solving framework. In order to get a first intuition of the behavior of the initial solution in a stochastic environment, a short simulation process is applied.

In the following, new VNS solutions are created within a predefined algorithm stopping criterion. As outlined in chapter 2.2.1, new solutions $newSol$ are created by applying a problem-specific shaking operator k and creating new neighborhood structures from $N_k(k = 1, 2, ..., k_{max})$. Each newly created solution then undergoes a local search procedure to find the local minimum of the created solution structure (lines 7-8). At this stage, the newly created solutions are compared to the current incumbent $baseSol$ with reference to the deterministic objective function value of the considered solutions. If $newSol$ outperforms $baseSol$ in the deterministic scenario, it is deemed promising and evaluated through a short simulation procedure to get an estimate of the stochastic objective function value $sf(newSol)$ (line 10).

If the stochastic objective function estimate improves the performance of $baseSol$ (i.e., $sf(newSol) < sf(baseSol)$ in the case of a minimization problem), $newSol$ is set as new incumbent solution and k is set to 1 according to the general VNS algorithm. Moreover, the solution is added to a set of elite solutions that undergo a more detailed simulation procedure at the end of the simheuristic procedure to gain more detailed estimates of the stochastic objective function values and the reliability of created solutions.

The SimVNS algorithm is the central solving framework for the application to a range of COP settings in the context of urban freight transportation, outlined in chapter 6. Its competitiveness and behavior is tested on several large scaled problem settings derived from the literature and different case-studies described in chapters 7-9.

Algorithm 7: General SimVNS framework

```
Transform stochastic COP into deterministic counterpart
baseSol ← create initial solution
(baseSol, sf(baseSol), statistics) ← Simulation (baseSol, short)
while VNS stopping criteria not reached do
    k ← 1
    repeat
        newSol ← shake(baseSol, k)
        newSol ← localSearch(newSol)
        if detCosts(newSol) < detCosts(baseSol) then
            (newSol, sf(newSol), statistics) ← Simulation (newSol, short)
            if sf(newSol) < sf(baseSol) then
                EliteSolutions ← add(newSol)
                baseSol ← newSol
                k ← 1
            end
            else
                k ← k+1
            end
        end
    until k > k_max
end
foreach solution eliteSol ∈ EliteSolutions do
    (eliteSol, sf(eliteSol), statistics) ← Simulation (eliteSol, long)
end
return Set of stochastic solutions
```

CHAPTER 5

ON THE POTENTIAL USE OF SIMHEURISTICS TO MODEL HUMAN NETWORK BEHAVIOR IN TRANSPORTATION AND LOGISTICS

Chapter 3 outlines simheuristics as promising simulation-optimization approach to solve stochastic optimization problems. While the methodology is flexible enough to incorporate any kind of simulation paradigm, especially Monte Carlo simulation has been used to model system uncertainty in simheuristic applications. This chapter discusses the potential use of simheuristics in agent based models to represent the inherent uncertainty found in social networks shaped by strong interactions between different stakeholders. In particular, applications in the context of supply chain management are reviewed. From this critical analysis of existing simulation and optimization models, a second contribution emerges: arguments supporting the need for hybridizing simulation with optimization methods as a natural way to include social network behavior in OR models are provided, concluding in the proposal of an agent based simheuristic framework. Highlights of this chapter include:

- a detailed literature review on simulation and optimization approaches to model human behavior in social networks. Special focus is put on literature found on operations research methodologies to model behavioral traits in transportation and logistics challenges, e.g. manufacturing and production systems or urban city logistics (Gruler et al. 2016, in review process 2018a).[1]

[1]The work put forward by Gruler et al. (2016) is published in the SCOPUS indexed conference proceedings

- the conclusion that especially agent based simulation is currently used to model the inherent uncertainty and dynamism of such complex and large scaled systems (Gruler et al. in review process 2018a).

- the proposal of an agent based simheuristic framework that combines agent based models with metaheuristics. This represents a novel simulation-optimization approach to model and solve large-scaled optimization problems shaped by the complexity of stakeholder interaction in social networks (Gruler et al. in review process 2018a).

5.1 Operations research approaches to model human behavior in social networks

Operations Research (OR) methods such as simulation and optimization are frequently employed in the design, development and optimization of complex networks and systems (Derigs 2009). The realistic representation of these systems and networks through suitable models is hereby of major importance. Even though complex systems and networks from different application fields have been extensively studied by the OR community, the consideration of realistic stakeholder behavior in these models is not so usual (Crespo Pereira et al. 2011, Elkosantini 2015, Neumann and Medbo 2009).

However, behavioral factors (either associated to isolated individuals or complete collective entities) are usually among the most important components in any real-life system. As such, simplifying behavioral assumptions neglecting the major impact of uncertainty, randomness, and dynamism that characterizes individual stakeholder behavior often make OR methods inapplicable in practice (Bendoly et al. 2006, Schultz et al. 2010, Wang et al. 2015).

Nevertheless, the consideration of behavioral factors related to cognitive and social psychology is only one side of the coin. As individual agents are highly influenced by the contacts, ties, and connections shaping the group- and system dynamics of the social networks in which they operate, the modeling of social network interrelations is also of highest importance (Renfro 2001, Russel and Norvig 2003). Knoke and Yang (2008) even suggest that structural relations between different network actors follow the same patterns:

of the International Conference in Smart Cities 2016 in Málaga, Spain. Its findings were presented by the PhD-candidate Aljoscha Gruler. As first author of this publication, the student was mainly responsible for the review design and the collection and summary of related and relevant research documents.

i they are often more important in explaining behavior than individual traits such as age, gender, etc.

ii they affect the perceptions, beliefs, and actions of individual network agents through structural mechanisms of social networks.

iii they are dynamic over time.

The inclusion of human behavior in simulation and optimization models has received increased attention in recent years. Figure 5.1 shows a clear increase in Scopus-indexed publications related to human behavior in the context of simulation or optimization. Especially in the areas of computer science, engineering, and mathematics the incorporation of complex system dynamics through behavioral traits seems to be of interest (Figure 5.2).

Simulation is mostly used to evaluate complex systems in which multiple actors interact in specific multi-agent social networks, similar to the one outlined in Figure 5.3. In this context, agent based simulation (ABS) arose with the desire to study complex and adaptive systems and their behaviors (Heath and Hill 2010). Individual agents are thus modeled with unique attributes and behaviors, reacting to the actions, perceptions, and interrelations with other stakeholders in the modeled system environment (Bandini et al. 2009, Kennedy 2010, Macal and North 2010, Siebers et al. 2008).

While ABS is the most common simulation approach to model behavioral traits in a social network environment, discrete event simulation (DES) has also been applied to represent such environments (Robinson 2004). A clear difference of ABS and DES focused modeling is still not fully achieved in the context of OR (Siebers et al. 2010). Generally, ABS models represent a bottom up approach to represent different entities (agents) and their interactions, while DES is based on a process oriented, top down modeling approach. Table 5.1 compares the main characteristics of ABS models and DES models. The review of relevant literature completed in the following sub-sections characterizes existing models according to these criteria.

Apart from simulation techniques as natural way to incorporate human behavior dynamics and the resulting randomness in the evaluation of social network structures, optimization is usually required to increase the efficiency of related processes. Resulting optimization problems are either addressed by exact solution methods for smaller instances, or approximate methods such as metaheuristics for larger problem settings (Talbi 2009, Vazirani 2012).

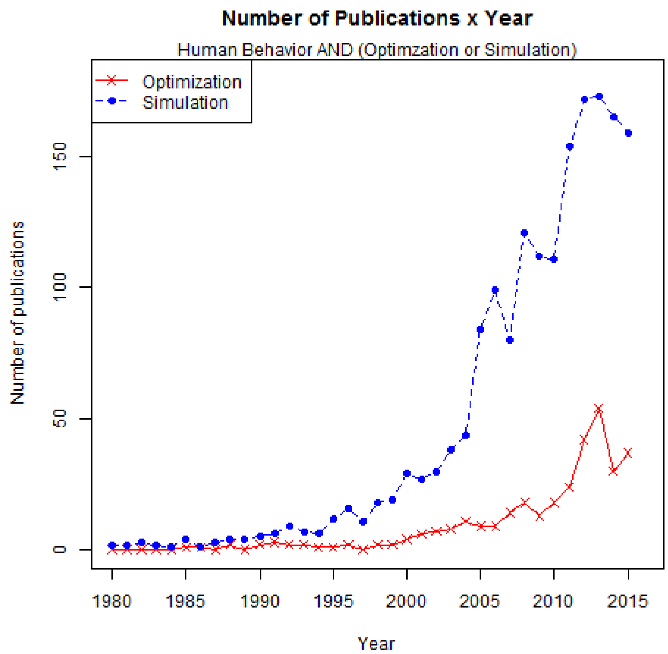

Figure 5.1: Evolution of publications related to human behavior in combination with simulation and/or optimization in Scopus indexed journals.

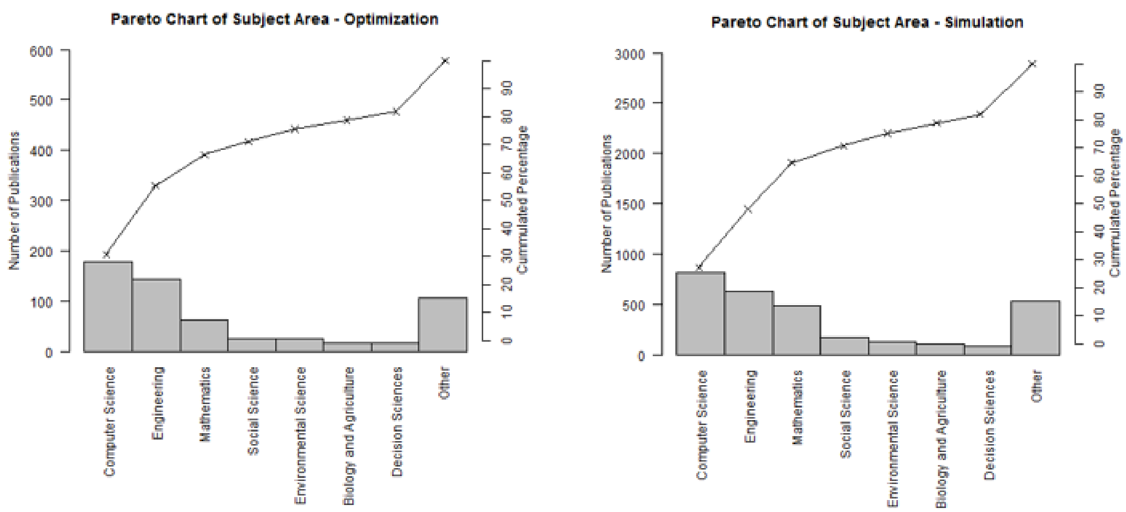

Figure 5.2: Subject area of publications related to human behavior in combination with simulation and/or optimization in Scopus indexed journals.

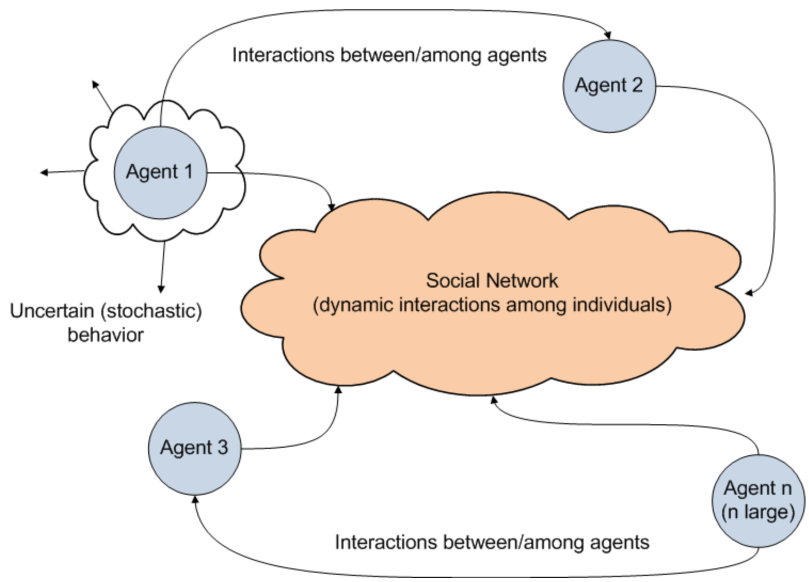

Figure 5.3: Representation of a multi-agent social network.

Table 5.1: Main characteristics of ABS models and DES models. Retrieved from Siebers et al. (2010).

ABS Models	**DES Models**
Focus on modeling entities and their interactions	Focus on modeling the system and its processes
Bottom up modeling approach	Top down modeling approach
Each agent has its own thread of control	Single thread of control
Passive entities	Active entities
Queues are a key element	No concept of queues

The following review of OR approaches to model social network environments is limited to the field of supply chain management (SCM), in which agent behavior and stakeholder interrelations plays a decisive role. Apart from presenting applications in the context of logistics & transportation (especially in urban environments), the review also includes models created for usage in manufacturing & production backgrounds. Main applications addressed in the reviewed publications are summarized in Table 5.2. Furthermore, Table 5.3 outlines the reviewed papers in detail, highlighting the proposed OR modeling approach.

Table 5.2: Overview of reviewed social network environment.

Social Network Environment	**Main Application Focus**
Supply Chain Management	**Manufacturing & Production** x Cooperation among workers x Workload balance and corporate social responsibility x Workers initiative and autonomy x Ergonomic conditions at work x Robustness of social network with increasing size **Logistics & Transportation** x Personal attitudes towards uncertainty in demands x Collaborative transportation management x Horizontal cooperation among carriers x Collaboration of urban freight stakeholders x Coordination in the use of shared parking spots

Table 5.3: Summary of reviewed papers

Area	**Paper**	**Simulation**			**Optimization**
		ABS	**DES**	**Other**	
Manufacturing & Production	Spier and Kempf (1995)			✓	
	Okuda et al. (1999)	✓			
	Yang et al. (2007)	✓			
	Li et al. (2011)	✓			
	Crespo Pereira et al. (2011)		✓		
	Zhang et al. (2015)	✓			
	Putnik et al. (2015)		✓		
Transportation & Logistics	Taniguchi et al. (2007)	✓			✓
	Yuan and Shon (2008)			✓	
	Boussier et al. (2009)	✓			
	Yu et al. (2010)		✓		
	Tamagawa et al. (2010)	✓			✓
	Chan and Zhang (2011)			✓	
	Li and Chan (2012)	✓			
	Teo et al. (2012)	✓			✓
	Duin et al. (2012)	✓			✓
	Wangapisit et al. (2014)	✓			✓
	Okdinawati et al. (2014)	✓			

5.2 Human network behavior in transportation and logistics

The following subsections review operations research approaches to model behavioral traits in the context of transportation & logistics. In particular, the modeling of network interactions in manufacturing and urban freight transportation systems is emphasized.

5.2.1 OR approaches to model behavioral traits in manufacturing systems

The importance of considering human behavior in manufacturing systems by integrating psychological and emotional aspects is stressed by Elkosantini and Gien (2009). In their work, they suggest a graphical and mathematical representation of production line workers, whereby special attention is paid to individual behavior and social relationships between workers. The authors highlight the influence of social interaction among employees on individual performance levels. Other OR models in the context of manufacturing & production address individual human factors such as fatigue, motivation, education, or personalities (Digiesi et al. 2009, Elkosantini 2015, Huerta et al. 2007, Khan et al. 2012, Riedel et al. 2009, Silva et al. 2013). Also in this context, Grosse et al. (2015) developed a framework that enables the integration of human-related factors into models associated with the planning of tasks.

Spier and Kempf (1995) were among the first authors in proposing the inclusion of human interrelations in simulation models. The authors use object oriented simulation (Garrido 2009) to test learning effects among workers in a small manufacturing line, showing that proactive and cooperative agents provide the best company performance. More recent work on similar issues apply ABS or DES to analyze, simulate, and evaluate production lines, workforce allocation in manufacturing cells, or the impact of engineers in the product design process. Okuda et al. (1999) stress that cooperation can be a key attribute in the planning of efficient production lines. The authors test different production process designs (e.g. U-shaped production lines and manufacturing cells) in terms of workload balance and total throughput in small-lot manufacturing, characterized by a high need for production flexibility. By using ABS, the impact of cooperation through human-oriented production lines is assessed. The paper concludes that human-oriented production processes achieve the most balanced working times and the highest company output through inter-worker learning effects.

Various simulation models focusing on workforce allocation in production lines have been developed in the past. However, most of them do not consider the impact of human behavior and collaboration in their models. Zhang et al. (2015) overcome this drawback by integrating different models of human agents in the context of dynamic systems with a discrete-event behavior, which they use to evaluate changeover processes in manufacturing processes. By modeling and simulating the dynamics of work processes together with the dynamics of human behavior, the authors show that the incorporation of different cooperation styles and skill levels can have noticeable effects on the expected throughput of the system. From the reported simulation experiments, it can also be concluded that changeover assignments based on collaborative strategies lead to the best system performance.

The effects of collaborative product design processes are studied by Yang et al. (2007). They argue that many simulation methods applied in the planning of efficient product design processes are very task-oriented and do not represent the central role of designers in the process, which is deeply impacted by human initiative and autonomy, but also by collaboration within project teams. They elaborate an agent based model (ABM) to predict, manage, evaluate, and improve manufacturing design processes. Therefore, the design evaluation depends on the degree of cooperative behavior among the product design team members. Furthermore, human factors such as efficiency of designer and organization, human workload, errors, and collaboration levels are taken into account.

Another ABM to represent the dominant role of product designers in product design processes is proposed by Li et al. (2011). The designer agents in their model have distinctive characteristics such as initiative, autonomy, and collaboration skills. They construct a simulation model of a motorcycle design project, allowing for the analysis of product design process traits such as organizational structure, scheduling strategies, and partner selection while considering individual and social behavioral traits.

ABS seems to be the predominant method of choice for modeling and simulating social interactions in manufacturing systems. However, there are some works that address the issue by using DES approaches. Crespo Pereira et al. (2011) propose a manufacturing DES environment to conduct training and research on how human operations take place. Their experimental system allows for considering human factors such as inter-group differences, worker experience, buffer capacities, work-sharing, and process state perception. Experimental results based on a real-life case show that inter-group variations, experience, and ergonomic conditions have a significant impact on the process outcome. Also using DES, Putnik et al. (2015) test the robustness of large production networks in environments with demand uncertainty. By modeling the behavior of socially connected individuals, their work shows that system robustness and production rates depend on system sizes and social networks. According to their simulation experiments, large social networks with lots of business relations positively impact network robustness, while the production rate exhibits a nontrivial relation to the number of connections.

5.2.2 OR approaches to model behavioral traits in urban freight transportation

In the face of increasing market complexity driven by rapidly changing customer preferences, globalization, and fierce competition, the need for effective supply chain management (SCM) among suppliers, manufacturers, distributors, and retailers leads to complex dynamic systems. In response to this, many innovative planning models of logistics and transportation systems such as collaborative transportation management (CTM) or city logistics (CL) are based on the idea of stakeholder collaboration (Crainic et al. 2009, Taniguchi et al. 2012, Benjelloun and Crainic 2009). Consequently, behavioral factors on an individual and network level have to be considered in the design of sustainable and integrated transportation & logistics structures (Geary et al. 2006, Sarimveis et al. 2008).

In the context of CTM, different simulation approaches have been used to include cognitive behavior (e.g., individual thinking, deciding, and reasoning processes) and social factors (e.g., relationships and inter-organizational influences). As such, Yuan and Shon (2008) propose a CTM model based on the collaboration in transportation management among different supply chain partners. Their simulation tool is developed as realistic representation of a beer supply chain with four levels. The authors show that transportation costs and vehicle utilization levels can be significantly improved by collaboration and coordination of transportation activities. Chan and Zhang (2011) use MCS to evaluate benefits of CTM in long-term relationships between retailers and carriers. The authors illustrate the concept of carrier flexibility to optimize delivery lead times. Their results show that collaboration between both parties can reduce retail costs while improving service levels.

A conceptual framework for a behavioral multi-agent model considering the impact of cognitive and social behavior is presented by Okdinawati et al. (2014). They propose the inclusion of Drama Theory (see Bryant (2003, 2004)) in their model. This allows for considering stakeholder behavior in conflict and collaboration scenarios during the hierarchical decision-taking process of CTM strategies on an operational, tactical, and strategic level.

Using ABS, Li and Chan (2012) describe the impact of CTM on SCM with stochastic demands. They simulate a three-level supply chain while taking into account factors such as company characteristics, their types of action, and changes in company behavior. By comparing the efficiency level reached in non-cooperative scenarios with the cooperative case, the authors show that CTM can reduce global costs while increasing supply chain flexibility. Their work concludes that CTM is an efficient approach to tackle demand disruptions.

Yu et al. (2010) use DES to test different information sharing scenarios between supply chain members. More specifically, they consider information sharing about demand, inventories, capacities, and their different combinations. Their results suggest that especially information sharing concerning customer demands is critical for supply chain success. Furthermore, they show that a full cooperative scenario based on shared information and assets is ideal for obtaining higher levels of efficiency in most supply chains. There are some metaheuristic approaches that address similar concepts (e.g. Horizontal Cooperation) in which interactions between network actors are highly important (Juan et al. 2014*a*, Pérez-Bernabeu et al. 2015), but these optimization methods have not yet reached the same integration level of behavioral issues as simulation approaches.

Related to CL, Tamagawa et al. (2010) develop a multi-agent methodology to evaluate different CL measures (road pricing, truck bans, motorway tolls) taking into account the behavior of partners in urban freight transportation. More specifically, the modeled agents represent motorway operators, administrators, residents, shippers, and freight carriers. The authors develop an acceptable network environment for all stakeholders by considering conflicting objectives, transportation cost, profits, and environmental effects. To evaluate different road networks, they apply a genetic algorithm to calculate different routing options from the resulting Vehicle Routing Problem (VRP) with time windows. Furthermore, a learning prototype affecting the behavior of different agents is implemented. This paper extends a similar work of Taniguchi et al. (2007), in which the authors show that the implementation of road pricing can reduce pollution emissions but may increase freight shipment costs. To avoid such effects, cooperative freight transportation systems are proposed.

Teo et al. (2012) test government measures affecting urban road networks (e.g., road pricing for trucks) in an e-commerce delivery system. Their ABM considers the behavior of major stakeholders in the transportation environment. In particular, they propose a reinforcement learning strategy for administrators to represent realistic agent behavior. Furthermore, the resulting routing problem is optimized with an insertion heuristic. According to their outcomes, when the government administrator considers freight vehicle road pricing, truck emissions can be significantly reduced.

A multi-agent approach to evaluate the financial and environmental impact of implementing urban distribution centers in urban areas is presented by Duin et al. (2012). The authors consider and test the dynamic behavior among different CL stakeholders. Moreover, the impact of stakeholders' behavior and actions towards city measures like tolls, operational subsidies, time windows, and entry restrictions within city centers is evaluated. Experimental results suggest that the development of a positive business environment for urban freight consolidation centers depends not only on physical factors such as traffic congestion, but also on the actions and behavior of each system agent. Their ABM also incorporates a genetic algorithm for routing optimization.

Joint delivery systems, urban distribution centers, and car parking management within city centers are the CL measures analyzed by Wangapisit et al. (2014). Their focus lies on the interaction and cooperation among urban freight stakeholders when CL measures are implemented. The authors use ABS combined with reinforcement learning and an insertion heuristic to solve extended VRP versions with pick-up-and-delivery and time windows. Their results suggest that urban distribution centers and joint delivery systems can improve the environmental impact of urban freight transportation. They fine-tune the distribution center implementation by applying urban parking management and subsidies for shopping street associations. Car parking management in an ABM is also the matter of research in the paper by Boussier et al. (2009). Their simulation models considers the behavior of different agents, focusing of shared parking spaces between private and commercial vehicles. Furthermore, the use of electric vehicle fleets in the development of 'greener' transportation systems is taken into account in some works (Juan et al. 2014*b*, 2016).

5.3 The need for an integrated simulation-optimization approach

Simulation techniques seem to offer a natural and efficient way to model both uncertainty and system dynamics over time. In particular, ABS has been successfully applied in a range of different application fields. Simulation itself, however, is not an optimization tool. Thus, whenever the problem at hand requires maximization or minimization of a given objective function (or several ones in the case of multi-objective optimization), simulation alone is not enough. A logical way to proceed in those cases is to combine simulation with optimization techniques. Since most social networks tend to be large-scale, the integration of simulation with metaheuristics (i.e., simheuristics) might become an effective way to include human factors inside NP-hard combinatorial optimization problems. As analyzed in Juan et al. (2013*b*), these hybrid algorithms can also benefit from parallel and distributed computing techniques.

Accordingly, an open research line in modeling human factors inside large-scale social networks is the one related to exploring the fundamentals and potential applications of 'agent based simheuristics', where metaheuristic-driven algorithms make use of ABS to account for the uncertainty and dynamism present in these networks. As depicted in Figure 5.4, given an optimization problem involving human factors in social networks (i.e., a stochastic and dynamic large-scale system), the metaheuristic algorithm acts as an engine that proposes 'promising' solutions (one at a time) to the ABS module. Each of these solutions is then analyzed by the ABS component, which provides estimates on the real performance of the proposed solution under the uncertainty and dynamic conditions associated with human factors. The feedback from the ABS module is used by the metaheuristic to guide the search process. This iterative process continues until a time-related ending condition is met. At that point, the best-found solution (or a set of top solutions with different properties) is offered to the decision-taker.

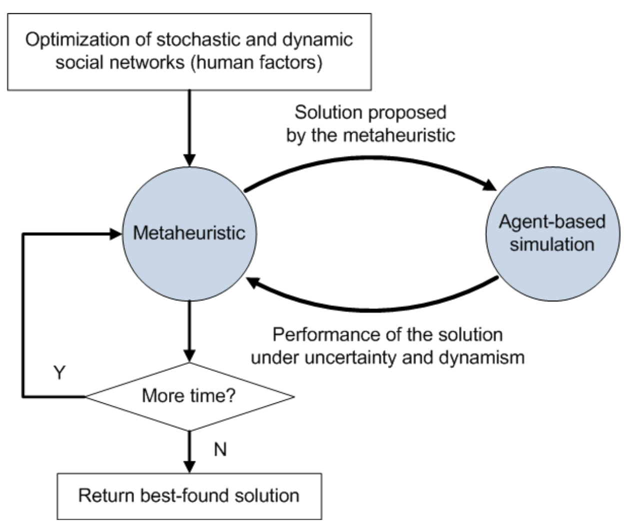

Figure 5.4: Agent based simheuristic framework.

(II) APPLICATIONS

Chapter 6

Promising application areas in urban freight distribution

Urban freight distribution planning in the context of smart city logistics concepts are shaped by diverse stakeholders, multiple facility layers, and different modes of transportation (Bektaş et al. 2015). Similar to any kind of complex system, related optimization problems involve decision making challenges on operational, tactical, and strategic levels. On the operational side, issues related to schedules of workers and vehicles along with the control and adjustment of established plans must be addressed. Tactical planning approaches assist the deployment of resources, e.g. by defining departure times, vehicle loads, or customer allocations. The strategic planing level is related to the system design and the evaluation of long-term scenarios. Typical optimization problems include for example the opening of new facilities or the quantification of long-term strategic collaboration agreements (Benjelloun and Crainic 2009).

This dissertation develops metaheuristic and simheuristic algorithms for a number of problem settings. In the context of municipal waste management, the Waste Collection Problem is addressed by extending the well-known Vehicle Routing problem (VRP) to incorporate additional landfill visits, time dependency, vehicle capacities and multiple collection fleet depots. Regarding the design of integrated supply chain networks, rich versions of the Inventory Routing Problem and the Location Routing Problem are discussed. All of the aforementioned

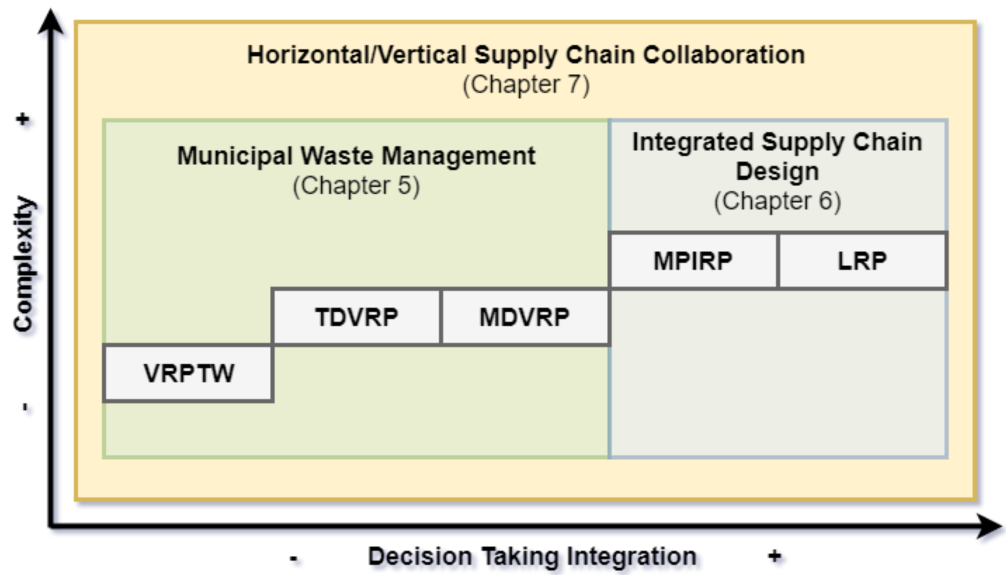

Figure 6.1: Complexity and decision-taking integration of central problem settings addressed in this thesis.

problem settings are consolidated in the quantification of supply chain collaboration concepts.

The central underlying combinatorial optimization problems (COPs) discussed in this dissertation are summarized in Figure 6.1. On the one hand, the outlined figure compares the problem settings according to their relative complexity from an algorithmic point of view. On the other hand, the level of decision-taking integration related to the discussed COPs is shown. Typically, increasing decision-taking integration based on collaborative supply chain design leads to higher complexity regarding the underlying optimization problems. To summarize, the highlights of this chapter include:

- the presentation of the Waste Collection Problem (WCP) as underlying optimization problem in operational waste management. A rich problem version incorporating capacitated vehicles, time windows, and driver lunch breaks is formulated. Moreover, the effects of time dependency in waste collection and the integration of customer clustering decisions formulated as multi-depot Vehicle Routing Problem (MDVRP) are depicted (Gruler et al. 2017*a*,*c*, in review process 2018b).

- a mathematical formulation of the Inventory Routing Problem (IRP) and Location Routing Problem (LRP). In particular, the former is presented as multi-period problem extension, while the latter is outlined as multi-echelon LRP arising in the creation of urban consolidation centers (Gruler et al. 2018*b*,*c*).

- a discussion of the optimization problems arising in different horizontal collaboration scenarios. Different levels of collaboration agreements between value chain actors are defined. Furthermore, the optimization problems arising with each collaboration scenario are highlighted (Quintero-Araujo et al. 2016, 2017*b*,*c*).[1,2]
- a detailed literature review on related state-of-the-art solving approaches found in the literature. The main focus of this review is put on metaheuristic approaches to address deterministic and stochastic versions of the presented problem settings.

6.1 Problem settings arising in municipal waste management

In the face of rising population densities in urban areas around the world, a large number of cities are currently reorganizing their municipal responsibilities (United Nations - Department of Economic and Social Affairs 2015). In this context, solid waste management is arguably "the most important municipal service" a city provides for its residents (The World Bank 2012). A number of strategic, tactical, and operational issues — for example related to the location of disposal sites or landfills, clustering of service territory, vehicle routing, etc. — need to be addressed (Ghiani et al. 2014*a*).

Especially the collection phase is highly important. On the one hand, uncollected garbage can lead to pollution of the environment and health issues, while noise and road congestions through extensive use of waste collection vehicles decrease urban living standards. On the other hand, waste collection represents up to two thirds of operational waste management costs (Malakahmad et al. 2014, Son 2014, Tavares et al. 2009). Consequently, the Waste Collection Problem (WCP) for effective route planning in municipal waste collection is of high practical importance, especially in the context of smart city initiatives (Neirotti et al. 2014).

[1] The work put forward by Quintero-Araujo et al. (2016) is published in the SCOPUS indexed conference proceedings of the Spanish National Conference on Metaheuristics and Evolutionary and Bio-inspired Algorithms (MAEB) 2016 in Salamanca, Spain. Its findings were presented by the IN3-researcher Carlos Quintero-Araujo. As co-author of this publication, the student was mainly responsible for the literature review, experiment design, and analysis of results.

[2] The work put forward by Quintero-Araujo et al. (2017*b*) is published in the SCOPUS indexed journal Progress in Artificial Intelligence. As co-author of this publication, the student was mainly responsible for the algorithm framework, experiment design, and analysis of results.

On the one hand, this dissertation proposes use of simheuristics for a rich version of the WCP including time windows, driver lunch breaks, vehicle capacities, and stochastic demands. On the other hand, the effect of time-dependent vehicle routing in a waste collection environment under the consideration of travel time uncertainty is discussed. Finally, the multi-depot vehicle routing case in which customers need to be assigned to different vehicle fleet terminals is discussed in the context of garbage collection in clustered urban areas.

6.1.1 The Waste Collection Problem

Typically, the WCP is either modeled as a rich Vehicle Routing Problem (VRP) (Toth and Vigo 2014, Caceres-Cruz et al. 2014) or as an Arc Routing Problem (ARP) (Corberán and Laporte 2014), depending on the type of waste to be collected. While the collection of household refuse in small bins from private homes is often modeled as an ARP, the VRP as node routing model is 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. This work addresses the WCP as a VRP in the following. The reader is referred to Ghiani et al. (2014*b*) and Han and Ponce-Cueto (2015) for a more detailed discussion of both modeling types.

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 at which collected waste is disposed. The arcs (edges) connecting any two nodes are characterized by travel costs, e.g. distance, time, or CO_2 emissions. Figure 6.2 illustrates an example of a WCP solution with two routes. Vehicles start at the central depot to visit a number 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 returns to the central depot. As can be seen in Route 2, multiple landfill visits during the same trip are also possible. 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.

Given the practical nature of the WCP, realistic problem instances discussed in the literature typically include several hundred waste containers and several constraints related to maximum route travel times, driver lunch breaks, time windows, etc. (Benjamin and Beasley 2010, Buhrkal et al. 2012, Kim et al. 2006). These impose certain limits on the use

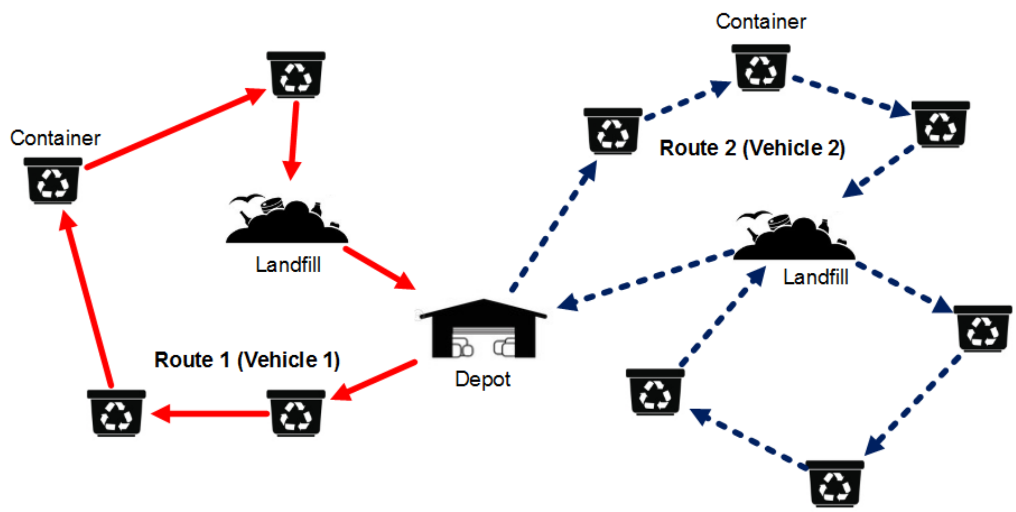

Figure 6.2: Illustration of the Waste Collection Problem.

of exact methods to solve this NP-hard problem, calling for the application of metaheuristic algorithms that are able to generate near-optimal solutions to large-scaled and realistic WCP settings in calculation times of only a few seconds/minutes.

6.1.1.1 Problem description

The general WCP can be described as extension to the VRP 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 $K = \{1, 2, \dots, k\}$, each of them having a capacity C; *(ii)* a set $V^f = \{1, 2, \dots, m\}$ describing m landfills at which collected waste must be disposed at least once before visiting the ending depot; *(iii)* a set of waste containers (customers) $V^c = \{m+1, \dots, m+n\}$ 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 (see Figure 6.3). Each node $i \in V \setminus V^d$ has an associated time window represented by $[a_i, b_i]$ (with $0 \le a_i < b_i$). 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, $c_{ij} = c_{ji} \ge 0$, and travel times, $t_{ij} = t_{ji} \ge 0$. The travel time associated with going from any node $i \in V \cup V^b$ to the virtual lunch

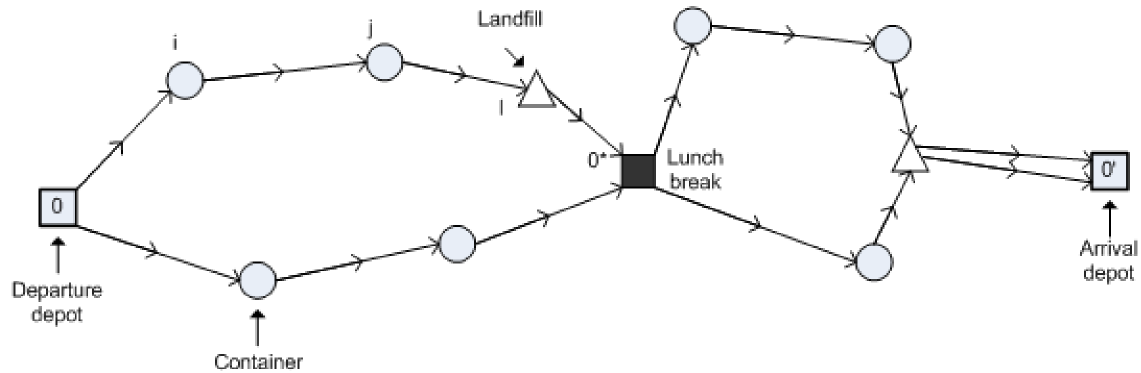

Figure 6.3: Graphical description of lunch node formulation for the WCP.

break node (and vice versa) is equal to zero, i.e.: $t_{i0^*} = t_{0^*i} = 0$. The travel costs associated with 'crossing' the virtual lunch break node are given by the travel costs 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.

The mathematical model for the WCP outlined in the following 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 the mathematical 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 $M_1 = \max\{b_i\}(\forall i \in V \setminus V^d) + \max\{s_i\}(\forall i \in V \setminus V^d) + \max\{t_{ij}\}$ $(\forall (i,j) \in A)$.

The objective function of minimizing total cost is formulated in Equation (6.1), which represents the costs of the edges selected (including the ones 'crossing' a lunch break node). Constraints (6.2) imply that each vehicle leaves the starting depot, while constraints (6.3) impose that each vehicle must visit a landfill right before reaching the ending depot. Constraints (6.4) ensure that each container is visited exactly once. Constraints (6.5) guarantee that inflow and outflow to each non-depot node must be equal. Constraints (6.6) force to the compliance of time windows. Constraints (6.7) define the earliest possible starting time for the next customer taking into account service and travel times. Constraints (6.8) reset the vehicle load to zero when leaving from or arriving at a depot. Constraints (6.9) take care of the accumulating load levels after visiting each container. Constraints (6.10) force that vehicles are empty after a visit to a landfill. Constraints (6.11) and (6.12) introduce a lunch break during each route. Constraints (6.13) 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 (6.14) limit the maximum waste a vehicle may carry at any time. Constraints (6.15) 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 (6.16) and (6.17) define variable domains.

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

Subject to:

(6.2) $\sum_{j\in V\setminus V^d} x_{0jl} = 1 \quad \forall l \in K$

(6.3) $\sum_{i\in V^f} x_{i0'l} = 1 \quad \forall l \in K$

(6.4) $\sum_{i\in V} \sum_{l\in K} x_{ijl} = 1 \quad \forall j \in V^c$

(6.5) $\sum_{\substack{i\in V\\ i\neq j}} x_{ijl} = \sum_{\substack{i\in V\\ i\neq j}} x_{jil} \quad \forall j \in V \setminus V^d, \forall l \in K$

(6.6) $a_i \leq h_{il} \leq b_i \quad \forall i \in V \setminus V^d, \forall l \in K$

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

(6.8) $d_{il} = 0 \quad \forall i \in V^d, \forall l \in K$

(6.9) $d_{jl} - C(1 - x_{ijl}) \leq d_{il} + q_i \leq d_{jl} + C(1 - x_{ijl}) \quad \forall i \in V^c \cup V^b \cup \{0\}, \forall j \in V \setminus V^d, \forall l \in K$

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

(6.11) $\sum_{i\in V} x_{i0^*l} = 1 \quad \forall l \in K$

(6.12) $\sum_{j\in V} x_{0^*jl} = 1 \quad \forall l \in K$

(6.13) $h_{il} + r_i + r_{0^*} + t_{ij} \leq h_{jl} + (2 - x_{i0^*l} - x_{0^*jl})(M_1 + r_{0^*}) \quad \forall (i,j) \in A, \forall l \in K$

(6.14) $d_{il} \leq C \quad \forall i \in V^f, \forall l \in K$

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

(6.16) $d_{il} \geq 0 \quad \forall i \in V, \forall l \in K$

$$(6.17) \quad x_{ijl} \in \{0,1\} \qquad \forall (i,j) \in A, \forall l \in K$$

6.1.1.2 Literature review

Probably the first work to address municipal solid waste collection was introduced by Beltrami and Bodin (1974). Since then, various solution techniques for different variants of the WCP and its extensions have been proposed. While some works formulating the WCP as an ARP can be found (Ghiani et al. 2005, Bautista et al. 2008), the following discussion focuses on recent publications using VRP formulations. More extensive literature reviews are provided by Beliën et al. (2014), Ghiani et al. (2014*b*), Golden et al. (2014) and Han and Ponce-Cueto (2015).

Most works on the deterministic WCP focus on 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. The authors used their approach 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 VNS metaheuristic. They consider the landfills as intermediate facilities, which are inserted in pre-constructed routes using dynamic programming. In the same work, the authors 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 bin 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 bin 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.

Only focusing on waste collection routing, 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. The authors reported reduced routing distances of up to 10%. Furthermore, a benchmark set of 10 realistic instances based on the original case study ranging from 102-2100 nodes is provided. This benchmark set was later employed by Ombuki-Berman et al. (2007) to test a multi-objective Genetic Algorithm. Furthermore, the same benchmark set was used by Benjamin and Beasley (2010) and Buhrkal et al. (2012) to test their metaheuristic solution methods. Benjamin and Beasley (2010) combined Tabu Search with VNS. By exchanging containers and landfills within and between routes, the solution search space is systematically increased. Buhrkal et al. (2012) put forward an Adaptive Large Neighborhood Search metaheuristic. Based on an initial solution, this approach applies a range of destroy-and-repair methods to examine several solution neighborhoods. It is called adaptive since the choice of methods depends on the solution quality obtained during the construction of earlier solutions. Moreover, an acceptance criterion for new solutions based on Simulated Annealing is included. 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 consider a heterogeneous vehicle fleet and flexible depot destinations in their approach.

Concerning the WCP with stochastic demands, the literature is more scarce. Ant Colony Optimization and a hybrid approach based on a Genetic Algorithm and Tabu Search for a case study with 50 containers in Malaysia is presented in Ismail and Irhamah (2008) and Ismail and Loh (2009). After planning a priori routes, waste levels are simulated according to a discrete probability distribution. Routes undergo a recourse action (i.e., an additional disposal trip) whenever actual demand exceeds the planned collection amount. Nolz et al. (2014) formulated a collector-managed Inventory Routing Problem for a case study on the collection of infectious waste. By using real information obtained through radio frequency identification, their Adaptive Large Neighborhood Search algorithm is able to consider stochastic inputs. Alshraideh and Abu Qdais (2017) combined a multi-period WCP with time windows and stochastic demands in an areal case study of medical waste collection from 19 hospitals in Northern Jordan. They used a Genetic Algorithm and a probability constraint regarding a pre-defined service level to solve the problem.

Related to the dynamic WCP in combination with modern Information- and Communication Technology (ICT), Johansson (2006) tested the introduction of volumetric sensors in Malmoe (Sweden) through analytic modeling and discrete-event simulation. She compares static routing with its dynamic counterpart in which containers raise alarms when a certain waste level is exceeded, suggesting that dynamic waste collection routing could lead to improved operations. Later, Faccio et al. (2011) elaborated a real-time tractability system for multi-objective waste collection in an Italian city. They discuss the use of ICT (e.g., volumetric sensors, Radio Frequency Identification, GPS, etc.) to connect containers, vehicles, and the operations center in an economic feasibility analysis. More related to simulation than optimization, Wang (2001) developed an integrated simulation model for solid waste collection with both deterministic and stochastic waste generation and household set-out rates. The proposed decision support tool can be used to evaluate collection systems concerning environmental and operational costs and optimize the system design under different circumstances. Also related to stochastic waste collection, Yeomans (2007) integrated grey programming into evolutionary simulation-optimization to solve solid waste collection problems with high levels of uncertainty.

6.1.2 Time-dependent vehicle routing

Time dependency is an important aspect in the modeling of realistic vehicle routing scenarios. Especially in urban areas, factors such as traffic congestions lead to substantial variations in travel speeds. For example, traffic peaks can typically be expected during morning and evening hours. Municipal route planners need to incorporate expected speed variations in order to establish efficient vehicle routing schedules (Figliozzi 2012). Especially in the context of urban waste collection time dependency is an important issue, as traffic peaks should be avoided to minimize the negative implications of garbage collection regarding traffic flows and ensure smooth waste collection operations.

6.1.2.1 Problem description

Figure 6.4 illustrates the effects of time-dependent and stochastic travel speeds. Given the distance of traversing any edge in a routing problem, the travel durations to pass this edge can be calculated as quotient of travel distance and the expected vehicle speed. In time-dependent routing scenarios, driving velocities vary according to different time periods within the route planning horizon. Apart from the expected travel speeds, realistic problem settings should also consider travel time variances due to different levels of planning uncertainty. The effects of different travel time assumptions are highlighted as optimistic and pessimistic vehicle speeds below, showing that variances in vehicle velocities can significantly impact the necessary time to visit a number of nodes, whereas the traveled distance is the same in all cases. This input uncertainty naturally occurs in most real-life routing problems, especially in metropolitan areas where actual travel times between different points are almost impossible to predict.

An important aspect in time-dependent vehicle routing models is the no-passing/first-in-first-out (FIFO) property. This ensures that a vehicle leaving node i at time t to visit node j arrives at the destination node before any similar vehicle traversing the same route with starting time $t+\epsilon$ ($\epsilon > 0$) (Figliozzi 2012).

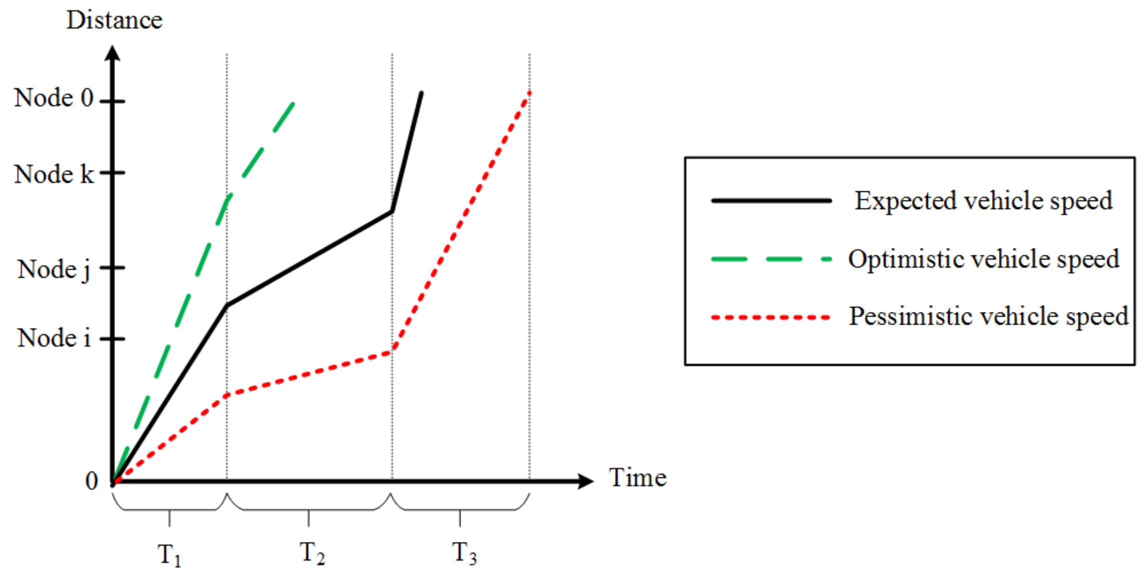

Figure 6.4: The effect of stochastic travel durations due to time-varying vehicle speeds in time-dependent routing scenarios.

6.1.2.2 Literature review

In the field of vehicle routing optimization, time dependency was not considered up to the early 2000s apart from a few exceptions. Malandraki and Daskin (1992) formulated travel times as a step function of the time of day. This drawback in the travel time function was improved by Hill and Benton (1992), who developed the first travel-time-model based on time-varying vehicle speeds, which implies the FIFO characteristic. Later, Ichoua et al. (2003) used an improved version of this vehicle speed model in combination with a parallel tabu search heuristic to show the benefits of time-dependent vehicle routing compared to its static counterpart. The impact of time-dependent travel times to avoid traffic congestions was also addressed more recently in the work of Kok et al. (2012), who showed that late arrivals at customers and extra duty times through traffic jams can be significantly reduced through smart congestion avoidance strategies.

An iterated local search algorithm for the time-dependent VRP with time windows (TDVRPTW) was presented by Hashimoto et al. (2008). Computational experiments include a variety of problem instances with up to 1000 nodes. The TDVRPTW was also addressed in the works of Balseiro et al. (2011) and Harwood et al. (2013). The first-mentioned authors developed an ant colony system hybridized with insertion heuristics which is tested on problem instances with up to 100 clients. The latter established quick estimates of time-dependent travel times for the single vehicle VRP (traveling salesman problem). Their results show that their estimations can lead to significant computational time reductions in neighborhood-based metaheuristics.

The TDVRP with simultaneous pickup and deliveries was addressed by Zhang et al. (2014) through an integrated ant colony and tabu search approach. A total of 100 customers are considered. Recently, much attention has also been paid to the environmental effects of routing (in the context of so called pollution routing problems). Kuo (2010) developed a simulated annealing algorithm for establishing emission-minimizing vehicle routes while taking into account varying edge traversing times. Computational results are provided using benchmark instances with up to 100 customers. The trade off between travel times and CO_2 emissions in time-dependent VRPs was analyzed by Jabali et al. (2012). The time-dependent pollution routing problem was also analyzed in the work of Franceschetti et al. (2013). The authors proposed an integer linear programming formulation for cases without any traffic congestion. Environmental considerations are also included in the work of Soysal et al. (2015*a*), who addressed the time-dependent two-echelon VRP through a comprehensive mixed integer linear programming (MILP) formulation.

All previously cited works focused on the deterministic version of the TDVRP. For stochastic problem settings the literature is more scarce. Lecluyse et al. (2009) developed a tabu search metaheuristic for the TDVRP with stochastic travel times. Nahum and Hadas (2009) developed an extended version of the well-known savings algorithm to address the stochastic TDVRP. Taş et al. (2014) proposed a tabu search and adaptive large neighborhood search metaheuristic for the TDVRP with soft time windows and stochastic travel times.

6.1.3 The multi-depot Vehicle Routing Problem

A well-known VRP extension is the MDVRP, in which the final delivery of products is done from several depots to a set of customers (Montoya-Torres et al. 2015). In contrast to the simple vehicle routing case with a single depot, customers have to be allocated to different depots in a combinatorial assignment problem, before each depot–node assignment combination is solved as VRP. In particular, this problem setting is discussed in this thesis in the context of collaborative transportation & logistics concepts in waste collection of clustered urban areas.

6.1.3.1 Problem description

A simple example of the benefits of integrating customer allocation and vehicle routing decisions in urban waste collection can be seen in Figure 6.5. In the non-collaborative scenario (a), waste management service providers (each represented by a single depot) do not share information about waste containers to be emptied and plan their respective collection routes individually. It can be intuitively observed that the collaborative scenario (b) in which containers, landfills, and depots are shared leads to lower routing costs, less traffic, higher service levels, and a lower environmental impact through the waste transportation activities. Applications of this horizontal collaboration concept in waste collection can be especially beneficial in large clustered cities with various waste management service providers responsible for different areas of a municipality and highly clustered metropolitan areas (e.g. the Ruhr area in Germany or greater Barcelona).

The MDVRP can be formally described on a graph $G = (V, E)$, where V is a set of nodes and E the set of connecting edges. Node set V is further partitioned into two subsets: $V_c = (v_1, v_2, ..., v_N)$ and $V_d = (v_{N+1}, v_{N+2}, v_M)$, which represent the customer and depot nodes, respectively. Each customer $v_i \in V_c$ has a non-negative demand d_i, while each arc in E has an associated travel cost c_{ij}. The nodes are visited by a fleet of K vehicles with capacity C based at each depot. The problem consists in defining a set of vehicle routes in such a way that: *(i)* each route starts and ends at the same depot, *(ii)* each customer is visited exactly once, *(iii)* the total demand of each route does not exceed the vehicle capacity, *(iv)*, each route starts and ends at the same depot, and *(v)* the total cost of the distribution is minimized (Renaud et al. 1996).

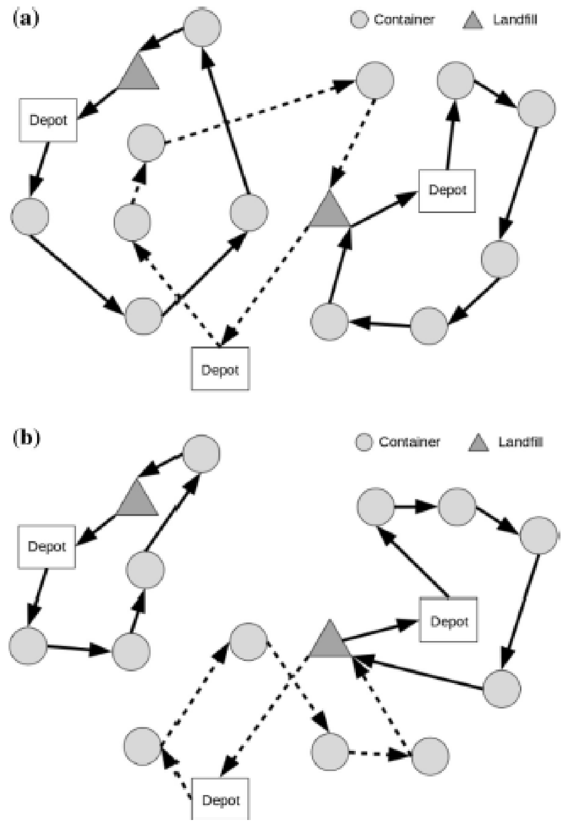

Figure 6.5: Non-collaborative (a) and collaborative (b) scenarios in waste management.

6.1.3.2 Literature review

The most efficient solving approaches for the MDVRP are based on metaheuristic approaches. Pisinger and Ropke (2007) propose an adaptive large neighborhood search metaheuristic which requires the fine-tuning of as much as 14 parameters. Vidal et al. (2012) use a hybrid genetic algorithm to solve different VRP variants, among them the MDVRP. The integration of Biased Randomization techniques inside an ILS framework designed to solve routing problems with multiple depots is discussed in the work of Juan et al. (2015*b*). The proposed methodology first allocated customers to the available depots, before each customer-depot-assignment is solved as a single-depot VRP instance through a multi-start procedure. Similarly, the MDVRP is decomposed into an customer assignation problem and the resulting single depot VRP by de Oliveira et al. (2016). The authors propose a cooperative co-evolutionary algorithm to solve the COP. Mancini (2016) formulates the MDVRP with a heterogeneous vehicle fleet and multiple periods, and proposes an efficient adaptive large neighborhood search matheuristic to solve the problem. Regarding stochastic versions of the MDVRP, Calvet et al. (2018) propose a simheuristic based the combination of simulation and a multi-start metaheuristic to solve MDVRP while integrating stochastic demands. Moreover, the authors consider a limited depot capacity in their approach. For a more detailed literature review on recent solving approaches for different MDVRP extensions, the reader is referred to Karakatič and Podgorelec (2015) and Montoya-Torres et al. (2015).

In contrast to the general MDVRP, the literature is scarce for the special case of waste collection routing, even non-existent for the stochastic case. A closely related problem setting to the multi-depot WCP (MDWCP) is discussed by Crevier et al. (2007), who apply an adaptive memory principle combined with integer programming and tabu search metaheuristics to consider the MDVRP with inner-route replenishment points. Hemmelmayr et al. (2013) consider multiple depots and landfills in a case study for node routing for the collection of waste from public waste delivery points to landfills by applying a hybrid approach. Combining variable neighborhood search and dynamic programming, the authors solve smaller problem instances with up to 75 collection points. Additionally, Ramos et al. (2014) improve the economic and environmental impacts of recyclable waste collection by solving the WCP with multiple depots as a mixed integer linear programming model.

6.2 Problem settings arising in integrated distribution network design

Supply chain management is of micro- and macroscopic importance. On the one hand, the costs associated with moving and storing goods constitute a major economic factor for organizations of different sectors (European Commission 2011). On the other hand, the usage of freight delivery vehicles leads to negative externalities such as air pollution, excessive noise, and traffic congestion (Hall et al. 2012, United Nations 2011, U.S. Environmental Protection Agency 2013).

Decision takers generally face three main tasks in the design and management of distribution networks: *(i)* operationally focused vehicle routing, *(ii)* tactical decisions regarding inventory replenishment levels, and *(iii)* the strategic decision of facility location. These decisions are closely related and should be made jointly to optimize overall supply chain management costs (Li et al. 2013). From an optimization point of view, the creation of integrated supply chain networks yields different challenging problem settings. This thesis addresses rich versions of the Inventory Routing Problem (IRP) and the Location Routing Problem (LRP), which are closer described in the following.

6.2.1 The multi-period Inventory Routing Problem

The concept of vendor managed inventories (VMI) is based on the transfer of inventory management decisions to the central supplier. In a VMI, a total of n retail centers (RCs) is stocked from a single supplier located at a central warehouse. Inventory levels at each RC and necessary replenishment quantities delivered by the supplier are defined through final customer demands. In non-collaborative supply chains, each RC defines its own replenishment levels based on its own inventory management decisions, which directly effects the delivery route planning process of the supplier. On the contrary, the implementation of VMI centralizes inventory and routing decisions at the supplier, allowing the optimization of both decisions from an overall supply chain perspective (Andersson et al. 2010, Coelho et al. 2013).

From an optimization point of view, this supply chain strategy is represented by the Inventory Routing Problem (IRP). This combinatorial optimization problem (COP) can be seen as an extension to the well-known Vehicle Routing Problem (VRP), making the problem setting NP-hard (Caceres-Cruz et al. 2014, Lenstra and Kan 1981). A visual representation of the multi-period IRP case is provided in Figure 6.6. Due to the inherent complexity of the IRP, especially metaheuristic solving methodologies are used to create inventory and routing plans for large sized IRP instances. As is the case of other COP's however, most solving frameworks are only capable of providing oversimplified problem solutions, in which the natural uncertainty of most real-life systems is left unaccounted for.

6.2.1.1 Problem description

The symbols and variables used to mathematically describe the multi-period IRP are listed in Table 6.1. Let $V = \{0,1,\ldots,n\}$ denote a finite set of locations consisting of the depot (node 0) and n RCs. The set of RCs will be denoted by $V^* = V \setminus \{0\}$. With the goal of minimizing total expected cost, the stochastic and periodic IRP combines inventory and routing decisions over a finite planning horizon P with $|P| \geq 1$ periods. The customers' aggregated demand at each RC $i \in V^*$ during a period $p \in P$ is a random variable, D_{ip}, which follows a known probability distribution. In this work, it is assumed that these random demands are independent across RCs and throughout periods –although they do not need to be identically distributed. Likewise,

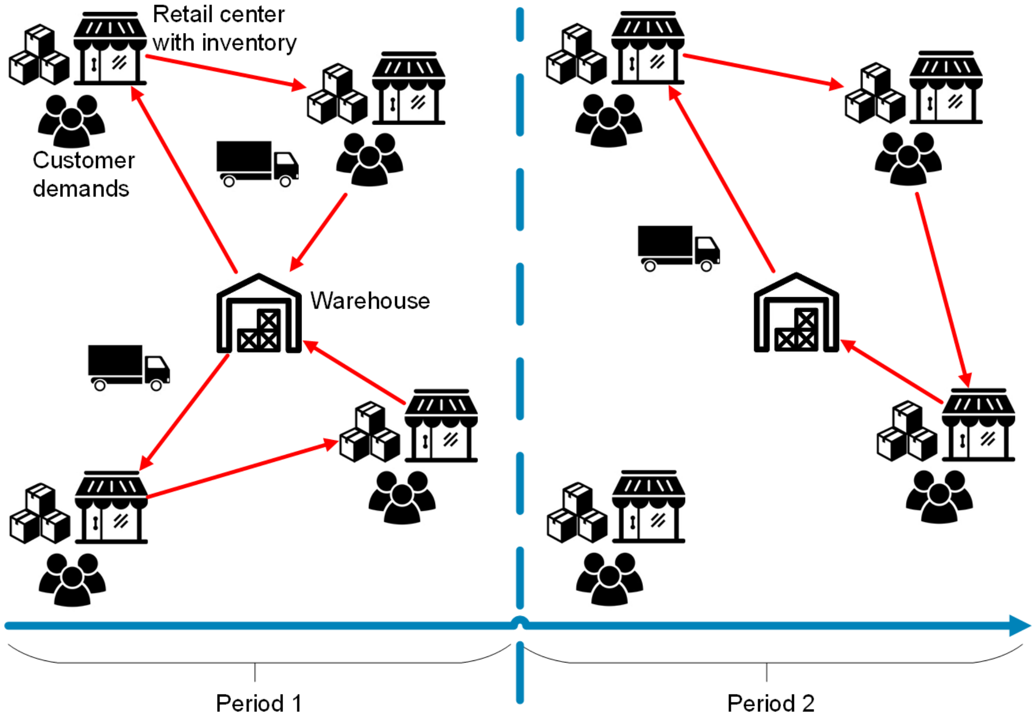

Figure 6.6: A simple 2-period Inventory Routing Problem.

it will be assumed that the customers' aggregated demand at each RC and period will always be satisfied. Thus, should a stock-out occur during a period p at RC i, an additional shipment from the depot to i will be placed by the end of period p to cover the non-satisfied demand. The cost of this extra shipment will be accounted as stock-out cost.

Regarding inventory management, the decision variables refer to the quantity of product, $q_{ip} \geq 0$, that must be served at RC i at the beginning of period p ($\forall i \in V^*$, $\forall p \in P$). If $l_i^+ > 0$ denotes the maximum storage capacity of RC i, and L_{ip}^0 denotes the initial stock available at RC i during period p ($0 \leq L_{ip}^0 \leq l_i^+$), then $q_{ip} \leq l_i^+ - L_{ip}^0$.

The initial stock level for the first period ($p = 1$) is given as an input, i.e., $L_{i1}^0 = l_{i1}^0$, $\forall i \in V^*$. By the end of each period, once the customers' aggregated demands are known, the initial stock level for the next period can be computed as $L_{i(p+1)}^0 = max\{L_{ip}^0 + q_{ip} - D_{ip}, 0\}$. Likewise, at this point the holding- or stock-out inventory cost at RC i and period p can be obtained by using Equation 6.18, where λ represents the unitary cost of holding surplus inventory by the end of a period, and c_{0i} represents the cost of a direct shipment from the depot to RC i (this

Table 6.1: Symbols used in the mathematical multi-period IRP formulation.

Symbol	Indices	Meaning
P	$p = 1,...,\|P\|$	Set of periods included in the planning horizon
K	$k = 1,...,\|K\|$	Set of (homogeneous) vehicles
V	$i,j = 0,1,...,n$	Set of locations, including the depot 0 and n RCs
V^*	$i,j = 1,...,n$	Set of RCs ($V^* = V \setminus \{0\}$)
c_{ij}	$i,j \in V$	Cost of traveling from $i \in V$ to $j \in V$
$h > 0$		Maximum vehicle capacity
$l_i^+ > 0$	$i \in V$	Maximum storage capacity of RC i
L_{ip}^0	$i \in V$	Initial stock available at RC i during period p
D_{ip}	$i \in V^*, p \in P$	Customers' aggregated demand at RC i during a period p
$q_{ip} \geq 0$	$i \in V^*, p \in P$	Quantity served at RC i at the beginning of period p
$y_{ip} \geq 0$	$i \in V^*, p \in P$	Binary variable that defines if RC i is visited at period p
x_{ij}^{pk}	$i,j \in V, k \in K$	Binary variable that defines if vehicle k goes from i to j at period p

value is multiplied by 2 in order to account for the return trip to the depot):

$$f(q_{ip}, D_{ip}) = \begin{cases} \lambda(L_{ip}^0 + q_{ip} - D_{ip}) & \text{if surplus} \quad L_{ip}^0 + q_{ip} \geq D_{ip} \\ 2 \cdot c_{0i} & \text{if stock-out} \quad L_{ip}^0 + q_{ip} < D_{ip} \end{cases} \tag{6.18}$$

Accordingly, the total inventory cost can be expressed as shown in Equation 6.19:

$$I(q_{ip}, D_{ip} \mid i \in V, p \in P) = \sum_{p \in P} \sum_{i \in V^*} f(q_{ip}, D_{ip}) \tag{6.19}$$

For each period $p \in P$, a VRP needs to be solved for those RCs i with $q_{ip} > 0$. As discussed in Toth and Vigo (2014), the VRP can be defined on a complete and undirected graph $G = (V, E)$, where V includes the depot from which n demand points (RCs) are served with a set K of homogeneous vehicles, and E is the set of edges connecting each pair of facilities in V. Each of the vehicles in the fleet has a maximum loading capacity given by $h > 0$. There is a traveling cost, $c_{ij} = c_{ji} > 0$ associated with moving from a facility i to a different facility j ($\forall i, j \in V, i \neq j$). The routing cost at period p depends on the binary decision variables x_{ij}^{pk}, which define whether or not the edge connecting facilities i and j is traversed at period p by a vehicle $k \in K$. Notice that this might depend upon the specific values of the customers' demands D_{ip}, i.e., $x_{ij}^{pk} = x_{ij}^{pk}(D_{ip})$. Accordingly, the total routing cost across all periods can be expressed as shown in Equation 6.20:

$$R(x_{ij}^{pk}, D_{ip} \mid i, j \in V, p \in P, k \in K) = \sum_{p \in P} \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} c_{ij} x_{ij}^{pk} \tag{6.20}$$

The objective of simultaneously setting the q_{ip} and x_{ij}^{pk} decision variables in order to minimize the expected overall inventory and routing cost is formulated in Equation 6.21:

$$E[I(q_{ip},D_{ip})+R(x_{ij}^{pk},D_{ip})] = \sum_{p\in P}\left(\sum_{i\in V^*} E[f(q_{ip},D_{ip})] + \sum_{i\in V}\sum_{j\in V}\sum_{k\in K} c_{ij}E[x_{ij}^{pk}]\right) \tag{6.21}$$

Constraints 6.22 define the range of each inventory-refill decision variable:

$$0 \le q_{ip} \le l_i^+ - L_{ip}^0 \qquad \forall i \in V^*, \forall p \in P \tag{6.22}$$

Equation 6.23 relates the aggregated demand at period p with the initial inventory levels at the next period:

$$L_{i(p+1)}^0 = max\{L_{ip}^0 + q_{ip} - D_{ip}, 0\} \qquad \forall i \in V^*, \forall p \in \{1,2,\ldots,|P|-1\} \tag{6.23}$$

Equations 6.24 and 6.25 state that, for each RC i, $y_{ip}=1$ if $q_{ip}>0$ and $y_{ip}=0$ otherwise (where M is a very large number):

$$q_{ip} \le l_i^+ y_{ip} \qquad \forall i \in V^*, \forall p \in P \tag{6.24}$$

$$y_{ip} \le M q_{ip} \qquad \forall i \in V^*, \forall p \in P \tag{6.25}$$

Given the set of RCs that are served at period p ($q_{ip}>0$), the established vehicle routes are stated by setting the variables x_{ij}^{pk}, $\forall i,j \in V, k\in K$. For all $i \in V^*$ and $p \in P$, let y_{ip} be a binary variable that takes the value 1 if RC i has to be serviced at the beginning of period p (i.e., if $q_{ip}>0$), and takes the value 0 otherwise.

Constraints 6.26 imply that each vehicle k leaves from, and returns to, the depot exactly once each period:

$$\sum_{i\in V^*} x_{0i}^{pk} = \sum_{i\in V^*} x_{i0}^{pk} = 1 \qquad \forall k \in K, \forall p \in P \tag{6.26}$$

Constraints 6.27 guarantee that each visited RC $i \in V^*$ is left after the service operation of any time period:

$$\sum_{j\in V\setminus\{i\}} x_{ij}^{pk} + \sum_{j\in V\setminus\{i\}} x_{ji}^{pk} = 2\cdot y_{ip} \qquad \forall i \in V^*, \forall k \in K, \forall p \in P \tag{6.27}$$

Equations 6.28 are subtour elimination constraints (the set of RC of a subtour would violate the corresponding constraint) for each period:

$$\sum_{i\in S}\sum_{j\notin S} x_{ij}^{pk} \le 2\sum_{i\in S} y_{ip} \qquad \forall S \subset V^*, \forall k \in K, \forall p \in P \tag{6.28}$$

Meanwhile, Equations 6.29 avoid RC supplies exceeding vehicle loading capacities:

$$\sum_{i \in V^*} \sum_{j \in V} x_{ij}^{pk} q_{ip} \leq h \qquad \forall k \in K, \forall p \in P \tag{6.29}$$

Finally, Constraints 6.30 and 6.31 enforce binary conditions on the auxiliary and routing decision variables:

$$y_{ip} \in \{0,1\} \qquad \forall i \in V^*, \forall p \in P \tag{6.30}$$

$$x_{ij}^{pk} \in \{0,1\} \qquad \forall i,j \in V, \forall k \in K, \forall p \in P \tag{6.31}$$

The multi-period IRP with stochastic customer demands consists in minimizing the objective function 6.21 subject to the constraints 6.22 to 6.31.

6.2.1.2 Literature review

Two extensive literature reviews on different IRP settings and solving techniques are presented by Andersson et al. (2010) and Coelho et al. (2013). Apart from other structural problem variants related to vehicle fleet compositions and further routing related aspects, the most important IRP problem alternatives are highlighted in Table 6.2. For a clearer distinction, the characterization of this work and the most closely related publications are depicted. In this context, the problem setting addressed in this thesis establishes inventory and routing plans over multiple time periods in a one-to-many supply chain setting. In contrast to an order-up-to-level inventory strategy which defines a global refill stock level for all RC's, this dissertation discusses the maximum-level strategy, which defines an individual inventory plan at each client for every time period. Furthermore, the possibility of product stock outs at the end of each period is considered. Final customer demands are considered to be of stochastic nature. Some metaheuristic solving methodologies for deterministic and stochastic IRP variants are discussed in more detail in the following.

Liu and Lee (2011) propose a variable neighborhood tabu search (VNTS) for the IRP with time windows. Based on an initial solution, different neighborhood structures in reference to vehicle routing and inventory control strategies are investigated within the TS framework. The authors consider up to 100 customers over 100 planning periods. Different neighborhood structures are also used in the adaptive large neighborhood search (ALNS) metaheuristic

Table 6.2: Structural IRP variants and relationship of this paper to closely related works.

Dimension	Structural Variants			
Time horizon	Single-period[b]	Multi-period[*,a,c]	Cyclic	-
Supply Chain structure	One-to-one	One-to-many[*,a,b,c]	Many-to-many	Many-to-one
Inventory policy	Maximum-level[*,b]	Order-up-to level[a,c]	-	-
Inventory decisions	Stock outs[*,b]	Backlogging[a,c]	Non-negative	-
Input variables	Deterministic	Stochastic[*,a,b,c]	-	-

[*] *this thesis*
[a] *Bertazzi et al. (2013)*
[b] *Juan et al. (2014c)*
[c] *Solyalı et al. (2012)*

developed by Aksen et al. (2014). The authors study a selective and periodic IRP in the collection of vegetable oil from different origin nodes. Problem settings with up to 100 source nodes and a 7 day planning horizon are addressed. Popović et al. (2012) develop a VNS algorithm for a multi-product, multi-period IRP in fuel delivery with homogeneous multi-compartment vehicles. A two-phased VNS for the multi-product IRP is discussed by Mjirda et al. (2014). During the first solution stage, the associated VRP is solved, which is then iteratively improved considering both transportation and inventory costs. Unlike previously cited authors, a many-to-one supply chain network in which different suppliers serve a single assembly line is discussed.

Abdelmaguid et al. (2009) put forward a heuristic approach for the finite multi-period IRP with backlogging. After applying a constructive heuristic to estimate the transportation costs for each customer in each considered period, an improvement heuristic is applied. Then, customer delivery amounts are exchanged between periods to improve the initial solution. They report solutions for problem settings with up to 15 customers and a 7 day planning horizon. The multi-period IRP is also addressed by Archetti et al. (2012). However, stock out situations are not considered in their work. The authors develop a hybrid heuristic based on a Tabu Search scheme combined with ad-hoc designed mixed-integer programming models. A three-phase heuristic for the multi-product, multi-period IRP is discussed by Cordeau et al. (2015), whereby each stage represents a decision process. First, replenishment plans are constructed using a Lagrangian-based method, specifying which customer to serve and how much to deliver during each period. Secondly, the vehicle routes are constructed. Finally, planning and routing decisions are combined into a mixed-integer linear programming model. They solve problems with up to 50 customers and 5 different products.

The same case of inbound logistics with up to 98 suppliers is also studied by Moin et al. (2011) to test their hybrid genetic algorithm (GA) for the multi-product, multi-period IRP. The algorithm follows the allocation-first, route-second strategy. A GA for the multi-period IRP in a one-to-many supply chain network and the consideration of lost sales was recently presented by Park et al. (2016). Their experiments are performed using problem sets with up to 12 customers and 12 time periods. The special case of inventory routing in the petroleum and petrochemical industry is addressed by Li et al. (2014), who propose a TS metaheuristic. With the objective of minimizing route travel times, particularities of this problem setting include the high importance of avoiding stock-outs and other operational constraints. A population-based Simulated Annealing algorithm for the multi-product, multi-retailer IRP with perishable goods is presented by Shaabani and Kamalabadi (2016).

Nambirajan et al. (2016) also extend the classic IRP formulation. A closer supply chain collaboration is considered by including replenishment activities at a central depot and different warehouses in a three echelon supply chain. First, the replenishment policy of a set of manufacturers to a single depot is defined. Then, the routing of the central depot to multiple warehouses is planned by using a three stage heuristic based on clustering, allocation, and routing. An iterated local search algorithm for the cyclic IRP over an infinite planning horizon is discussed by Vansteenwegen and Mateo (2014). Other heuristic and metaheuristic techniques for the cyclic IRP have also been presented by Chitsaz et al. (2016), Raa and Dullaert (2017), and Zachariadis et al. (2009).

Unlike for the deterministic case, literature on the IRP under uncertainty is more scarce. Random demands for inventory routing over an infinite horizon is addressed in Jaillet et al. (2002), who present incremental cost approximations in a rolling horizon framework. The stochastic IRP is formulated as Markov decision process by Adelman (2004). The author applies cost approximations by using dual prices of a linear program. Further approximation methods for the IRP with demand uncertainty modeled as a Markov decision problem are discussed by Kleywegt et al. (2004). Another approach in which the stochastic IRP is modeled as Markov decision process is presented in Hvattum and Løkketangen (2008) and Hvattum et al. (2009). The authors model random demand through general discrete distributions, while their solution framework is based on the use of scenario trees. Solutions to the scenario tree problem are obtained by using a standard MIP-solver, a greedy randomized adaptive search procedure (GRASP), and a progressive hedging algorithm (PHA).

More recent work on stochastic inventory routing include the one of Bertazzi et al. (2013), who consider an IRP with stock outs and a finite horizon, solved with a dynamic programming model and a hybrid roll-out algorithm. Bertazzi et al. (2015) address the IRP with stochastic demand and transportation procurement by developing a rollout-based matheuristic algorithm. A similar problem is addressed in a robust optimization approach through MILP formulations by Solyalı et al. (2012). Especially the works of Bertazzi et al. (2013) and Solyalı et al. (2012) discuss other variants of the problem addressed in this paper. Thus, while the former considers an order-up-to level inventory strategy –in which each retail center is filled to its maximum capacity each time it is visited–, the main goal in our version is precisely to find out the optimal values for these refill strategies. Also, our approach allows modeling customers' demands by using different probability distributions, while Solyalı et al. (2012) is a robust-based approach which assumes a uniform random behavior for these demands.

Huang and Lin (2010) develop a modified ant colony optimization metaheuristic for the multi-product IRP with demand uncertainty. A robust inventory routing policy, considering stochastic customer demands and replenishment lead-times, is discussed by Li et al. (2016). The robustness of inventory replenishment and customer selection policies for the dynamic and stochastic IRP is addressed in Roldán et al. (2016). Yu et al. (2012) solve the stochastic IRP with split deliveries and service level constraints. Soysal et al. (2015*b*) include environmental concerns in their solution for the IRP with demand uncertainty by estimating CO_2 emissions in the route planning process. Greenhouse gas emissions are also minimized in the work of Niakan and Rahimi (2015), who propose a fuzzy probabilistic approach to a multi-objective IRP for medical drug distribution. Rahim et al. (2014) solve the multi-period IRP with stochastic stationary demand through a deterministic equivalent approximation model. Also addressing the IRP with stochastic demands, Chen and Lin (2009) consider a real life multi-period, multi-product case. In addition, the authors incorporate risk aversion into their model. Finally, Juan et al. (2014*c*) propose a hybrid simulation-optimization approach, combining a multi-start metaheuristic with MCS, to address the single-period IRP with stochastic demands.

6.2.2 The two-echelon Location Routing Problem

The establishment of efficient and sustainable city logistics systems is of major importance in the creation of livable, environmentally-friendly, and healthy urban areas (Taniguchi et al. 2016). In this context, collaborative supply chain strategies constitute promising approaches to reduce the negative effects of road freight transportation (Leitner et al. 2011, Pomponi et al. 2015). One promising collaboration concept to reduce the negative externalities of urban road freight transportation involving an advanced level of company interaction is the construction of urban consolidation centers (UCCs). Instead of directly serving a large number of customers located within city borders from different delivery points, consolidated final customer deliveries from one or several companies are completed from these satellite facilities, which are typically situated in close proximity to city centers (Allen et al. 2007). This enables the use of smaller delivery trucks with higher vehicle utilization levels (Savelsbergh and van Woensel 2016).

Through the construction of UCCs, multi-level distribution networks are supported from which a range of COPs can be deducted. While satellite locations are typically defined through the Location Routing Problem (LRP) (Prodhon and Prins 2014, Quintero-Araujo et al. 2017*a*), multi-level VRPs such as the two-echelon VRP arise in the creation of efficient delivery routes (Cattaruzza et al. 2017). The two-echelon LRP (2E-LRP) addressed in this thesis combines these NP-hard optimization problems. An illustrative 2E-LRP example solution can be seen in Figure 6.7. Apart from establishing first-level (from the central depots to the UCCs) and second-level (from the UCCs to the final customers) routing plans, the most efficient satellite facilities from a set of possible locations needs to be defined.

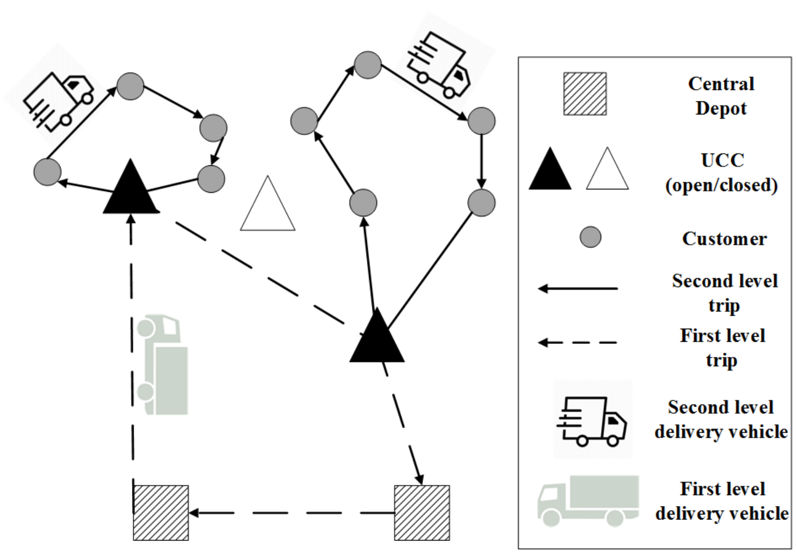

Figure 6.7: Example of a 2E-LRP solution.

6.2.2.1 Problem description

The LRP is defined on a graph $G = (V, A)$, where the set $V = I \cup J$ includes different types of nodes: *(i)* a finite set of customers I, each of them with a demand $d_i > 0$ ($\forall i \in I$); and *(ii)* a finite set of potential depot locations J, being $D_j > 0$ the capacity of depot j ($\forall j \in J$) and $O_j \geq 0$ the cost of opening that depot. A is the set of arcs linking each pair of nodes and, for each $a \in A$, C_a represents the cost of traversing this arc. A set K of homogeneous vehicles is available, being $Q > 0$ the capacity of each vehicle. It is also assumed that there is a fixed cost, VF, per vehicle (route) employed. Let S be a subset of nodes, and $\delta^+(S)$ (respectively $\delta^-(S)$) the set of arcs leaving (respectively entering) S. Finally, let $L(S)$ be the set of arcs with both ends in S. As pointed out in Prins et al. (2006), the LRP can be formulated as follows, where Y_j refers to whether or not depot j is opened, X_{ij} defines whether or not customer i is assigned to depot j, and f_{ak} indicates whether or not arc a is traversed by vehicle k:

$$\text{Min Z} = \sum_{j \in J} O_j Y_j + \sum_{a \in A} \sum_{k \in K} C_a f_{ak} + \sum_{k \in K} \sum_{a \in \delta^+(J)} VF f_{ak} \tag{6.32}$$

Subject to:

$$\sum_{k \in K} \sum_{a \in \delta^-(i)} f_{ak} = 1 \qquad \forall i \in I \tag{6.33}$$

$$\sum_{i \in I} \sum_{a \in \delta^-(i)} d_i f_{ak} \leq Q \qquad \forall k \in K \tag{6.34}$$

$$\sum_{a \in \delta^+(v)} f_{ak} - \sum_{a \in \delta^-(v)} f_{ak} = 0 \qquad \forall k \in K, \forall v \in V \tag{6.35}$$

$$\sum_{a \in \delta^+(i)} f_{ak} \leq 1 \qquad \forall k \in K, \forall i \in I \tag{6.36}$$

$$\sum_{a \in L(S)} f_{ak} \leq |S| - 1 \qquad \forall S \subseteq I, \forall k \in K \tag{6.37}$$

$$\sum_{a \in \delta^+(j) \cap \delta^-(I)} f_{ak} + \sum_{a \in \delta^-(i)} f_{ak} \leq 1 - X_{ij} \qquad \forall i \in I, \forall j \in J, \forall k \in K \tag{6.38}$$

$$\sum_{i \in I} d_i X_{ij} \leq D_j Y_j \qquad \forall j \in J \tag{6.39}$$

$$f_{ak}, X_{ij}, Y_i \in \{0,1\} \qquad \forall a \in A, \forall k \in K, \forall i \in I, \forall j \in J \tag{6.40}$$

The objective function (6.32), is the minimization of total costs, including: opening costs, traversing costs, and fixed costs associated with the use of vehicles. Constraints (6.33) establish that each customer is visited exactly once. Vehicle capacity constraints are represented by (6.34). Constraints (6.35) and (6.36) guarantee the continuity of each route and the return of any vehicle to the origin. Sub-tour elimination constraints are represented by inequalities (6.37). Expressions (6.38) guarantee that a customer is only assigned to an open depot. Constraints (6.39) specify that the depot capacity cannot be exceeded. Finally, expressions (6.40) define the domain of the decision variables.

6.2.2.2 Literature review

A comprehensive survey on two-echelon routing problems was recently presented by Cuda et al. (2015). The authors highlighted three problem extensions according to the involved level of tactical and/or strategical planning decisions:

i the tactically focused two-echelon VRP, in which routing plans between different echelons are established.

ii the two-echelon LRP, in which strategic facility location decisions are included.

iii truck-and-trailer problems, in which customers are served by different trucks and trailers according to a set of restrictions.

The authors concluded that the current literature on two-echelon routing problems is still lacking the consideration of input uncertainty.

Drexl and Schneider (2015) reviewed relevant literature on variants and extensions of the location-routing problem. Even though multi-echelon problem settings were not considered, the authors highlighted the use of simulation to solve the LRP with stochastic demands as done by Mehrjerdi and Nadizadeh (2013). These authors proposed a greedy clustering method to solve the capacitated LRP. Customer demands are hereby simulated using fuzzy logic. While their solving methodology has similarities to the one described in this thesis, the authors do not consider multiple echelons. Furthermore, the simheuristic allows for applying any kind of probability function instead of relying on fuzzy logic to account for demand stochasticity.

Recently, further extensions to the 2E-LRP have been presented. Rahmani et al. (2016) proposed a mixed-integer linear model for small-scale instances and extensions of some nearest neighbor and insertion approaches for the same problem setting. The authors developed new clustering-based approaches for LRPs. Computational experiments showed that the clustering approach is very competitive and outperforms other heuristics for smaller problem instances with less than 200 nodes. Dalfard et al. (2013) applied hybrid genetic and simulated annealing algorithms for the "E-LRP with vehicle fleet capacity and maximum route length constraints. The authors compared their results to solutions obtained with the software LINGO, suggesting that their proposed algorithm is more effective. Vidović et al. (2016) presented a mathematical formulation of a two-echelon location-routing problem in case of recycling logistics networks. Collecting points between end customers and transfer stations are defined using a mixed-integer linear programming model that maximizes the profit and creates a distance-dependent collection rate. For solving large problem instances, the authors put forward heuristic solving approaches.

6.3 Horizontal collaboration concepts in urban freight transportation

Current business environments are shaped by globalized markets, real-time communication, and rapidly changing customers' demands. Accordingly, companies are forced to efficiently reorganize their logistic processes to stay competitive by quickly reacting to market changes. In this context, horizontal collaboration (HC) is a promising supply chain management strategy to reduce transportation and logistics (T&L) costs while increasing customer service levels. HC is defined 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 collaboration towards achieving a common objective".

Regardless whether they are competitors or organizations operating in different markets, companies involved in HC agreements share information and resources to reduce T&L-related costs. This includes the potential reduction of negative environmental impacts associated with transportation activities (Lera-López et al. 2012). The importance of sustainable supply chain management is underlined by the fact that road transportation is estimated to account for around 18% of total greenhouse gas emissions in the EU (Hall et al. 2012). 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 (U.S. Environmental Protection Agency 2013).

6.3.1 Collaboration scenarios and resulting optimization problems

Changing monetary and environmental impacts of different HC levels when facing integrated routing-and-facility-location decisions can be defined (Table 6.3):

i delivery-routes and facility-locations are individually defined by each company in a non-collaborative scenario.

ii a semi-collaborative scenario involving customer-service exchanges between different companies is considered. By sharing client information and vehicle capacities, joint routing plans are supported. In these routing plans, customers might be assigned to different depots.

iii a fully-collaborative scenario involving integrated routing and facility location decisions. This scenario represents an advanced HC concept, in operational, tactical, and strategic decisions are jointly taken.

Each of the aforementioned HC scenarios corresponds to a different combinatorial optimization problem. Thus, each company faces a VRP in the non-collaborative scenario (Caceres-Cruz et al. 2014). Likewise, in the semi-collaborative scenario, centralized routing decisions result in a MDVRP. Finally, the fully-collaborative scenario requires the solution of a LRP, in which decisions on route planning and facility locations are combined.

A simple problem setting and three alternative HC scenarios regarding route- and facility-location planning are outlined in Figure 6.8. Diamond-shaped nodes represent depots of

Table 6.3: Overview of considered horizontal collaboration scenarios

Collaboration scenario	**Non-collaborative**	**Semi-collaborative**	**Fully-collaborative**
Joint decisions	None	Route planning, customer allocation	Route planning, customer allocation, facility location investment
Shared resources	None	Customer demands, vehicle capacities, logistics facilities capacity	Customer demands, vehicle capacities, logistics facilities
Related optimization problem	Multiple non-related VRPs	One common MDVRP	One common LRP

distinct companies (A, B, and C), while the remaining nodes play the part of customers (notice that customers with a look-alike shape belong to the same company). The initial location of different depots and their associated customers can be seen in Fig. 6.8*a*. In a non-collaborative scenario (Fig. 6.8*b*), both routing and facility-location decisions are decentralized. Therefore, every company establishes its own routing plans starting and ending at its central depot. From an optimization perspective, this leads to a different VRP (Toth and Vigo 2014) for each company, as it tries to establish efficient delivery tours.

The degree of joint decisions increases in the semi-collaborative supply chain scenario. By sharing customer information, storage facilities, and vehicle capacities, route planning can be improved through a more efficient customer-to-depot allocation. This situation corresponds to a MDVRP (Pérez-Bernabeu et al. 2015, Montoya-Torres et al. 2015), in which customer-allocation and routing decisions are combined (Fig. 6.8*c*). Notice that in this semi-collaborative scenario routing distances have been reduced with respect to the non-collaborative case.

Finally, Fig. 6.8*d* shows the fully-collaborative scenario, where routing and facility-location decisions are jointly taken by all the companies. This situation is represented by the LRP, which summarizes: *(i)* facility-location decisions; *(ii)* customer-to-depot-assignment; and *(iii)* delivery-route planning (Prodhon and Prins 2014). This simple example illustrates how an integrated routing-and-location decision might even vary the number of depots employed to serve all customers.

6.3.2 Literature review on horizontal collaboration concepts

Collaboration agreements can take place across vertical or horizontal levels of the supply chain. In the context of land-side T&L, vertical collaboration has been extensively analyzed in the literature. This has led to concepts such as vendor managed inventories, efficient customer response, etc. Meanwhile, the literature on HC in T&L is less explored (Leitner et al. 2011, Pomponi et al. 2015). After a general overview on works in the context of HC in road T&L, this section presents some HC frameworks outlining different collaboration stages. For an extensive literature review on HC in T&L, the reader is referred to Cruijssen et al. (2007*c*).

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. They also analyzed the use of multi-supplier warehouses, coordinated route planning, and load consolidation to support HC in the Italian grocery industry. Another early

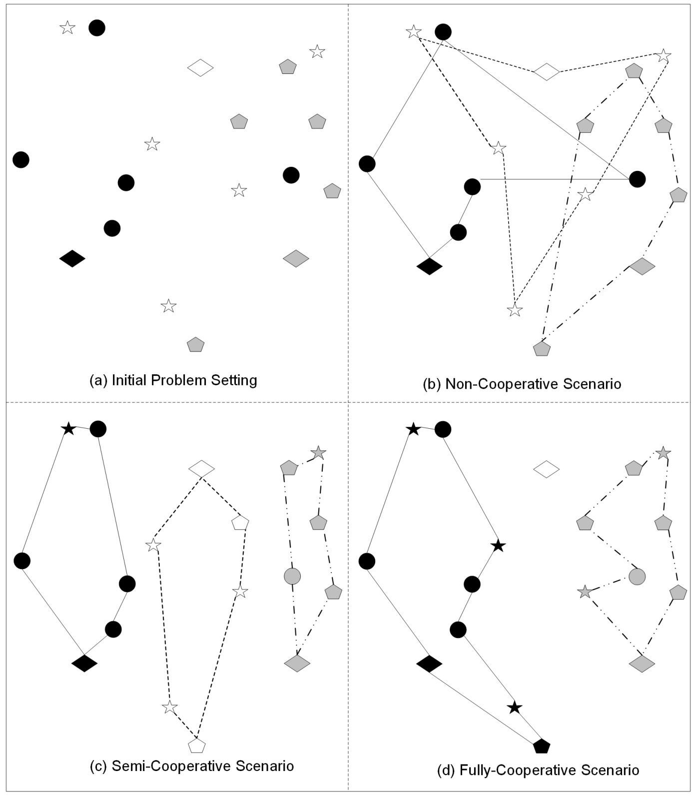

Figure 6.8: Graphical representation of different HC scenarios

work on HC was elaborated by Erdmann (1999), who proposed a simulation model to quantify the benefits associated with different levels of HC among freight carriers.

Cruijssen and Salomon (2004) studied how orders sharing among freight carriers can lead to savings between 5% and 15% due to improved transport planning. Joint route planning under varying market conditions was analyzed by Cruijssen et al. (2007*a*). Özener et al. (2011) discussed how customer exchanges among freight carriers with different levels of information sharing can lead to cost savings for the participating companies. Nadarajah (2008) showed possible route savings and increased vehicle utilization through cooperative vehicle routing and strategic location of consolidation points for less-than-truckload carriers. HC in the context of conjoint transportation planning of less-than-truckload shipments was also studied by Wang and Kopfer (2014), who introduced exchange mechanisms for customer request re-allocations and compared 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.

An optimization approach addressing backhauling routes 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). A fair cost and benefit-allocation among HC participants was addressed in Audy et al. (2012), Dai and Chen (2012), and Krajewska et al. (2008).

Juan et al. (2014*a*) analyzed the VRP with clustered backhauls as a particular case of HC. Following their work, Pérez-Bernabeu et al. (2015) presented a study 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-collaborative scenario (equivalent to a MDVRP) and two non-collaborative scenarios (multiple VRPs with clustered and scattered customer distributions). The reported results suggest that collaborative transport planning typically outperforms its non-collaborative counterpart in terms of both distance and CO_2 emissions, with distance-based savings of up to 15% and even higher reductions in the environmental impact.

Real-life applications of HC in urban distribution can be found in Montoya-Torres et al. (2016). These authors compared a non-cooperative scenario with a cooperative one related to tactical and operational decision-taking. For that, they used real-life data from three retail companies located in the city of Bogotá (Colombia). The non-collaborative case was solved as a VRP for each single company, whereas the collaborative case was based on shared depots and vehicle capacities, and thus modeled as a MDVRP. An extension of the previous work that considers stochastic customer demands was analyzed by Muñoz-Villamizar et al. (2015). Possible benefits through HC were quantified in terms of total distance, CO_2 emissions, number of routes, and vehicle utilization levels. Results showed benefits such as a reduction of 9% in the number of routes or savings up to 25% in routing distance. Furthermore, the application of HC strategies led to decreased CO_2 emissions with higher vehicle utilization levels. Quintero-Araujo et al. (2017*a*) developed a simheuristic algorithm to quantify the potential savings generated through HC when considering stochastic demands. Results showed an average saving of 4% in costs. They also showed an increased reliability of the planned routes when considering HC strategies.

Very few works have been presented showing the advantages of collaborative 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. A CHN determines the best hub combinations to minimize total shipping costs between hub and non-hub nodes. Moreover, the CHN strategy is combined with direct trucking for short distance deliveries and for serving exceeding demand that cannot be transported through the CHN. Thus, this combination provides both high capacity (due to inland barges) and flexibility (due to road transportation), guaranteeing economies of scale and scope. Because of higher lead times generated by using the CHN, the corresponding shipments must be sent in advance. A relaxed version of the hub network design problem was used to determine the optimal CHN configuration. The relaxed constraints were the following ones: *(i)* hubs are not fully interconnected; *(ii)* nodes can be assigned to different hubs; and *(iii)* non-hub nodes can be directly connected between them. An average logistics cost reduction of 14% was achieved for origin-destination relations that used the CHN strategy. A cooperative supply chain scenario in the medium-sized less-than-truckload industry was addressed by Hernández et al. (2012). The authors formulated a p-hub location problem which they solved with Langrangian relaxation to show the benefits of a centralized multi-carrier collaborative network. A Tabu Search metaheuristic was later developed for a similar problem-setting in the work of Wang and Kopfer (2014).

Pan et al. (2013) presented the concept of pooling supply chains for inter-supply chain freight consolidation. The value chain is represented by a three-echelon network modeled as a mixed integer linear programming. Their objective is the optimization of CO_2 emissions using both road and rail transportation for a French retail chain. Additionally, the authors estimated potential CO_2 reductions of 14% due to road transportation pooling. When combining road and rail transportation, the authors suggested that reductions could rise to 52%. An extension of the previous pooling concept was presented in Pan et al. (2014). Here, the authors introduced the concept of logistics pooling, which "corresponds to the co-design by partners (suppliers, clients, carriers, etc.) with a common objective of a logistics network, the resources of which are pooled (warehouses, platforms, transport resources, etc.) in order to share logistics networks and provide one or more third parties with the data required for management." In that sense, pooling involves a win-win relationship for all participants in the collaborative agreement, and ensures that applied network configuration is globally optimal for the partnership. These authors also propose three scenarios of network pooling, and compare them to the current situation (using environmental and economic indicators) of a distribution network in the French food industry.

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 among 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 collaborative strategies cannot be easily quantified for a single company, but are rather visible on an aggregated supply chain level (Cruijssen et al. 2007*b*). Generally, the success of any cooperation agreement is highly dependent on commitment, trust, and information sharing between the participating organizations (Singh and Power 2009).

Lambert et al. (1999) were the first authors to propose a HC taxonomy depending on the time horizon of the agreement. They identified three types of HC: type I is related to short-term, 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. They suggested that operational cooperation is mainly focused on joint execution and sharing of information, whereas HC on a tactical planning level involves more intensive planning and shared investments. Finally, strategic collaborative 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 degree of cooperation and the product-flow consolidation potential. In a more recent work, Pomponi et al. (2015) elaborated a theory-based framework for HC in logistics, developing coherent pairs of aims and shared assets for different collaborative stages, including operational, tactical, and strategic levels. While these authors characterized operational HC as related to shared information with the aim of cost reductions, collaborative 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 partnerships, which includes joint investments and a high degree of commitment among the participating organizations. In general, all discussed works stressed the importance of mutual trust among companies to enable a successful partnership, whereby higher trust is necessary as collaborative agreements are enhanced. Moreover, most authors mentioned that the development of different HC stages is a continuous process. Thus, a successful supply chain collaborative typically starts with combined activities that request a low involvement of the participating actors before more advanced cooperation projects are started.

CHAPTER 7

SUPPORTING SMART URBAN WASTE COLLECTION UNDER UNCERTAINTY

Waste management is among the most critical planing activities in modern cities, as it directly impacts urban living standards, traffic flows, and municipal budgets. This chapter proposes simheuristics as efficient decision support tool for different variants of stochastic Waste Collection Problem (WCP) extensions. The highlights of this chapter include:

- the proposal of an efficient Variable Neighborhood Search (VNS) algorithm to solve the deterministic waste collection case (see chapter 6.1.1). The presented metaheuristic outperforms state-of-the-art benchmark algorithms on a set of large-scaled problem instances (with up to 2100 nodes) by over 2.5%. The VNS algorithm is compared to a GAMS implementation solved with CPLEX, emphasizing the superior scalability and calculation times of the metaheuristic over exact solving techniques (Gruler et al. 2017*c*).

- the application of the SimVNS algorithm to the WCP with stochastic demands. Managerial insights provided by the developed simheuristics are particularly highlighted through a detailed risk and reliability analysis of the obtained results (Gruler et al. 2017*c*).

- the development of a simheuristic framework for time-dependent vehicle routing under travel time uncertainty (see chapter 6.1.2). The algorithm is tested as decision-support tool in a real-life case study with nearly 900 waste collection points completed in the medium-sized Catalan city of Sabadell. As opposed to applying simheuristics to theoretical instances taken from the literature, especially the importance of suitable data preparation in such real-life optimization cases is pointed out. Results show operational cost savings of over 10% (Gruler et al. in review process 2018b).

- the proposal of a simulation-optimization approach based on Biased Randomization and Variable Neighborhood Search for the multi-depot WCP (see chapter 6.1.3) with stochastic demands arising in clustered urban areas. Obtained results suggest that collaborative activities among waste management service providers in metropolitan areas yield potential cost-savings of over 30% in some cases (Gruler et al. 2017*a*).

The VRP with time windows (VRPTW) and the MDVRP (with different realistic extensions) are the central COP settings addressed in this chapter. As highlighted in Figure 7.1, the complexity of these COPs is relatively low compared to other optimization problems discussed in this dissertation. Both problem settings are mainly focused on operational decisions regarding vehicle routing (VRPTW) and combined routing and customer allocation (MDVRP). However, their computational interest and importance in the context of urban waste collection is underlined by the large amount of network points to be considered, the inherent complexity and uncertainty of urban transportation activities, and the need for near-instantaneous decision-taking on a daily basis.

7.1 A simheuristic based on Variable Neighborhood Search for urban waste collection under demand uncertainty

The following subsections describe the development of a simheuristic algorithm based on a VNS simheuristic (SimVNS) as described in chapter 4.2. The competitiveness of the underlying metaheuristic is shown on a range of experiments, before the integration of simulation to consider stochastic demands is outlined.

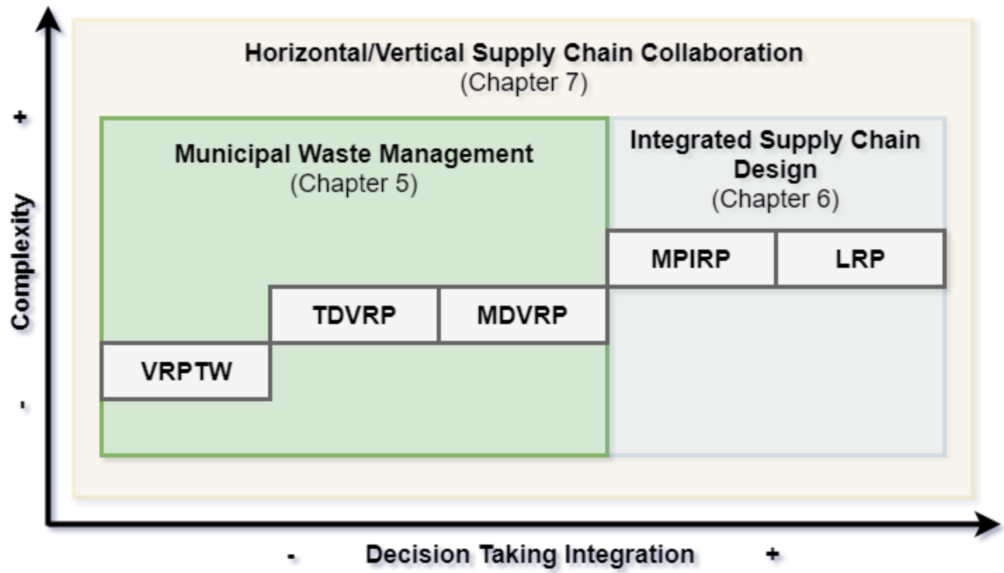

Figure 7.1: Complexity and decision-taking integration of central problem settings addressed in chapter 7.

7.1.1 A VNS metaheuristics for the the deterministic WCP

7.1.1.1 Algorithm description

In order to solve the deterministic WCP, a VNS metaheuristic as described in chapter 2.2.1 is proposed. 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 Juan et al. (2013*a*). 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 7.2 - 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, a simple transformation based on the average savings associated to each arc is employed (Figure 7.2 - right).

Based on the initial solution $baseSol$, different neighborhood structures $N_k(k = 1, ..., k_{max})$ are created. The shaking procedures applied in this work to create new solution structures are outlined in Table 7.1. Within each neighborhood $N_k(baseSol)$, different local descent heuristics described in Table 7.2 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

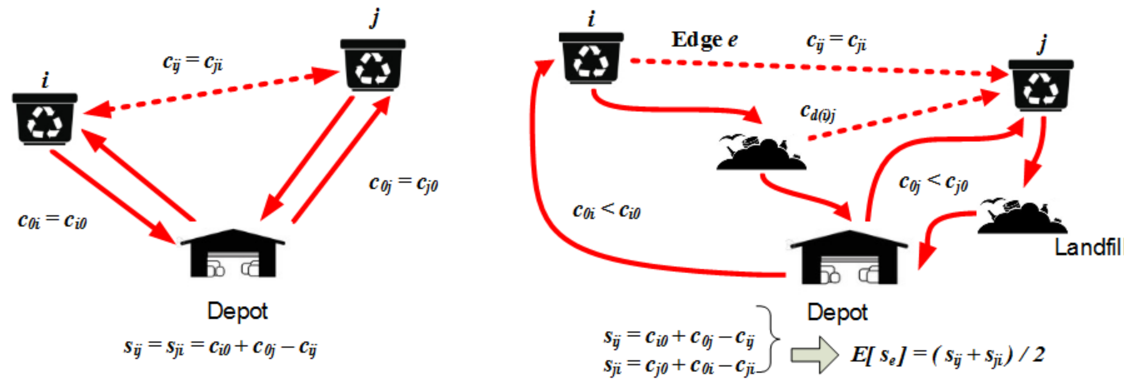

Figure 7.2: Savings of the original CWS heuristic (left) and expected savings proposed for the WCP (right).

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 ending at a disposal site — is stored in a hash-table data structure, thus allowing for new solutions benefiting 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. The list of neighborhood operators is shuffled every time $k > k_{max}$. A description of the VNS procedure for the deterministic WCP can be seen in Algorithm 8.

Table 7.1: VNS shaking operators to solve the WCP

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

Table 7.2: Local Search operators to improve WCP solutions

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 8: A VNS metaheuristic for the deterministic 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 7.1
        improving ← true                                   // Start Local Search
        while improving do
            newSol* ← localDescent(newSol, randomLSoperator)   // see Table 7.2
            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
```

7.1.1.2 Performance compared to an exact approach

In order to show the performance of the VNS metaheuristic in comparison to an exact approach, the mathematical WCP model formulated in chapter 6.1.1.1 is implemented in GAMS (Version 23.5.2). The CPLEX solver (Version 12.2.0.0) was used to solve 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, three smaller instances with 20, 24, and 44 containers were generated. 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.

Table 7.3 shows the result comparison of CPLEX and the described VNS algorithm for the aforementioned instances. For each solving method, the best solution found (Z), the time consumed to find that solution ($TC\ Z$) and the maximum computing time allowed (TC) is included. 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 the 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 or near-optimal solutions in low computing times, even for small instances of the basic WCP version.

Table 7.3: Results comparison of CPLEX vs VNS metaheuristic for the WCP

	CPLEX			**VNS**			
Instances	Z	*TC Z (sec.)*	*TC (sec.)*	Z	*TC Z (sec.)*	*TC(sec.)*	*GAP*
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%*

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.

7.1.1.3 Performance compared to benchmarks from the literature

To test the competitiveness of the outlined algorithm, the benchmark instances provided by Kim et al. (2006) are used, which were later also adopted by Benjamin and Beasley (2010) and Buhrkal et al. (2012) to validate their solution approaches for the WCP. 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, the approach is compared 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.

The results are summarized in Table 7.4. Column (1) reports the best known solution (BKS) for each instance (listed as Kim_numberOfNodes) as reported in the works of Kim et al. (2006), Benjamin and Beasley (2010) 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, the VNS metaheuristic is tested with two different stopping criteria. On the one hand, the best solution (achieved with 10 different random number seeds) when applying the CTs listed in column (2) is reported in column (4). On the other hand, the average solution with 10 different random number seeds (5) and the best solution (6) with a stopping criterion of 300 seconds per instance as suggested by Benjamin and Beasley (2010) is listed.

It can be seen that the proposed algorithm outperforms current BKS's by an average of -0.85% and -2.65%. Moreover, the VNS procedure reaches 9 new BKS's (11 with the extended algorithm running time). As can be observed, the percentage gap compared to the BKS

Table 7.4: Computational results for the deterministic case and comparison with BKSs

Instance	(1) BKS	(2) CT BKS (s)	(3) BKS average	(4) Best sol[1]	(5) Sol average[2]	(6) Best sol[2]	(7) CT 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)

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 the 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 useful in the solution of the WCP.

7.1.2 A VNS-based simheuristic for the WCP with stochastic demands

7.1.2.1 Algorithm description

In contrast to deterministic cases of the WCP, waste levels cannot be predicted with full certainty when solving a more realistic stochastic version of the problem. The fact that actual waste levels in containers are only known when reaching designated pick-up points can lead to route failures whenever collected garbage exceeds the planned collection amount. In these cases, the collection vehicle needs to add an additional and expensive landfill visit to its route. The proposed simheuristic methodology outlined in Algorithm 9 enables an estimation of the solution quality of previously created outputs using the VNS metaheuristic proposed in the previous section by integrating Monte Carlo simulation (MCS) into the solution procedure. The simheuristic structure for the WCP can theoretically be combined with any metaheuristic approach addressing the problem setting. As has been discussed in chapter 3 however, the quality of the stochastic solution is directly related to the results obtained in the deterministic metaheuristic process. For this reason, the use of an efficient deterministic solution process such as the proposed VNS metaheuristic is beneficial.

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 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. In order to avoid jeopardizing computational times, a restricted number of solutions is considered for the more extensive simulation run at this stage. The number of stored $eliteSols$ is limited to a maximum of 10. Even though a larger number of solutions could be stored at this point, an augmented elite solution list has not shown any significant changes in the final ranking of the best stochastic solutions.

In addition to calculating the stochastic objective function value of promising deterministic solutions, the outlined methodology allows for estimating solution reliabilities by considering the proportion of runs where the solution plan can be implemented without any route failure

Algorithm 9: A VNS based simheuristic for the stochastic WCP with stochastic demands

```
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) localSearch(newSol) 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 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. $reliab_r = simRunsWithRouteFailue/simRuns$. 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 conducting a closer risk and sensitivity analysis of the considered solutions, as explained in the following section.

7.1.2.2 Computational experiments and analysis of results

Since there is a lack of stochastic benchmark instances with similar characteristics, the non-clustered instances of Kim et al. (2006) are used as reference. The deterministic instances are then 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, the simheuristic 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.

The approach is tested with low ($Var[w_i] = 0.05$), medium ($Var[w_i] = 0.15$), and high variance levels ($Var[w_i] = 0.25$) 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, this thesis proposes the inclusion of vehicle safety stocks k to better deal with unexpected demands, as discussed in more detail by Juan et al. (2011). 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 reliabilities), 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 are considered: 0, 0.02, 0.04, 0.06, 0.08, and 0.1. Combined with the three variance levels, this leads to a total of 18 different scenarios for each instance. Tables 7.5-7.7 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.

Figure 7.3 shows the expected total costs and reliabilities for the average of all tested instances for each waste variance level/safety capacity factor combination. As can be observed, the highest total costs for each waste variance level are 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 7.4, 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 7.5, 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. In Table 7.8, 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 table it can be concluded that the solution with the lowest mean does not always have the lowest standard deviation (see, for example, Kim444). Thus, this information can be used by decision-takers to select the solution that he/she prefers according to his/her risk preference. In a similar manner, the proposed solution approach allows for considering different risk-aversion levels of decision takers 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.

To assess the relationship between reliability levels and associated solution costs, Pearson's product-moment correlation test has been completed by calculating the normalized values of the reliabilities, expected route failure costs, and the total costs of all elite solutions

Table 7.5: Computational results for the stochastic case with a low waste 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 7.6: Computational results for the stochastic case with a medium waste 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 7.7: Computational results for the stochastic case with a high waste 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

Table 7.8: 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

for each instance. Hereby, a 4% vehicle safety capacity and all variance levels have been considered. When comparing reliability levels and total solution costs, only a very weak negative correlation of -0.072 (p-value = 0.3035) can be observed. As could be expected, however, the negative correlation between reliability levels and expected route failure costs is more clear, with a Pearson correlation of -0.674 (p-value < 2.2e-16).

7.2 A simheuristic algorithm for time-dependent waste collection management with stochastic travel times

The following subsections outline a simheuristic procedure to solve the time-dependent Waste Collection Problem with stochastic travel times. The elaborated algorithm is applied to a large-scale case study regarding waste collection in the Catalan city of Sabadell.

7.2.1 A time-dependent travel speed model for the WCP

The applied travel speed model for time-varying vehicle velocities is based on the discussions of Ichoua et al. (2003). The planning horizon (defined by the depot opening hours) is divided into p time periods $T_1, T_2, \ldots, T_p$. Travel durations tt_{eT} to cross any edge in $e \in E$ can be calculated as the quotient of travel distances and vehicle speeds v_T ($T \in \{T_1, T_2, \ldots, T_p\}$), such that $tt_{eT} = d_e / v_T$. In the specific case of waste collection in Sabadell, different travel speeds

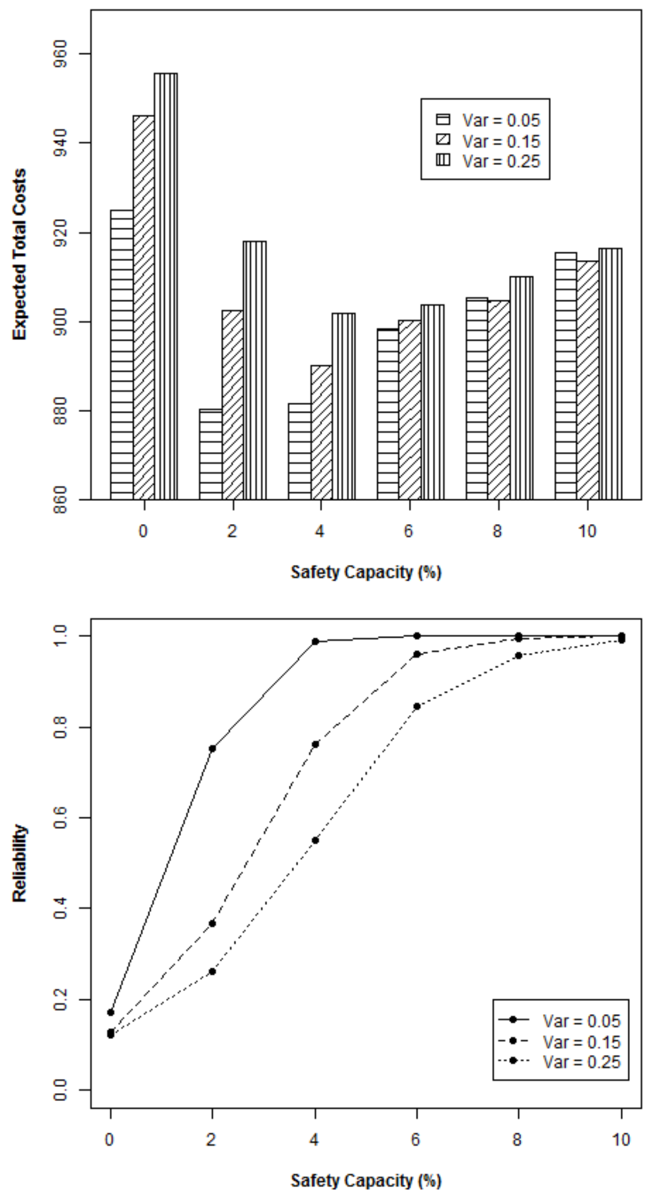

Figure 7.3: Expected total costs (a) and reliabilities (b) over all instances.

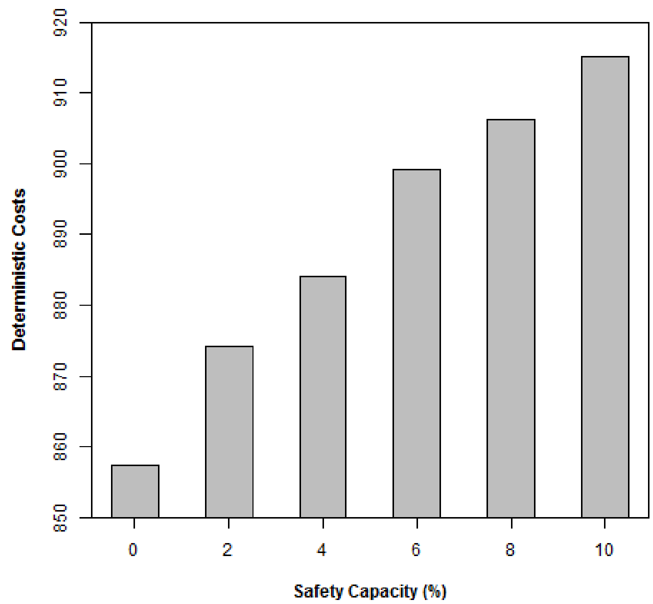

Figure 7.4: Deterministic costs over all instances and variance levels.

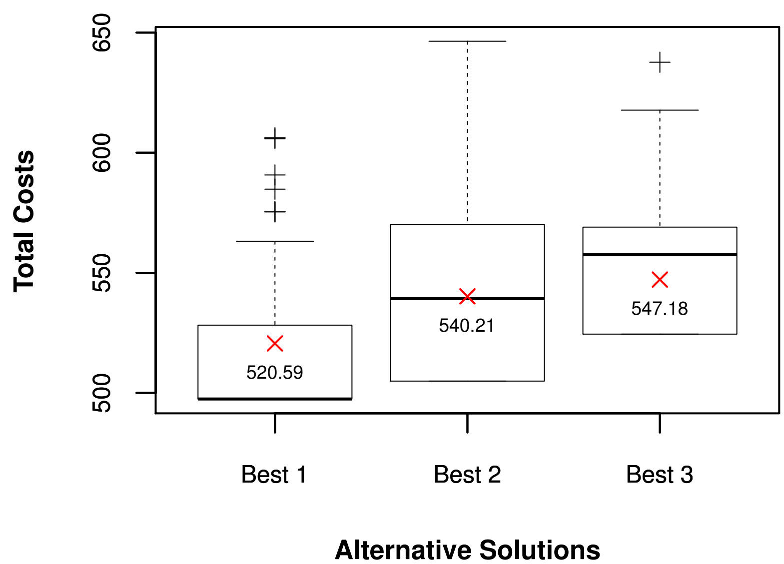

Figure 7.5: Boxplot of total costs of each long simulation run of the Kim277 instance for the best three solutions considering a high waste variance level and a 2% safety capacity level.

can be defined for different edges, e.g., due to rush hour traffic or other events such as opening or closing hours of schools. For this reason, edge set E is partitioned into S subsets with E_s ($s = 1, 2, \ldots S$). Thus, travel speeds can be formulated as tt_{sT} to show the travel speed of any edge of the edge subset E_s during time period T. This step-wise travel speed model along different times of the planning horizon is a natural way of estimating travel durations of different edges in real-world conditions. Furthermore, it implies the satisfaction of the FIFO property.

7.2.2 The Waste Collection Problem in Sabadell

Sabadell is a medium-sized city of roughly 200,000 inhabitants located within the autonomous Spanish region of Catalonia. Collection vehicles are located at a central depot and collected garbage is disposed in a single landfill. Expected waste levels in each container, average service times at each node, and the average vehicle travel speeds during different time periods are known. The problem setting consists of a total of 921 paper waste containers which are currently visited on 9 different routes. The locations of the vehicle depot, the landfill, waste containers, and the original route assignation can be seen in Figure 7.6 (the central depot and the landfill are marked by the square symbols).

Time is a major issue for the waste collection service provider with whom this study was completed. On the one hand, the operational times directly affect the operational costs associated with the waste collection process in terms of necessary wages and vehicle usage costs. On the other hand, an important routing constraint is that collection routes need to be completed between 9 a.m. and 4 p.m., as these are the opening hours of the central depot at which the collection vehicles are stationed. Moreover, different time periods within the daily planning horizon can be identified regarding expected traffic speeds:

- heavy traffic on all streets is expected during the rush hour from 9 a.m. to 10 a.m. and from 1 p.m. to 2 p.m.

- traffic jams are expected in streets close to primary schools in the time periods of 9 a.m. to 10a.m., 12 p.m. to 1 p.m., and 3 p.m. to 4 p.m.

Especially the latter observation is of importance in the planning of waste collection routes. Containers in the affected streets should not be visited within the depicted time period. Due to parents picking up their children from primary schools, streets within a

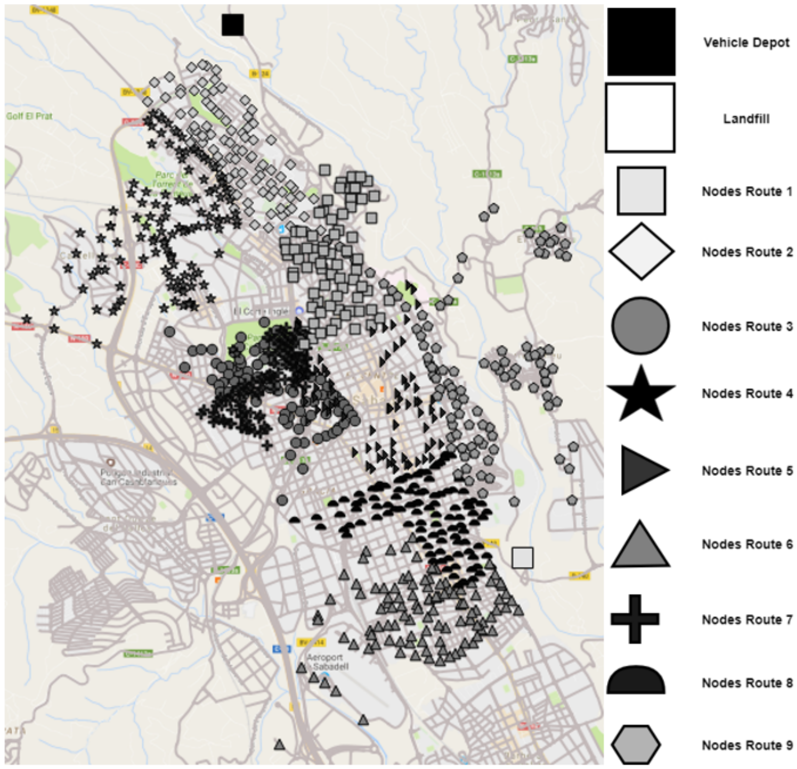

Figure 7.6: Node locations and original route assignation.

certain distance radius of the school building should be avoided in the given period if possible. According to the experience of the decision-taker, a radius of 500 m around primary schools is considered. Apart from delays in the collection process, visiting these streets during the most busy hours affects many citizens and can even be dangerous due to children exiting the primary school facilities. The influenced streets in the city center of Sabadell for which the additional constraints apply are highlighted in Figure 7.7.

7.2.3 Algorithm description

The different stages of the proposed simheuristic solving methodology for the TDWCPST are summarized in Figure 7.8. By integrating simulation into a biased randomized VNS algorithm (BR-VNS), a set of promising stochastic solutions are constructed. These solutions are then refined in a more intensive simulation procedure. Finally, the defined set of solutions undergoes a more detailed risk analysis according to different criteria.

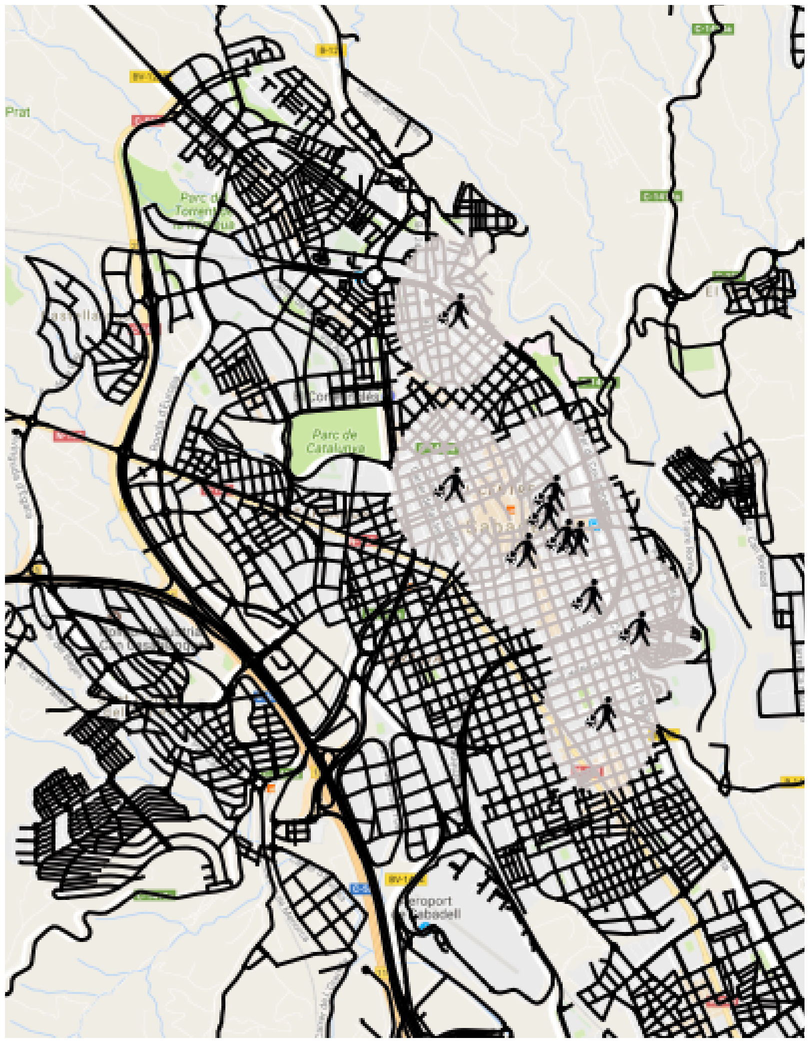

Figure 7.7: Streets to be avoided during highly occupied traffic periods.

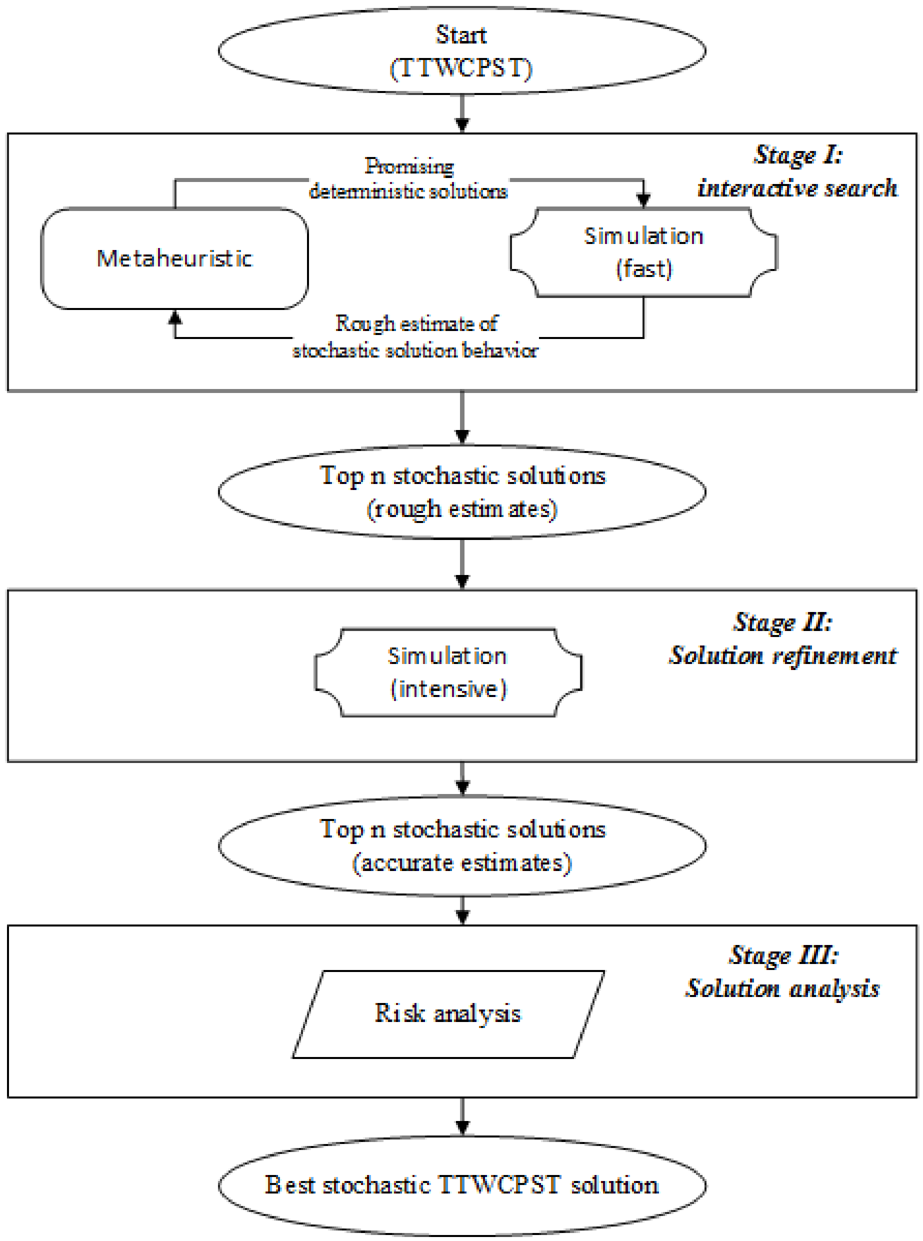

Figure 7.8: Simheuristic solving framework for the TDWCPST.

A simheuristic procedure to solve the TDWCPST is outlined in Algorithm 10. Similar to the approach described in chapter 7.1.1.1, the elaborated simheuristic starts by creating an initial WCP solution by applying the Clarke-and-Wright savings heuristic. The use of the randomized edge selection process and the adoption to the WCP is proposed at this stage. Once an initial solution is constructed and set as the current incumbent $baseSol$ and $bestSol$ solutions, an VNS procedure is started. As shaking operator a double-bridge move is applied. Hereby, a solution is partitioned into four pieces of random size, which are subsequently joint in a arbitrary order. As local search movement a 2-opt algorithm is used.

Up to this point, deterministic (expected) travel durations between the network nodes are considered. In order to account for uncertainty in input variables, MCS is applied to any promising solution found in the metaheuristic search. A TDWCP solution $newSol$ is deemed promising if its deterministic travel durations outperform those of the currently incumbent $baseSol$ or if a Simulated Annealing-like acceptance criterion is met. The travel durations between all edges of a promising solution are simulated from a log-normal probability distribution during $nSim$ simulation runs. At this stage, any other probability distribution could be applied, but the log-normal one is a “natural” choice to model non-negative random variables.

During each simulation iteration, expected travel durations tt_{sT} between any two points are defined as distribution mean of the probability function. Variance factor k defines travel duration variance levels. With $E[tt_{sT}] = tt_{sT}$ and $Var[tt_{sT}] = k \cdot tt_{sT}$, the location parameter μ_i and scale parameter σ_i defined for the probability function can be formulated as:

$$\mu_i = \ln(E[tt_{sT}]) - \frac{1}{2} \cdot \ln\left(1 + \frac{Var[tt_{sT}]}{E[tt_{sT}]^2}\right)$$
$$\sigma_i = \left|\sqrt{\ln\left(1 + \frac{Var[tt_{sT}]}{E[tt_{sT}]^2}\right)}\right|$$

As a result of time varying travel speeds, the variability in solution waste collection durations estimated after each simulation run can be expected to increase with higher variance levels. In particular, waste collection close to primary school locations is penalized by significantly reduced travel speeds during predefined time periods. After the simulation phase, the stochastic travel durations of $newSol$ are defined the average of all simulation results.

If the stochastic costs of the considered solution outperform the estimated stochastic travel durations of the incumbent $baseSol$ and/or $bestSol$, they are updated respectively. Moreover,

Algorithm 10: A simheuristic for the TDWCPST

```
Input: nodes, costMatrix, α, nSim_short, nSim_long, k
initSol ← generateBRSolution(nodes, costMatrix, α)                    // BR-CWS
baseSol ← initSol
stochDuration(baseSol) ← infinite
bestSol ← baseSol
elitSols ← ∅
while stopping criterion not reached do
    newSol ← perturbate(baseSol, costMatrix)                // perturbation stage
    newSol ← localSearch(newSol, costMatrix)                // local search stage
    delta ← detDuration(baseSol) - detDuration(newSol)
    if delta ≥ 0 then
        credit ← delta
        stochDuration(newSol) ← simulation(newSol, nSim_short, k)
        if stochDuration(newSol) ≤ stochDuration(baseSol) then
            includeInEliteSolutionSet(newSol)
            baseSol ← newSol                           // simulation driven baseSol
            if stochDuration(newSol) < stochDuration(bestSol) then
                bestSol ← newSol
            end
        end
    end
    else if -delta ≤ credit then
        credit ← 0
        stochDuration(newSol) ← simulation(newSol, nSim_short, k)
        baseSol ← newSol
    end
end
for eliteSol ∈ eliteSols do
    stochDuration(eliteSol) ← simulation(eliteSol, nSim_long, k)
end
return bestSol
```

each solution that is defined as incumbent $baseSol$ during any stage of the simheuristic procedure is included in a TDWCPST solution set $eliteSols$. After the algorithm stopping criterion is reached, solutions included in this exclusive set of elite solutions undergo a more intensive simulation phase defined by a higher number of simulation runs. This enables a more accurate estimation of the best found time-dependent WCP solutions in stochastic travel time scenarios.

7.2.4 Computational experiments and analysis of results

The proposed simheuristic solving framework is applied to the real-life Waste Collection Problem setting of Sabadell described in chapter 7.2.2. The algorithm is implemented as a Java application and tests are run on a personal computer with 4GB RAM and an Intel Pentium®processor with 2.16GHz. Necessary algorithm parameters to complete the described tests are specified as follows:

- Geometric distribution parameter α: 0.3
- $nSim_{short}$: 100
- $nSim_{long}$: 1000
- BR-VNS topping criterion per instance: 30 seconds

According to the observations of the decision-taker, the average vehicle speed in normal traffic conditions is 25 km/h. The travel speed is divided by 5 and 25 during heavy traffic and traffic jams, respectively. Average vehicle service times at each container are set to 90 seconds, while 45 minutes are necessary to empty a vehicle at the landfill. Distances between any two points are calculated with Djikstra's shortest path algorithm (Dijkstra 1959). A detailed process description of creating a realistic distance-matrix between various points using open source software is given in Appendix F.

Stochastic travel times are generated with three different variance factors $k = 1, 2.5, 10$, representing different (low/medium/high) uncertainty levels. All variance scenarios are represented in Figure 7.9, showing the travel times of edge subset s during time period T with an expected traversing time of $E[tt_{sT}] = 25$ time units. The shadowed area under each curve represents 95% of the simulated values. In the low-variance scenario ($k = 1$), 95% of actual driving times fall between 16.64 and 36.15 time units with a high density around the expected value. As the variance level is increased, the density of the simulated times for all edges decreases and a higher variability can be observed. The overall driving duration of a solution will increase as the expected travel time uncertainty increases. Moreover, the special case of $k = 0$ is equivalent to the deterministic routing case.

In order to evaluate the performance of the outlined simheuristic algorithm, its results are compared to the 9 paper waste collection routes currently completed on a daily basis in Sabadell. The comparison of the current routes and the best found solution of the BR-VNS

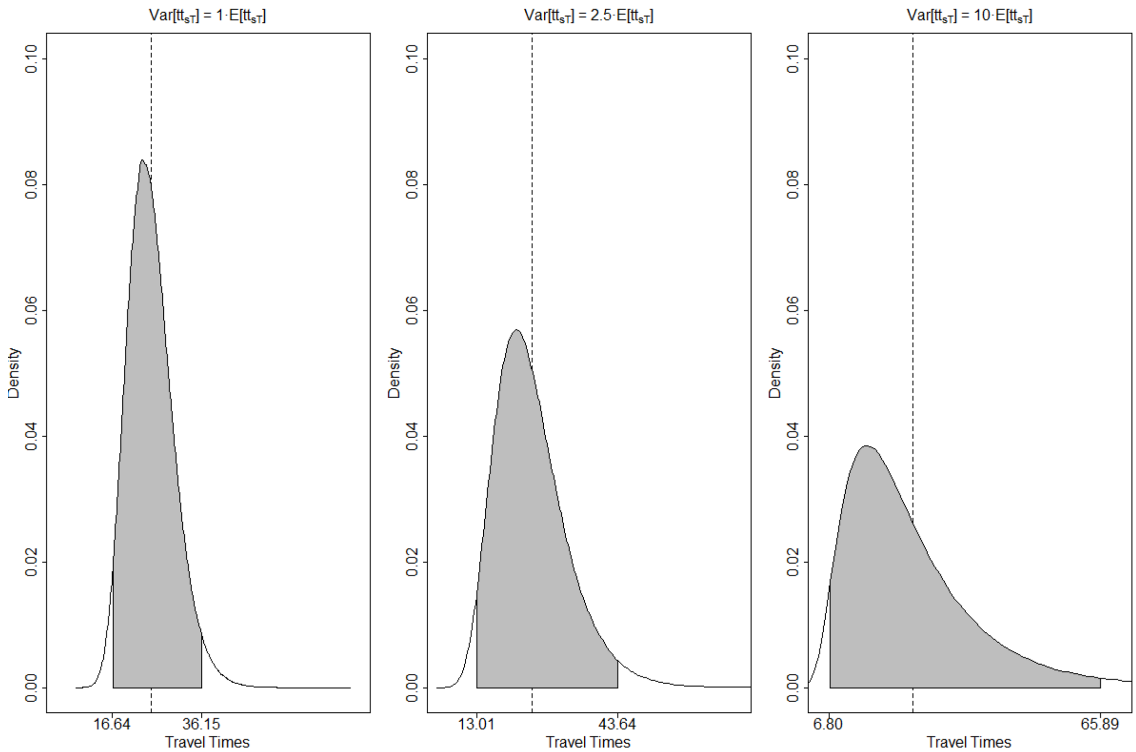

Figure 7.9: Log-Normal distribution of different variance levels around an expected travel time of 25 time units.

algorithm in different variance scenarios is listed in Tables 7.9 (deterministic case and low variance) and 7.10 (medium and high variance). Each route holds between 79-122 waste containers to be emptied. To enable a fair comparison, the current order of visiting waste containers is evaluated in accordance with the necessary algorithm parameters described before.

In all travel duration variance scenarios, the biased randomized VNS is able to significantly outperform the current waste collection routes (by over 12% on average). Moreover, the solution travel durations in different uncertainty scenarios provided by the metaheuristic show that estimated travel durations increase with higher variance levels. The best results with the simheuristic algorithm are obtained when considering all 921 waste containers in a "global" waste collection instance. In this case, new route-to-container assignments are established instead of solely focusing on reordering pre-established waste collection routes. For example, in the deterministic routing case, and using a running time of 120 seconds, the

Table 7.9: Driving durations (in minutes) of currently completed routes in comparison to best algorithm solution (deterministic case and low variance scenario)

Route	k = 0		%-Diff	k = 1		%-Diff
	Current [1]	Best [2]	[1]-[2]	Current [3]	Best [4]	[3]-[4]
1	392.5	357.3	-9.0	391.3	362.7	-7.3
2	379.9	265.0	-30.2	381.3	271.6	-28.8
3	470.8	345.5	-26.6	455.5	346.0	-24.0
4	386.4	342.3	-11.4	384.2	341.8	-11.0
5	374.3	335.1	-10.5	387.9	342.7	-11.7
6	396.2	371.4	-6.2	397.1	388.7	-2.1
7	372.8	340.4	-8.7	364.2	340.6	-6.5
8	393.9	326.7	-17.0	399.8	342.1	-14.4
9	407.9	323.0	-20.8	411.1	323.6	-21.3
Total	***3,574.5***	***3,006.7***	***-15.9***	***3,572.3***	***3,059.9***	***-14.3***

Table 7.10: Driving durations (in minutes) of currently completed routes in comparison to best algorithm solution (medium and high variance scenario)

Route	k = 2.5		%-Diff	k = 10		%-Diff
	Current [1]	Best [2]	[1]-[2]	Current [3]	Best [4]	[3]-[4]
1	391.6	363.0	-7.3	392.7	367.5	-6.4
2	381.4	281.3	-26.2	388.1	293.4	-24.4
3	457.9	349.8	-23.6	460.2	363.3	-21.0
4	383.9	342.6	-10.7	384.2	340.2	-11.4
5	389.7	342.7	-12.0	395.4	355.2	-10.2
6	397.2	386.9	-2.6	397.3	387.5	-2.5
7	362.3	337.7	-6.8	360.4	340.1	-5.6
8	398.8	344.0	-13.8	398.9	355.0	-11.0
9	410.6	329.4	-19.8	414.0	346.5	-16.3
Total	***3,573.3***	***3,077.3***	***-13.9***	***3,591.1***	***3,148.7***	***-12.3***

global solution yields an overall driving duration of 2,820.5 minutes, with only 8 necessary garbage collection routes.

Apart from focusing on solution quality dimensions — such as the the expected travel durations or the expected driving distance required to collect all waste —, the simulation phase of the simheuristic framework can be used to obtain more detailed insights into the robustness of different TDWCPSD solutions. Thus, statistical values such as the standard deviation of travel durations, the median, or the third quartile can be obtained during the simulation runs without increasing the computing effort.

Table 7.11 shows different attributes of three elite solutions of the global TDWCPSD with all garbage containers in a high variance scenario ($k = 10$). The deterministic and stochastic travel duration, driving distance, standard deviation, median, third quartile, and the number of waste collection routes of each TDWCPST solution can be seen. As highlighted in the radar chart shown in Figure 7.10, each solution outperforms the others in a different decision-taking dimension. While solution B is the most promising solution regarding deterministic travel durations, solution A shows the best results in terms of expected travel times and overall travel distance. However, the standard deviation of travel durations obtained during the long simulation run (which can be seen as a reliability indicator of a given solution) is the lowest for solution C. This solution behavior is also observed in the multiple boxplot shown in Figure 7.11. It can be clearly seen that the most promising deterministic solution B yields the highest travel duration variance, suggesting a low reliability of the constructed waste collection routes. Likewise, the median and third quartile could be considered in a closer risk analysis according to the preferences of the waste collection route planner.

Table 7.11: Analysis of different TDWCPST solutions (high variance scenario)

Solution	**Det. Duration (min)**	**Stoch. Duration (min)**	**Distance (km)**	**Stand. Dev.**	**Median**	**Third Quartile**	**# Routes**
A	2,879.61	2,936.05	264.58	31.98	2,932	2,956	8
B	2,827.49	2,938.67	278.45	64.59	2,930	2,969	9
C	2,897.58	2,952.18	280.27	26.46	2,951	2,967	8

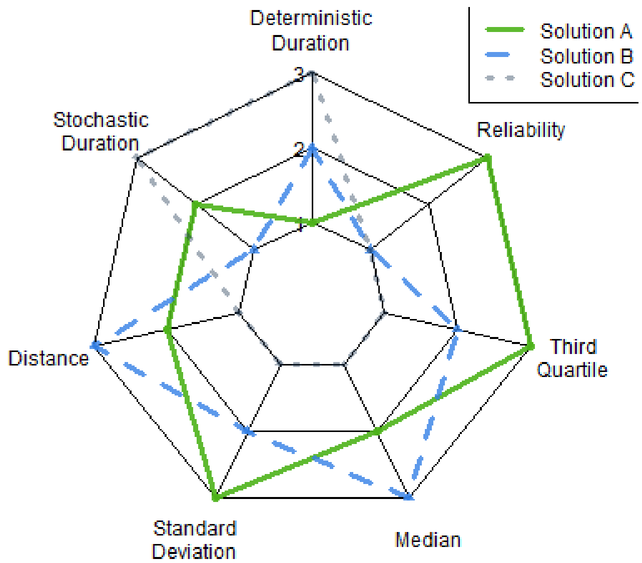

Figure 7.10: Ranking of TDWCPST solutions according to different quality dimensions.

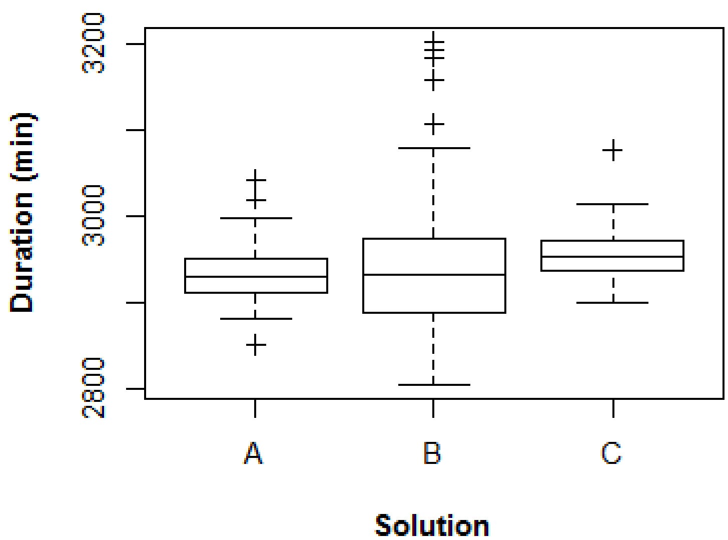

Figure 7.11: Comparison of simulation results for different TDWCPST solutions.

7.3 Supporting multi-depot and stochastic waste collection management in clustered urban areas

The following paragraphs outline a simheuristic framework based on Biased Randomization (BR), Variable Neighborhood Search (VNS) and Monte Carlo simulation (MCS) to address the multi-depot WCP with stochastic demands (MDWCPSD). This approach supports the analysis of possible benefits of applying collaboration concepts on an operational level through shared information and facilities between different waste management service providers in clustered urban areas.

7.3.1 Algorithm description

In contrast to a deterministic WCP setting in which input variables are considered to be known during the route planning phase, actual garbage loads to collect are only revealed once a collection vehicle reaches a pick up point in reality. Given a WCPSD, the first step of the applied simheuristic procedure is to transform the stochastic problem setting into its deterministic counterpart. Hereby, the expected waste levels of each container on a waste collection route are used as deterministic input variables. This deterministic WCP is then solved using an efficient optimization approach. Therefore, a randomized version of the well-known Clarke-and-Wright savings (CWS) heuristic is applied. By adapting this multi-start routing algorithm to the WCP with the algorithm adoptions described in chapter 7.1.1.1, a number of predefined (a-priori) solutions are constructed during a predefined stopping criterion, as shown in Algorithm 11.

After the generation of multiple solutions, a set of d deterministic solutions is tested for its behavior in a stochastic environment by repeatedly sampling random waste levels using MCS. In order to keep computational efforts reasonable, not all deterministic solutions are tested at this point, but only the most 'promising' deterministic solutions are sent to the simulation stage. Hereby, the waste levels of each container to be served are modeled using a log-normal distribution with waste level variance Var and the expected waste level at each container as mean. During $nIterSim$ simulation runs, a tested predefined solution is completed considering the uncertainty of pick-up amounts by only revealing the actual waste level at a container once a collection vehicle reaches it. Hereby, the order of containers to visit is not changed. However, limited vehicle capacities will lead to route failures when collected garbage exceeds the initially planned amount, making additional landfill trips necessary. The

Algorithm 11: Solution generation for the MDWCP

```
S ← ∅                                          // set of elite solutions
while stopping criteria not reached do
    sol ← solveBiasedRandomizedCWS
    if isEliteSolution(sold, d)                // save d best deterministic sols
     then
        S.add(sol)
    end
end
i ← 1
while i ≤ d                                    // Run short simulation on promising sol
 do
    evaluateReliability(S_i, Var, nIterShort)
    i ← i + 1
end
S ← resortSolutions(S)
return S
```

proposed solving framework penalizes route failures with an additional round trip to the closest landfill, before the planned route is continued.

By summing up total route failure costs in all simulation runs and dividing them by $nIterSim$, an unbiased estimation of expected route failures can be obtained. At this stage, it often happens that the most promising deterministic WCP solutions turn out to be less competitive in a stochastic environment due to high expected additional routing costs. Beside expected route failure costs as quality indicator of the predefined route under uncertainty, the described procedure allows for estimating the solution reliability by considering the proportion of routes in which a route failure occurs during the simulation runs. Finally, the solutions are re-ranked according to the total of routing and expected route failure costs. If necessary at this point, a longer simulation run can be conducted with the most promising stochastic solutions to get more reliable results of a number of stochastic elite solutions.

In order to consider multiple depots in the planning of waste collection routes with stochastic waste levels, Biased Randomization and VNS are integrated (BR-VNS) at different stages of the simulation-optimization approach, as shown in Algorithm 12. Considering a WCP with multiple depots, the first step in the solution process is to solve the node-depot assignment problem to define which waste containers are emptied from which depot. For this

Algorithm 12: Simheuristic procedure for the MDWCP

```
S ← ∅                                              // set of elite solutions
D ← ∅                                   // set of depot-node allocation maps
D ← generateInitialMaps(nMaps)                  // Generate node-depot maps
S ← generateEliteSolutions(D)              // Run simheuristic on each map
while stopping criteria not reached do
    D* ←perturbate(D)                              // perturbate elite maps
    S* ←generateEliteSolutions(D*)
    if acceptNewSolution(S, S*) then
        D ← D*                                        // Update current map
        S ← S*                                   // Update elite solutions
    end
end
i ← 1
while i ≤ d                   // Run extensive simulation on promising sol
 do
    evaluateReliability(S_i, Var, nIterShort)
    i ← i + 1
end
S ← resortSolutions(S)
return S
```

purpose, a priority list of containers for each depot is constructed according to a distance-based criterion. After calculating the distance of each waste container to each depot $k \in V_d$, a priority list based on the marginal savings μ_i^k of emptying container i from depot k compared to serving it from the best alternative depot k^*, such that $\mu_i^k = c_i^{k^*} - c_i^k$ is built. Next, the nodes are randomly assigned to the depots according to a round-robin criterion. Hereby, the depots iteratively 'choose' an (unassigned) container to serve.

The process of assigning nodes to a depot is randomized but using a skewed distribution instead of a uniform one. After sorting the priority list of containers, a skewed geometric distribution is applied in such a way that containers with a higher position in the priority list are more likely to be selected by the respected depot (thus making the randomized selection process 'biased' or 'oriented'). The exact probabilities of each container to be included in a specific node-depot collection map are defined through a distribution parameter p $(0 < p < 1)$. This randomized process allows for constructing of $nMaps$ different node-depot allocation maps. The competitiveness of each map is evaluated by solving the deterministic WCP setting for the depot and its assigned nodes, before the WCP costs for each depot are summed up to obtain a preliminary MDWCP solution. After all maps have been constructed, the d most promising node-depot allocations are defined.

With each promising solution, a short simulation run with $nIterShort$ iterations is started next to evaluate the performance of the pre-defined routing plan in a stochastic environment. Based on the deterministic routing and route failure costs, a stochastic initial solution is defined and used as initial upper limit ($currentBest$) in the VNS process started in the following. The node-depot allocation maps are hereby perturbed by applying a destroy-and-repair method to the current best solution during a time-based termination criteria ($maxTimeVNS$). During each perturbation, $p*$ percent of containers are exchanged between different node-depot allocations before a new short simulation is performed to assess the quality of the newly constructed map and compare it to the current best.

Whenever a new best solution considering total costs is found, the new solution is listed as promising (in $promisingSolsStoch$) and replaces the current best. In order to escape local minima in the solution search, an acceptance criterion is implemented allowing a solution worsening if the last iteration from x to x^* (such that $f(x^*) < f(x)$) was an improvement and the difference between the current best and new solution is not greater than the latest improvement. Once the VNS procedure is finished, the m best solutions in $promisingSolsStoch$ undergo a long simulation run to define the expected route failure costs and the solution reliabilities more closely. Finally, a list of elite MDWCPSD with the respective total costs and solution reliabilities are returned by the process.

7.3.2 Computational experiments and analysis of results

In order to test the proposed solving approach, the benchmarks provided by Kim et al. (2006) are adapted. The original set of instances considers different-sized (102–2100 nodes) deterministic WCPs with a single depot, multiple landfills and capacitated vehicles. In order to make them suitable for the MDWCPSD, the deterministic load levels at each container are used as expected waste levels and the mean of the log-normal distribution from which waste levels are modeled during the assignment problem is redundant in the non-collaborative scenario without HC, it is not possible to consider different container allocations and their respective routing costs. The algorithm is implemented as Java application on a personal computer with an Intel BYT-M 4CoreTM processor with 2.66 GHz and 4 GB RAM, using the following parameters:

- $nMaps$: 100 (initial node-depot assignment maps created)
- Var: 0.05 (waste level variance)
- d: 5 (promising deterministic solutions)
- m: 5 (promising stochastic solutions)
- $nIterSimShort$: 500 iterations
- $IterSimLong$: 5,000 iterations
- $detSolTime$: 5 seconds
- $maxTimeVNS$: 300 seconds
- p^* 0.3% (nodes exchanged during perturbation)
- p: 0.4 (distribution parameter for Biased Randomization)
- $maxDemand$: 60%

In Table 7.12, the best found solutions for the collaborative and non-collaborative scenario of each instance (and one row with the total over all tested problem settings) are listed. Column (1) shows the number of used vehicles. The opened depots are listed in column (2), before columns (3)–(5) show the fixed costs, variable (route-failure) costs and total costs, respectively. Furthermore, the percentage difference of total costs for each scenario is outlined.

The obtained results concerning total costs, used vehicles and opened depots for the collaborative scenario (i.e. the MDWCPSD solution) and the non-collaborative counterpart are outlined in Figure 7.12. Concerning the total expected costs, the routing costs of each instance can be improved, with an average gap of -12% over all instances. Next to possible route savings, HC leads to fewer used vehicles (91 compared to 105 in the non-collaborative scenario over all instances) and fewer opened depots (41–55). While the objective function of this thesis application was to reduce total routing costs, the number of used vehicles and opened depots can also be an important driver for HC in practice, as municipalities need to consider acquisition and maintenance costs for collection vehicles. Moreover, opening costs and running expenses of vehicle depots should not be neglected. Looking at the results more closely, the large differences on the positive effects of HC concerning total costs can be explained with the topology, i.e. the geographical distribution of the containers with respect to

Table 7.12: Numeric comparison of collaborative and non-collaborative waste management

Instance	Scenario	Vehicles (1)	Depots (2)	Fixed Costs (3)	Variable Costs (4)	Total Costs (5)
Kim102	Collaborative	4	3	154.46	0	154.46
	Non-Collaborative	3	3	190.99	0.28	191.27
	%-Difference					-19.25
Kim277	Collaborative	2	2	495.47	17.59	513.06
	Non-Collaborative	2	2	503.52	12.54	516.06
	%-Difference					-0.58
Kim335	Collaborative	6	3	194.99	1.38	196.37
	Non-Collaborative	8	5	304.88	1.77	306.65
	%-Difference					-35.96
Kim444	Collaborative	11	2	74.61	0.85	75.45
	Non-Collaborative	11	2	79	0.91	79.91
	%-Difference					-5.91
Kim804	Collaborative	9	9	925.02	5.57	930.59
	Non-Collaborative	20	20	1579.69	3.66	1583.35
	%-Difference					-41.23
Kim1051	Collaborative	17	2	2133.22	55.36	2188.58
	Non-Collaborative	18	3	226.68	46.74	2273.42
	%-Difference					-3.73
Kim1351	Collaborative	9	4	902	12.8	914.8
	Non-Collaborative	9	4	909.28	27.61	936.89
	%-Difference					-2.36
Kim1599	Collaborative	12	3	1098.3	21.57	1119.87
	Non-Collaborative	13	3	1307.04	19.53	1326.57
	%-Difference					-15.58153735
Kim1932	Collaborative	9	5	1105.75	14.28	1120.03
	Non-Collaborative	9	5	1119.67	17.21	1136.88
	%-Difference					-1.48
Kim2100	Collaborative	12	8	1560.26	9	1569.26
	Non-Collaborative	12	8	1573.71	10.08	1583.79
	%-Difference					-0.92
Total	**Collaborative**	**91**	**41**	**8644.08**	**138.4**	**8782.47**
	Non-Collaborative	**105**	**55**	**9794.46**	**140.33**	**9934.79**
	%-Difference					**-11.6**

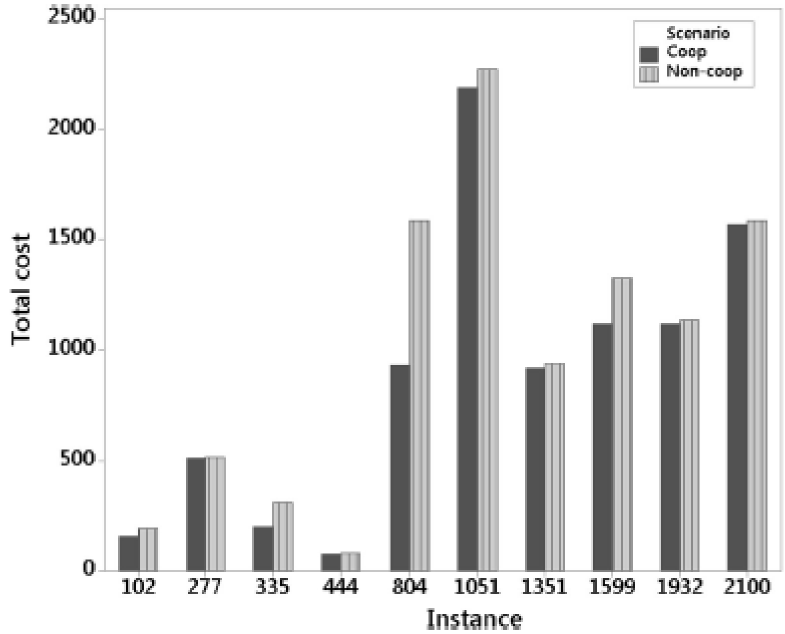

Figure 7.12: Comparison of total costs between collaborative and non-collaborative waste management scenarios.

the potential depots. Obviously, instances in which only scattered depot–node allocation maps can be established tend to yield significantly improved results in collaborative scenarios.

Chapter 8

Solving stochastic integrated distribution network design problems

The application of simheuristics to problem settings related to municipal waste management in chapter 7 have shown the potentials of the simulation-optimization methodology. While that chapter emphasized the use of simheuristic frameworks in large-scaled operational problem settings related to vehicle routing and customer clustering, this section focuses on the collaborative design of efficient distribution networks. In particular, the complex integration of several supply chain decision-taking problems on operational, tactical, and strategic levels is discussed. The highlights of this chapter include:

- the elaboration of a SimVNS simheuristic to solve the multi-period Inventory Routing Problem (IRP) with stochastic demands. Hereby, route planning and inventory replenishment decisions are centralized to reduce overall supply chain costs. The algorithm's competitiveness and performance for complex problem instances is shown. Moreover, the additional managerial insights through the simheuristic procedure are analyzed (Gruler et al. 2018*b*,*c*).

- the development of a simulation-optimization approach for the two-echelon Location Routing Problem (2E-LRP) arising in the creation of urban consolidation centers (UCCs). Computational experiments are completed on real-life data involving the location of multiple UCCs in a fast-moving consumer goods supply chain with over 100 customers in the Greek capital Athens. In comparison to a non-collaborative city logistics concepts, the use of UCCs suggests overall freight transportations savings of over 30%. Moreover, computational results suggest higher solution robustness regarding input uncertainty with an increasing number of open satellite locations (Gruler et al. 2017*b*).[1]

In comparison to the VRP with time windows and the MDVRP addressed in the previous chapter, the central problem settings of this chapter are shaped by higher complexity through increased decision-taking integration (as outlined in Figure 8.1). While the complexity of the multi-period IRP and the LRP are comparable from an algorithmic point of view, the latter optimization problem involves a higher degree of decision integration, as it combines operational routing with strategical facility location arrangement.

8.1 A Variable Neighborhood Search simheuristic for the multi-period Inventory Routing Problem with stochastic demands

The following sub-sections describe the simheuristic solving approach for the multi-period IRP with stochastic demands. Subsequently, a range of computational experiments is completed on benchmarks found in the literature to show the performance and applicability of the elaborated algorithm.

8.1.1 Algorithm description

A possible solution to the problem described in chapter 6.2.1 has the form of a matrix with $|V^*|$ rows and $|P|$ columns, where element (i,p) in this matrix will represent the refill policy associated with RC i at period p ($\forall i \in V^*$, $\forall p \in P$). The proposed approach to solve the stochastic multi-period IRP consists of three different stages:

[1]The work of Gruler et al. (2017*b*) was completed in cooperation with Prof. Dr. Angel A. Juan from the Universitat Oberta de Catalunya in Barcelona and Astrid Klueter (full-time PhD-student) and Prof. Dr. Markus Rabe from the Technical University in Dortmund. The findings were presented at the ASIM Dedicated Conference on Simulation in Production and Logistics 2017 in Kassel (Germany) by Astrid Klueter. The PhD-candidate strongly contributed to this work through the development of the simheuristic solving algorithm, the implementation of the simulation-optimization procedure in Java, and the analysis of obtained results. Astrid Klueter was mainly responsible for the completed literature review and provided the case-study data, which was obtained within the U-Turn project (U-Turn 2018). Prof. Dr. Juan and Prof. Dr. Rabe contributed through their expertise and guidance.

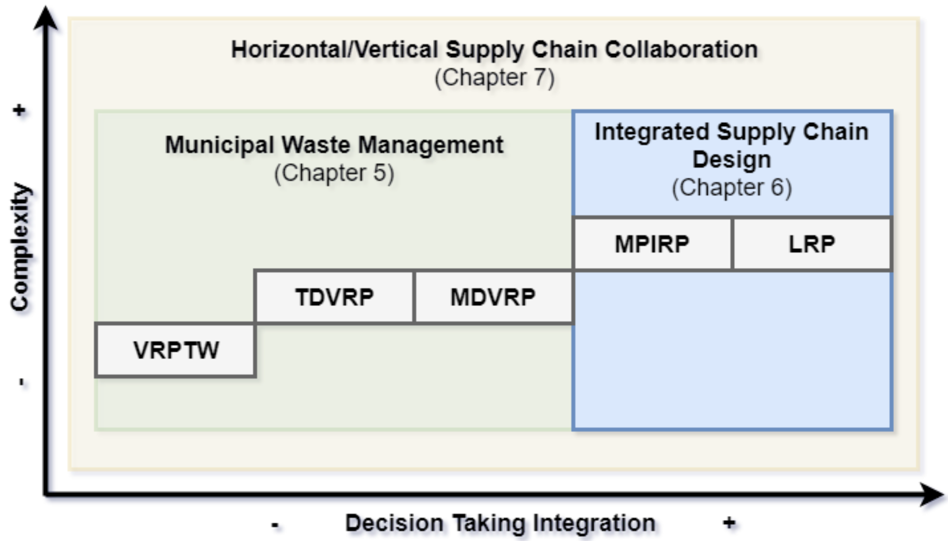

Figure 8.1: Complexity and decision-taking integration of central problem settings addressed in chapter 8.

1 Firstly, a constructive heuristic is employed to generate an initial solution. This initial solution will be a 'homogeneous' matrix containing the same value in all its cells, i.e.: it will propose a unique refill policy that will be systematically applied to all the RCs across the different periods. This strategy will generate a particular expected inventory cost (sum of all expected inventory costs for each RC-period combination) as well as a specific expected routing cost (sum of all expected routing costs for each period). Notice that both the inventory cost associated with each RC at the end of period p as well as the routing cost at period $p+1$ will depend on the precise values of the random demands of each RC at period p (since these values will determine the inventory levels associated with each RC at the end of period p).

2 Secondly, the constructive heuristic is integrated inside the destruction-construction phase of a VNS framework and then combined with Monte Carlo simulation in order to iteratively enhance the initial solution. This procedure is based on the construction of a number of different solution neighborhoods and the subsequent local search phase that explores a neighborhood of the current solution. MCS is employed here to generate realizations of the random demands and then obtain an estimate of both expected inventory and routing costs.

3 Finally, a refinement stage using a higher number of simulation runs is applied to the most 'promising' or 'elite' solutions obtained in the previous stage in order to obtain a more accurate estimation of the expected cost and select the final solution matrix.

With the aim of generating an initial solution, a constructive heuristic has been developed. The idea behind this heuristic is to assign a common policy to each RC and period. The policy selected will be the one providing the lowest expected total cost, which will include both expected inventory and routing costs. The heuristic is split into two phases. During the first one, different refill policies are tested, and the associated quantities to serve are estimated together with the expected inventory costs. During the second phase, routing costs are computed for each of these refill policies. In this phase, the quantities to serve generated in the previous phase are used. Finally, the policy providing the lowest total expected cost is implemented at every RC and period.

Algorithm 13 depicts the constructive heuristic in more detail. The input parameters are: the set of RCs, the set of time periods, the initial inventory levels, the maximum storage capacity of each RC, the random demand of each RC at each time period, the set of refill policies, and the maximum number of simulation runs that must be executed. In this thesis, the possible refill policies considered are:

- No stock refill, i.e., the RC can only count on its current stock level to satisfy the demand of its customers during the next period.
- Refill up to one quarter of total inventory capacity (1/4-refill), i.e., if necessary, additional product will be served from the depot to reach that level.
- Refill up to half of total inventory capacity (1/2-refill).
- Refill up to three quarters of total inventory capacity (3/4-refill).
- Refill up to full capacity (full-refill).

Thus, for each policy and RC, a short number of simulation runs is executed (e.g., 30 to 100 runs) to obtain initial estimates. During each of these runs, the quantity to be served is obtained for each RC-period combination (line 8). This quantity is used in the second phase of the heuristic, and it is computed considering the maximum storage capacity of the RC and its initial inventory level. For each RC and period, the specific value of the random aggregated demand is generated using random sampling (line 9). Hence, it is possible to compute the

Algorithm 13: Generate initial IRP solution

Inputs:
$V = \{0, 1, \ldots, |V|\}$: Set of depot (0) and RCs (V^*)
$P = \{1, 2, \ldots, |P|\}$: Set of time periods
L^0_{i1}: Initial inventory level of RC i at period 1
l^+_i: Maximum storage capacity of RC i
D_{ip}: Customers' aggregated demand at RC i during period p
T: Refill policies as a % of l^+_i (e.g., 0%, 25%, 50%, 75%, 100%)
$maxRuns$: Maximum number of runs in the Monte Carlo simulation
% Phase 1: Compute avg. multi-period inventory costs for each center-policy combination
foreach *refill policy* $t \in T$ **do**
  $expInvCost[t] \leftarrow 0$ % expected inventory cost associated with policy t
end
foreach *RC* $i \in V^*$ **do**
  $accumInvCost \leftarrow 0$
  $iter \leftarrow 0$
  while $iter < maxRuns$ **do**
    foreach *period* $p \in P$ **do**
      $q_{ip}[t][iter] \leftarrow \max\{t \cdot l^+_i - L^0_{ip}, 0\}$
      $d_{ip} \leftarrow$ generate random observation of D_{ip} % Monte Carlo simulation
      $L^0_{i(p+1)} \leftarrow \max\{L^0_{ip} + q_{ip}[t][iter] - d_{ip}, 0\}$
      $invCost \leftarrow computeInventoryCost(t, L^0_{i(p+1)})$
      $accumInvCost \leftarrow accumInvCost + invCost$
      $iter \leftarrow iter + 1$
    end
    $avgInvCostRC \leftarrow accumInvCost/maxRuns$ % avg. inventory cost of RC i under policy t
    $expInvCost[t] \leftarrow expInvCost[t] + avgInvCostRC$
  end
end
% Phase 2: Compute avg. multi-period routing cost and total cost for each policy
$initSol \leftarrow emptySol$
$cost(initSol) \leftarrow \infty$
foreach *refill policy* t *in* T **do**
  $accumRoutingCost \leftarrow 0$
  $iter \leftarrow 0$
  while $iter < maxRuns$ **do**
    foreach *period* $p \in P$ **do**
      $routingCost \leftarrow estimateRoutingCost(q_{1p}[t][iter], \ldots, q_{|V|p}[t][iter])$ % use savings heuristic
      $accumRoutingCost \leftarrow accumRoutingCost + routingCost$
    end
    $iter \leftarrow iter + 1$
  end
  $expRoutingCost \leftarrow accumRoutingCost/maxRuns$
  $totalCost \leftarrow expInvCost[t] + expRoutingCost$
  if $totalCost < cost(initSol)$ **then**
    $initSol \leftarrow setAllRefillDecisionsToValue(t)$
    $cost(initSol) \leftarrow totalCost$
  end
end
return $initSol$

inventory level at the end of the current period (line 10), which will be the initial inventory level for the next period. This is computed as the sum of the initial inventory level and the quantity served minus the aggregated customer demand. If a stock-out occurs, a penalty cost is applied and the final inventory level is set to 0 (it can never be negative at the beginning of a new period). The system evolves considering the dependencies between the realization of the demands at one period and the inventory levels at the beginning of the next one.

Finally, the inventory cost is computed (line 11) for each RC and policy. As pointed out already, if a stock-out occurs, the cost of a round trip to the depot is charged as part of the inventory cost. Otherwise, the inventory cost is obtained as the number of units in stock multiplied by a λ parameter. In the computational experiments this parameter is set to 0.25, as suggested by other authors (Juan et al. 2014*c*). This process (lines 6-13) is repeated until the total number of simulation runs has been reached. Inventory costs are accumulated in each run (line 12), and then average inventory costs are computed for each RC (line 14). The resulting value is added to the total expected inventory cost associated with the current policy (line 15).

At the end of this first phase, the expected inventory costs for each considered replenishment policy are obtained. Also, the computed quantities to serve, for each RC and period, are stored for each simulation run. These quantities are used in the second phase to estimate the expected routing costs associated with each policy. Thus, for each series of delivery quantities the Clarke-and-Wright savings heuristic is employed to estimate the associated routing cost (line 23). Finally, the expected routing cost is computed (line 26). At the end of this phase, the policy involving the lowest expected total cost (inventory plus routing) is chosen.

During the second stage of the simheuristic methodology, the classical descendant VNS algorithm as described in chapter 2.2.1 is applied. Algorithm 14 describes the process. In the first phase the VNS keeps a given number of elite solutions consisting of the best solutions found in trajectory. It starts by assigning the initial solution generated by Algorithm 13 to the current base solution $baseSol$ and adding it into a an empty pool of elite solutions $eliteSols$. Then, it continues with the main VNS loop, which is applied until a predefined stopping criteria is reached. Inside this loop, the VNS constructs k-neighborhoods by a shaking operator (line 6), in order to allow the movement through the neighborhoods.

The shaking operator works as follows. The number of policies to be modified from the original policy matrix is given by the value k. These policies are then reset (destruction process) and re-defined (re-construction process) by using the constructive heuristic designed to obtain the initial solution (the only difference is that now it only affects to a subset of elements in the policy matrix). Then it performs (line 7) the subsequent local search procedure to get a local minimum within the current solution neighborhood. This local search consists in selecting one policy matrix element at random and changing the associated policy for the one providing the best result. The process is iteratively repeated while new improvements in total expected costs are achieved. Each time a local minimum is generated, it is included into the set of elite solutions $eliteSol$ if the number of solutions has not reached its size (lines 8-9) or it is better than the worst elite solution (lines 11-12). As in classical VNS, if the local minimum is better than the base solution it is the new base solution and the value of k is set again to 1 (lines 13-15). Otherwise, this value is increased by 1 (line 17) until the maximum number k_{max}.

The aim of this stage is to refine the elite solutions achieved by the VNS algorithm (Algorithm 14, lines 18-22). In order to achieve this goal, the constructive heuristic is applied to each of these solutions using a larger number of simulations ($maxLongRuns$). Finally, the solution exhibiting the minimum total expected cost is returned in form of a matrix including the replenishment policy for each RC-period combination.

8.1.2 Computational experiments and analysis of results

A set of computational experiments has been carried out to illustrate the utility of the simheuristic approach for solving the multi-period IRP with stochastic demands. The set of 27 VRP instances proposed by Augerat et al. (1998) and adapted for the IRP by Juan et al. (2014*c*) are used as a testbed. These instances contain between 27 and 80 RC nodes, a single central depot, and a fleet of 5-10 homogeneous vehicles. The algorithm is implemented as a Java application and executed with the following parameter specifications:

- Inventory holding cost: $\lambda = 0.25$.
- Algorithm stopping criteria: 100 seconds × number of considered periods.
- # Simulation runs in Phase 1: 30.
- # Simulation runs in the Refinement phase: 1000.
- Maximum value for the shaking operator k: 40%.

The aggregated customer demands are assumed to follow a log-normal probability distribution with the same average values as the ones proposed in the original instances. Moreover,

Algorithm 14: SimVNS for the periodic IRP

Inputs:
$V = \{0, 1, \ldots, |V|\}$: Set of depot (0) and RCs (V^*)
$P = \{1, 2, \ldots, |P|\}$: Set of time periods
maxRuns: Maximum number of simulation runs in the VNS phase
maxLongRuns: Maximum number of runs in the refinement phase
k_{max}: Maximum percentage of policies to reset (defines the number of neighborhoods)
eliteSetSize: Number of best solutions for the second phase *initSol*: initial solution

```
% Phase 1: VNS with Monte Carlo simulation
baseSol ← generate initial solution using Algorithm 1
eliteSols ← {baseSol}
while stopping criteria not met do
    k ← 1
    repeat
        newSol ← shaking(k, maxRuns, baseSol)
        newSol ← localSearch(newSol)
        if number of sols in eliteSols < eliteSetSize then
            eliteSol ← add(eliteSol, newSol)
        end
        else
            if cost(newSol) < cost(worstSol(eliteSols)) then
                eliteSols ← update(eliteSols, newSol)
            end
        end
        if cost(newSol) < cost(baseSol) then
            baseSol ← newSol
            k ← 1
        end
        else
            k ← k + 1
        end
    until k > k_max
end
% Phase 2: Refinement of best solutions
bestSol ← baseSol
for each sol ∈ eliteSols do
    sol ← longSimulation(sol, maxLongRuns)
    if cost(sol) < cost(bestSol) then
        bestSol ← sol
    end
end
return bestSol
```

following Juan et al. (2014*c*) three different variance levels are considered: low (factor = 0.25), medium (factor = 0.50), and large (factor = 0.75). As the main novelty with respect to previous works, three different planning horizons are analyzed: 3, 5, and 7 time periods. The obtained results are reported in Tables 8.1 to 8.3. The number of retail centers n and vehicles k in each problem setting are reflected in the instance name. For each considered planning horizon and demand variance level, the results for a single period planning approach (i.e., planning one period at a time) and the multi-period framework discussed in this thesis are outlined. In contrast to the holistic multi-period framework put forward in this work, the single period approach does not consider future periods by simply minimizing total costs for a single period before updating the initial stock levels for subsequent periods. While this typically leads to low stock levels at the end of each single period, it neglects the increasing transportation costs in subsequent planning periods, leading to significantly higher total costs in comparison to a multi-period planning approach.

The average total costs over all instances for each variance level and planning horizon of the holistic multi-period planning framework can be seen in Figure 8.2. Cumulated routing and inventory costs are depicted for the initial solution –in which the same replenishment policy is applied at all retail centers in each individual period– and our best solution (OBS) found by the simheuristic for the multi-period IRP. In both approaches increasing costs can be observed with higher levels of demand-uncertainty, which can be explained with higher inventory (holding or stock-out) costs.

Furthermore, it can be seen that the improved inventory decision provided by the algorithm decreases the average total costs in all cases. The same holds for the distribution of the average percentage improvement of the initial solution with the best algorithm solution for the tested benchmark set, as shown in Figure 8.3. The output in form of an individual replenishment policy matrix across all time periods for each RC reaches an average improvement of over 3%. Finally, Figure 8.4 shows the expected routing- and inventory costs for different replenishment policies and variance levels. For each variance level, higher inventory replenishment levels lead to lower expected inventory (stock-out and holding) costs. At the same time, higher replenishment levels lead to an increased proportion of routing costs in all cases.

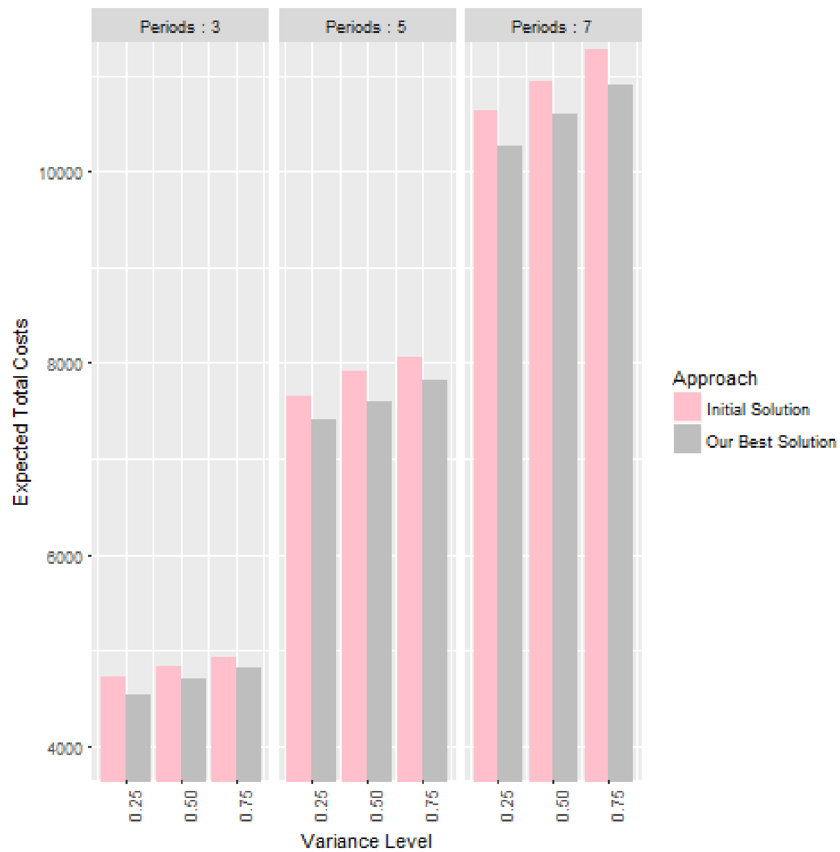

Figure 8.2: Expected total costs over all instances for different variance levels and planning horizons.

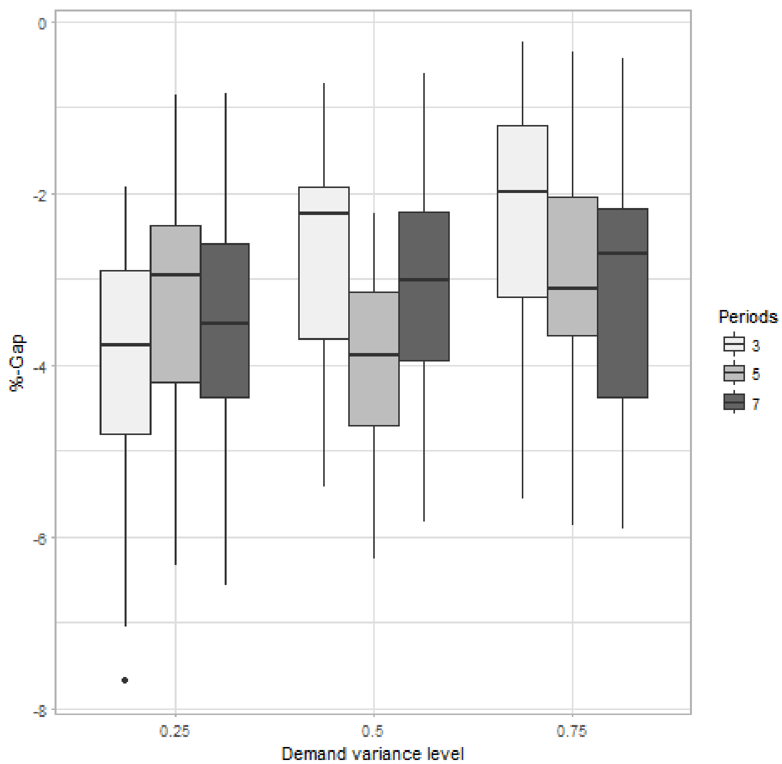

Figure 8.3: Boxplot of %-gaps between initial- and best found solution for different planing horizons and demand variance levels.

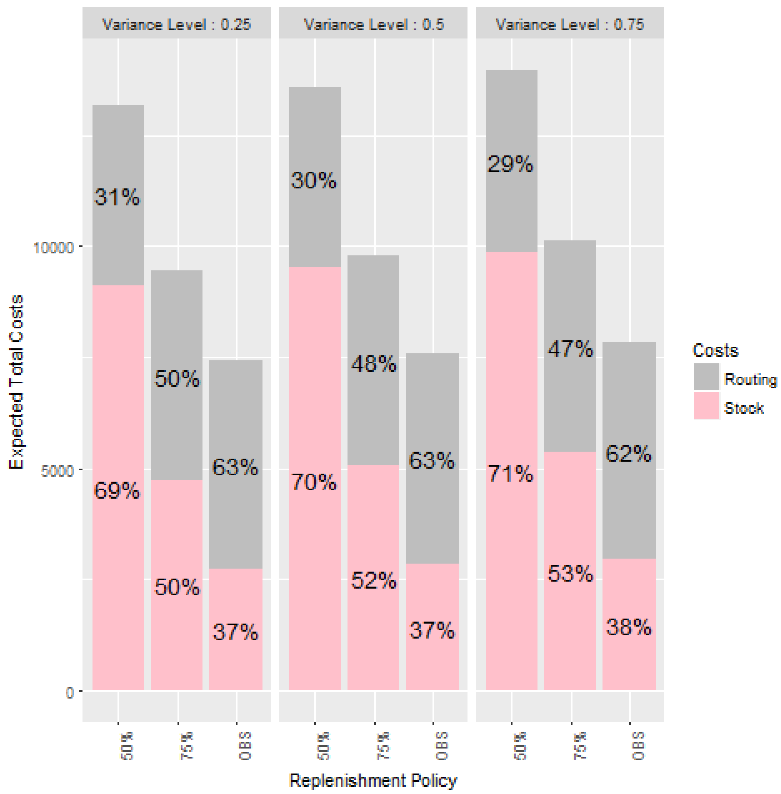

Figure 8.4: Expected routing and inventory costs for different replenishment policies and variance levels (5 period planning horizon).

Table 8.1: Comparison of best found solution to single-period approach and initial solution (*Variance = 0.25*).

	Periods : 3					Periods : 5					Periods : 7				
	Single Period (1)	**Multi Period InitSol (2)**	**Multi Period OBS (3)**	**%-Gap (1)-(3)**	**%-Gap (2)-(3)**	**Single Period (4)**	**Multi Period InitSol (5)**	**Multi Period OBS (6)**	**%-Gap (4)-(6)**	**%-Gap (5)-(6)**	**Single Period (7)**	**Multi Period InitSol (8)**	**Multi Period OBS (9)**	**%-Gap (7)-(9)**	**%-Gap (8)-(9)**
A-n32-k5	3968,9	3715,6	3615,1	-8,9	-2,7	6563,1	5872,4	5807,2	-11,5	-1,1	9523,5	8452,6	8069,6	-15,3	-4,5
A-n33-k5	3308,5	3213,5	2966,6	-10,3	-7,7	5573,8	5143,5	4922,7	-11,7	-4,3	8111,7	7217,8	6901,5	-14,9	-4,4
A-n33-k6	3576,5	3349,8	3184,5	-11,0	-4,9	5665,0	5493,7	5207,6	-8,1	-5,2	8111,7	7593,9	7174,4	-11,6	-5,5
A-n37-k5	3059,4	3045,1	2951,2	-3,5	-3,1	5163,6	5010,3	4929,7	-4,5	-1,6	7354,5	7156,7	6867,0	-6,6	-4,0
A-n38-k5	3724,5	3548,0	3399,3	-8,7	-4,2	6287,3	5814,4	5659,7	-10,0	-2,7	8943,4	8216,1	7946,9	-11,1	-3,3
A-n39-k6	4124,9	3852,0	3627,9	-12,0	-5,8	6701,6	6262,3	6004,1	-10,4	-4,1	9421,2	8620,6	8358,1	-11,3	-3,0
A-n45-k6	4694,5	4206,8	4114,3	-12,4	-2,2	7691,9	6935,3	6729,9	-12,5	-3,0	10637,6	9408,4	9329,8	-12,3	-0,8
A-n45-k7	5876,1	5452,9	5251,2	-10,6	-3,7	9665,6	8719,5	8531,7	-11,7	-2,2	13435,4	11968,5	11713,7	-12,8	-2,1
A-n55-k9	5730,4	5244,8	4970,5	-13,3	-5,2	9632,4	8383,7	8194,6	-14,9	-2,3	13134,4	11756,9	11278,7	-14,1	-4,1
A-n60-k9	7102,5	6325,8	6154,8	-13,3	-2,7	11864,4	10262,7	10174,6	-14,2	-0,9	16237,1	14300,9	13855,0	-14,7	-3,1
A-n61-k9	5245,1	4878,1	4621,9	-11,9	-5,3	8776,0	7954,4	7705,5	-12,2	-3,1	12302,1	11026,5	10701,3	-13,0	-2,9
A-n63-k9	8850,0	7913,2	7668,7	-13,3	-3,1	14579,3	12810,8	12479,3	-14,4	-2,6	19657,6	17629,7	17008,7	-13,5	-3,5
A-n65-k9	6388,9	5658,7	5549,5	-13,1	-1,9	10453,7	9304,1	9050,5	-13,4	-2,7	14757,2	12895,0	12581,8	-14,7	-2,4
A-n80-k10	9673,5	8716,3	8322,2	-14,0	-4,5	15563,4	13717,0	13463,4	-13,5	-1,8	19862,5	19268,0	18505,7	-6,8	-4,0
B-n31-k5	3447,5	3344,8	3108,5	-9,8	-7,1	5826,8	5442,8	5098,0	-12,5	-6,3	8164,6	7608,2	7121,1	-12,8	-6,4
B-n35-k5	4766,8	4554,3	4298,3	-9,8	-5,6	7890,5	7361,9	6987,0	-11,5	-5,1	11080,3	9927,0	9801,1	-11,5	-1,3
B-n39-k5	3082,7	2981,9	2910,9	-5,6	-2,4	5131,2	4920,7	4756,0	-7,3	-3,3	7223,2	6903,5	6637,6	-8,1	-3,9
B-n41-k6	4374,7	3942,5	3823,2	-12,6	-3,0	6970,2	6392,6	6208,5	-10,9	-2,9	9863,3	9096,5	8680,4	-12,0	-4,6
B-n45-k5	3882,0	3548,6	3411,1	-12,1	-3,9	6213,1	5755,0	5529,1	-11,0	-3,9	8661,0	7883,8	7761,7	-10,4	-1,5
B-n50-k7	4036,6	3655,6	3538,9	-12,3	-3,2	6860,1	6059,7	5856,7	-14,6	-3,3	9494,1	8354,4	8112,4	-14,6	-2,9
B-n52-k7	3894,4	3825,3	3652,4	-6,2	-4,5	6466,5	6276,2	6001,8	-7,2	-4,4	9064,2	8368,6	8257,8	-8,9	-1,3
B-n56-k7	3464,7	3380,2	3286,7	-5,1	-2,8	5848,2	5606,6	5516,4	-5,7	-1,6	8129,3	8113,3	7580,8	-6,7	-6,6
B-n57-k9	8205,8	7454,9	7174,5	-12,6	-3,8	13288,3	11987,2	11544,4	-13,1	-3,7	16863,3	16566,8	15867,6	-5,9	-4,2
B-n64-k9	4617,3	4339,3	4219,3	-8,6	-2,8	7580,0	7066,6	6889,1	-9,1	-2,5	10893,5	9872,0	9600,7	-11,9	-2,7
B-n67-k10	5793,1	5315,5	5125,7	-11,5	-3,6	9448,3	8581,6	8369,3	-11,4	-2,5	13218,5	12064,7	11535,8	-12,7	-4,4
B-n68-k9	6485,2	6107,6	5824,0	-10,2	-4,6	10720,7	9943,7	9414,4	-12,2	-5,3	15266,7	13490,3	13196,8	-13,6	-2,2
B-n78-k10	6498,5	5881,6	5653,7	-13,0	-3,9	10631,8	9664,1	9207,1	-13,4	-4,7	14778,4	13399,1	12756,9	-13,7	-4,8
Average	*5106,4*	*4720,5*	*4534,2*	*-10,6*	*-4,0*	*8409,5*	*7657,1*	*7416,2*	*-11,2*	*-3,2*	*11636,7*	*10635,5*	*10266,8*	*-11,7*	*-3,5*

Table 8.2: Comparison of best found solution to single-period approach and initial solution (*Variance = 0.5*).

	Periods : 3					**Periods : 5**					**Periods : 7**				
	Single Period (1)	**Multi Period InitSol (2)**	**Multi Period OBS (3)**	**%-Gap (1)-(3)**	**%-Gap (2)-(3)**	**Single Period (4)**	**Multi Period InitSol (5)**	**Multi Period OBS (6)**	**%-Gap (4)-(6)**	**%-Gap (5)-(6)**	**Single Period (7)**	**Multi Period InitSol (8)**	**Multi Period OBS (9)**	**%-Gap (7)-(9)**	**%-Gap (8)-(9)**
A-n32-k5	3770,6	3715,6	3625,1	-3,9	-2,4	6382,3	6287,8	6001,0	-6,0	-4,6	8924,2	8574,7	8375,4	-6,1	-2,3
A-n33-k5	3323,5	3215,6	3094,7	-6,9	-3,8	5604,6	5236,7	5014,6	-10,5	-4,2	7987,3	7327,7	7132,3	-10,7	-2,7
A-n33-k6	3310,1	3354,9	3222,8	-2,6	-3,9	5696,6	5587,1	5294,9	-7,1	-5,2	8342,3	7697,5	7538,5	-9,6	-2,1
A-n37-k5	3132,8	3115,8	3054,1	-2,5	-2,0	5254,6	5190,7	5043,2	-4,0	-2,8	7734,9	7314,1	7095,4	-8,3	-3,0
A-n38-k5	4035,2	3619,0	3546,9	-12,1	-2,0	6530,2	5967,5	5713,6	-12,5	-4,3	9197,1	8372,6	7947,8	-13,6	-5,1
A-n39-k6	3851,4	3883,7	3721,6	-3,4	-4,2	6413,6	6373,5	6171,8	-3,8	-3,2	9043,4	8859,2	8658,5	-4,3	-2,3
A-n45-k6	4697,0	4365,0	4278,0	-8,9	-2,0	7736,1	7044,2	6887,0	-11,0	-2,2	10867,8	9661,7	9603,9	-11,6	-0,6
A-n45-k7	5986,2	5576,7	5395,4	-9,9	-3,3	9592,5	8972,4	8634,6	-10,0	-3,8	13347,4	12557,8	11959,9	-10,4	-4,8
A-n55-k9	5781,2	5332,5	5172,4	-10,5	-3,0	9247,8	8670,3	8242,8	-10,9	-4,9	12897,0	11844,4	11487,6	-10,9	-3,0
A-n60-k9	7378,0	6550,7	6480,2	-12,2	-1,1	11647,1	10601,7	10276,3	-11,8	-3,1	16347,4	14956,4	14282,6	-12,6	-4,5
A-n61-k9	5262,3	4887,3	4824,9	-8,3	-1,3	8629,0	8126,6	7827,5	-9,3	-3,7	12234,6	11327,5	11010,2	-10,0	-2,8
A-n63-k9	9036,9	8165,7	8008,7	-11,4	-1,9	14446,4	13224,4	12733,0	-11,9	-3,7	20479,5	18163,6	17927,9	-12,5	-1,3
A-n65-k9	6220,4	5793,7	5663,9	-8,9	-2,2	10234,2	9495,2	9199,1	-10,1	-3,1	14493,6	13162,9	12930,1	-10,8	-1,8
A-n80-k10	9747,7	8784,2	8690,6	-10,8	-1,1	15732,4	14362,0	13951,5	-11,3	-2,9	21991,7	19902,1	19343,5	-12,0	-2,8
B-n31-k5	3657,3	3401,7	3265,3	-10,7	-4,0	5766,8	5513,7	5184,1	-10,1	-6,0	8159,0	7507,3	7203,2	-11,7	-4,1
B-n35-k5	4702,7	4683,0	4512,5	-4,0	-3,6	7635,5	7726,2	7274,8	-4,7	-5,8	10686,6	10516,3	10126,0	-5,2	-3,7
B-n39-k5	3435,4	3117,6	3025,5	-11,9	-3,0	5670,9	5189,6	4953,1	-12,7	-4,6	8005,6	7196,9	6882,3	-14,0	-4,4
B-n41-k6	4306,7	4134,7	3910,9	-9,2	-5,4	7090,2	6690,1	6370,8	-10,1	-4,8	9903,1	9375,6	8867,5	-10,5	-5,4
B-n45-k5	3807,5	3566,0	3540,1	-7,0	-0,7	6230,1	5953,3	5746,1	-7,8	-3,5	8818,3	8130,7	8020,3	-9,0	-1,4
B-n50-k7	3972,6	3862,1	3702,8	-6,8	-4,1	6533,1	6188,0	5995,3	-8,2	-3,1	9216,5	8563,6	8425,4	-8,6	-1,6
B-n52-k7	4263,6	3870,0	3795,7	-11,0	-1,9	6987,5	6447,7	6153,0	-11,9	-4,6	9718,9	8851,4	8510,5	-12,4	-3,9
B-n56-k7	3567,5	3526,3	3450,3	-3,3	-2,2	5913,3	6008,6	5651,3	-4,4	-5,9	8271,4	8336,9	7850,8	-5,1	-5,8
B-n57-k9	8299,4	7658,7	7418,5	-10,6	-3,1	13253,9	12408,3	11833,8	-10,7	-4,6	18283,5	17006,8	16444,4	-10,1	-3,3
B-n64-k9	4786,7	4473,3	4384,5	-8,4	-2,0	7582,0	7335,2	7079,8	-6,6	-3,5	11243,3	10213,0	9875,2	-12,2	-3,3
B-n67-k10	5853,4	5424,4	5201,8	-11,1	-4,1	9525,4	8772,9	8431,7	-11,5	-3,9	13397,7	12284,9	11837,1	-11,6	-3,6
B-n68-k9	7063,9	6312,6	6202,8	-12,2	-1,7	11084,4	10400,1	9749,5	-12,0	-6,3	15566,9	13968,2	13664,0	-12,2	-2,2
B-n78-k10	6591,1	6032,1	5930,3	-10,0	-1,7	10613,9	9807,6	9515,7	-10,3	-3,0	14829,2	13728,2	13219,3	-10,9	-3,7
Average	*5179,3*	*4830,5*	*4708,2*	*-8,5*	*-2,7*	*8448,7*	*7910,4*	*7590,0*	*-9,3*	*-4,1*	*11851,4*	*10940,8*	*10600,7*	*-10,3*	*-3,2*

Table 8.3: Comparison of best found solution to single-period approach and initial solution (*Variance = 0.75*).

	Periods : 3					**Periods : 5**					**Periods : 7**				
	Single Period (1)	**Multi Period InitSol (2)**	**Multi Period OBS (3)**	**%-Gap (1)-(3)**	**%-Gap (2)-(3)**	**Single Period (4)**	**Multi Period InitSol (5)**	**Multi Period OBS (6)**	**%-Gap (4)-(6)**	**%-Gap (5)-(6)**	**Single Period (7)**	**Multi Period InitSol (8)**	**Multi Period OBS (9)**	**%-Gap (7)-(9)**	**%-Gap (8)-(9)**
A-n32-k5	4049,3	3907,1	3824,3	-5,6	-2,1	6648,4	6352,0	6174,1	-7,1	-2,8	9421,6	8740,5	8602,7	-8,7	-1,6
A-n33-k5	3478,8	3278,6	3096,6	-11,0	-5,6	5811,4	5320,7	5149,9	-11,4	-3,2	8229,1	7427,6	7179,0	-12,8	-3,3
A-n33-k6	3385,6	3416,9	3231,4	-4,6	-5,4	5773,0	5537,4	5360,0	-7,2	-3,2	8331,3	7920,9	7657,8	-8,1	-3,3
A-n37-k5	3607,2	3174,0	3146,4	-12,8	-0,9	5933,0	5284,2	5184,4	-12,6	-1,9	8461,4	7388,1	7357,0	-13,1	-0,4
A-n38-k5	3994,4	3658,0	3580,7	-10,4	-2,1	6538,9	6140,9	5859,5	-10,4	-4,6	9321,5	8444,9	8296,6	-11,0	-1,8
A-n39-k6	4234,1	3905,3	3804,1	-10,2	-2,6	6978,9	6478,2	6243,1	-10,5	-3,6	9978,5	8963,8	8758,4	-12,2	-2,3
A-n45-k6	4823,4	4356,9	4308,5	-10,7	-1,1	8129,2	7214,7	7086,3	-12,8	-1,8	11294,6	10014,3	9884,7	-12,5	-1,3
A-n45-k7	5868,9	5556,5	5408,9	-7,8	-2,7	9653,2	9191,9	8831,0	-8,5	-3,9	13654,2	12721,7	12228,9	-10,4	-3,9
A-n55-k9	5842,7	5402,6	5281,0	-9,6	-2,3	9331,5	8758,3	8328,9	-10,7	-4,9	13321,2	12021,3	11812,5	-11,3	-1,7
A-n60-k9	7348,7	6612,8	6570,7	-10,6	-0,6	12043,3	10783,1	10579,3	-12,2	-1,9	16642,7	15060,4	14662,7	-11,9	-2,6
A-n61-k9	5621,3	4994,6	4921,6	-12,4	-1,5	9174,1	8228,6	7981,5	-13,0	-3,0	12921,1	11458,4	11147,4	-13,7	-2,7
A-n63-k9	8891,2	8277,6	8209,0	-7,7	-0,8	14632,1	13613,7	13342,9	-8,8	-2,0	20627,7	18948,1	18495,0	-10,3	-2,4
A-n65-k9	6445,6	5859,0	5845,6	-9,3	-0,2	10642,5	9735,8	9519,1	-10,6	-2,2	14931,6	13617,0	13294,8	-11,0	-2,4
A-n80-k10	10262,9	9052,6	8982,3	-12,5	-0,8	16682,3	14728,2	14498,9	-13,1	-1,6	23342,1	20895,4	19987,5	-14,4	-4,3
B-n31-k5	3776,9	3481,0	3345,0	-11,4	-3,9	6149,5	5689,5	5355,8	-12,9	-5,9	8822,3	7845,1	7622,9	-13,6	-2,8
B-n35-k5	5000,2	4679,3	4590,3	-8,2	-1,9	8239,4	7782,1	7497,6	-9,0	-3,7	11736,4	11018,1	10400,6	-11,4	-5,6
B-n39-k5	3558,3	3281,0	3127,0	-12,1	-4,7	5881,3	5386,1	5159,1	-12,3	-4,2	8233,0	7537,1	7143,6	-13,2	-5,2
B-n41-k6	4270,6	4174,6	4017,3	-5,9	-3,8	7067,4	6826,6	6516,8	-7,8	-4,5	9825,2	9493,7	9012,1	-8,3	-5,1
B-n45-k5	4170,6	3777,3	3614,0	-13,3	-4,3	6961,4	6024,9	5956,4	-14,4	-1,1	9792,8	8541,8	8364,6	-14,6	-2,1
B-n50-k7	4038,0	3845,5	3752,4	-7,1	-2,4	6627,0	6283,6	6058,3	-8,6	-3,6	9497,8	8722,0	8497,8	-10,5	-2,6
B-n52-k7	4345,3	3962,5	3910,4	-10,0	-1,3	7133,1	6537,4	6334,4	-11,2	-3,1	9854,8	9045,1	8804,2	-10,7	-2,7
B-n56-k7	3756,0	3593,0	3521,9	-6,2	-2,0	6237,1	5951,1	5826,6	-6,6	-2,1	8876,6	8413,0	8086,8	-8,9	-3,9
B-n57-k9	8721,5	7799,2	7646,2	-12,3	-2,0	14217,5	12782,3	12337,0	-13,2	-3,5	19837,2	17874,9	16957,6	-14,5	-5,1
B-n64-k9	5089,9	4546,4	4486,5	-11,9	-1,3	8431,3	7317,5	7291,3	-13,5	-0,4	11735,9	10326,3	10165,3	-13,4	-1,6
B-n67-k10	5924,4	5524,7	5426,9	-8,4	-1,8	9678,7	9013,6	8688,8	-10,2	-3,6	13516,2	12700,3	12084,7	-10,6	-4,8
B-n68-k9	6813,9	6560,4	6286,8	-7,7	-4,2	11481,3	10484,1	10175,9	-11,4	-2,9	15912,5	14891,3	14012,5	-11,9	-5,9
B-n78-k10	6905,5	6226,7	6163,4	-10,7	-1,0	11326,2	10141,9	9890,9	-12,7	-2,5	15725,3	14229,5	13605,3	-13,5	-4,4
Average	*5341,7*	*4922,4*	*4818,5*	*-9,6*	*-2,3*	*8792,7*	*8058,8*	*7823,2*	*-10,8*	*-3,0*	*12364,6*	*11268,9*	*10893,4*	*-11,7*	*-3,2*

8.2 A simulation-optimization approach for the Location Routing Problem arising in the creation of urban consolidation centers

The following sub-sections describe the simheuristic solving approach for the two-echelon LRP with stochastic demands. Subsequently, a range of computational experiments is completed on real-life benchmarks retrieved from a fast-moving consumer goods supply chain in the Greek capital of Athens to show the performance and applicability of the elaborated algorithm.

8.2.1 Algorithm description

A flowchart of the simheuristic solving framework for the 2E-LRP with stochastic demands can be seen in Figure 8.5. During a predefined stopping criterion (a maximum number of iterations is used in this work), m satellite facilities are randomly opened while ensuring that the overall UCC capacity is able to serve the total expected final customer demands. Within each algorithm iterations, the first-level routing costs between the central depots and the opened UCC locations are calculated with a nearest neighbor heuristic. It is assumed that a single vehicle tour is enough to stock all opened UCCs. Moreover, different routing maps established by assigning a sub-set of all final customers to each opened UCC via a round-robin criterion. Hereby, each UCC iteratively 'chooses' the next customer to be served from the non-assigned clients according to its geographical proximity.

Subsequently, different delivery routing plans are established for each routing map (consisting of a satellite location and the assigned sub-set of final customers). Within a multi-start framework, an efficient routing plan is created by using a biased randomized version of the Clarke-and-Wright savings heuristic.

During this optimization phase, deterministic (expected) final customer demands $\mathrm{E}[d_i]$ are considered at each client i. Whenever the deterministic costs of a new single VRP solution $newSol$ outperform the deterministic costs of the currently incumbent best solution $currentBest$, it undergoes a simulation phase to account for demand uncertainty. The simulation procedure is only applied to promising deterministic single VRP plans in order to avoid jeopardizing computational times through extensive simulation runs. For each promising $newSol$, final customer demands are simulation from a log-normal probability distribution during $nSim$ simulation runs. The outlined simheuristic methodology is flexible enough to incorporate any other kind of suitable probability function at this stage. In order to construct

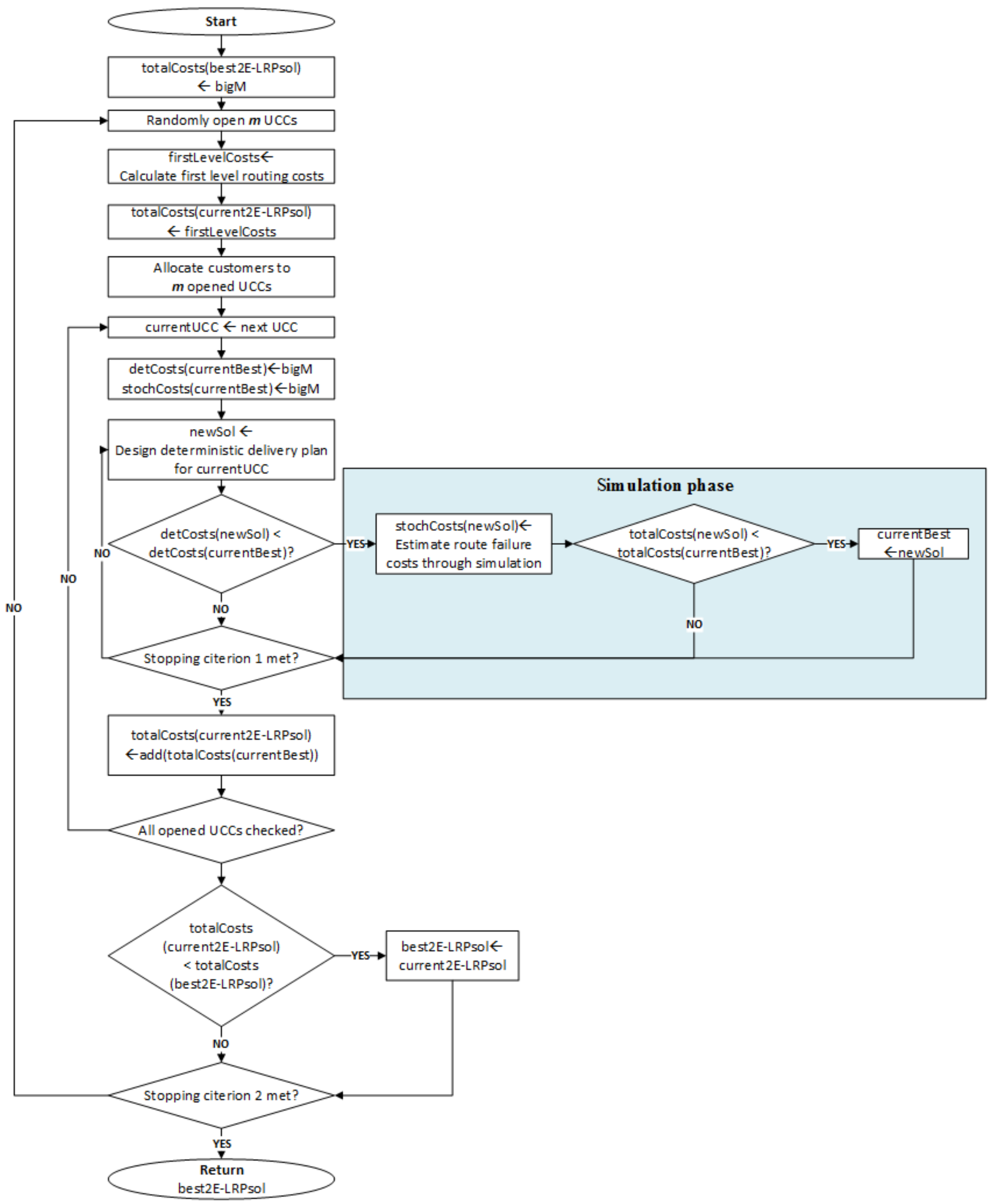

Figure 8.5: Flowchart of Simheuristic solving methodology for the 2E-LRP.

the log-normal distribution, expected demand values $\mathrm{E}[d_i]$ are used as distribution mean. Furthermore, stochastic demands are formulated as $\mathrm{Var}[d_i] = k \times \mathrm{E}[d_i]$, which allows for considering different demand variance levels k.

Due to the stochastic nature of customer demands, a vehicle completing a pre-established delivery route might run out of stock before the planned route is completed whenever the simulated demands exceed the vehicle capacity. In cases of such route failures, an additional trip to the UCC is necessary. For this reason, a route failure is penalized with a round trip from the customer at which the vehicle runs out of stock to the respective satellite location. The total route failure costs occurring during the simulation phase are summed and finally divided by the total number of applied simulation iterations in order to define the expected stochastic costs of an established solution. Thus, the total costs of a new single VRP solution are defined as the sum of the deterministic routing costs and the expected route failure costs obtained during the simulation phase. Whenever the total costs of any $newSol$ outperform the total costs of the current best found solution $currentBest$, the incumbent solution is updated.

Once the multi-start algorithm for a single UCC and its assigned clients is completed, the described process is repeated for all opened satellite locations. Finally, the quality of a 2E-LRP is defined as the total routing costs (considering the deterministic and stochastic values) of serving all clients in addition to the first-level routing costs to stock all UCC locations. The inclusion of simulation in the described procedure leads to several advantages. On the one hand, a reliable estimate of the overall solution costs in an uncertainty scenario is obtained. On the other hand, the expected route failure costs calculated during the simulation are used to define incumbent VRP solutions for each UCC in order to guide the metaheuristic solution search under the consideration of stochastic customer demands. Moreover, the simulation phase enables the comparison of different 2E-LRP solutions along additional decision dimensions instead of solely focusing on expected routing costs. Indeed, decision-takers might be interested in information such as the standard deviation or different quantiles of results obtained during the simulation runs, as a possible measure of a solution's reliability.

8.2.2 Computational experiments and analysis of results

The simheuristic algorithm is implemented as Java application and run on a personal computer with 4GB RAM and an Intel Pentium processor with 2.16GHz. The necessary algorithm parameters to complete the tests described in the following are defined as follows:

- Geometric distribution parameter α: 0.3
- Stopping criterion 1: 10 iterations
- Stopping criterion 2: 200 iterations
- Simulation runs $nSim$: 500
- Demand variance k: 2
- UCC capacity: 1000
- First-level vehicle capacity: 5000
- Second-level vehicle capacity: 100

The simheuristic solving framework is validated on a real-life case-study based on a fast moving consumer goods supply chain operating in the metropolitan area of Athens (Greece). A total of 342 customers scattered around the Athen's city center are currently directly supplied from five different depots (highlighted with the warehouse symbols in Figure 8.6). All depot, UCC, and customer locations are given as geographic Longitude/Latitude coordinates. Distances between any two nodes are calculated as Euclidean distances by transforming the location information into x/y coordinates. The costs (calculated with the biased randomized CWS in combination with simulation as described above by considering the current depot/customer maps) of serving all customers with the current depot/customer assignments and no satellite locations are outlined in Table 8.4. As can be seen, all clients are currently served with a deterministic routing distance of 1895.12 km. Additionally, route failure costs amount to an expected value of 179.69 km.

Table 8.4: Current costs of serving all customers without the use of UCCs.

Depot	**# UCCs**	**# Customers**	**Demand**	**Det Costs**	**Stoch Costs**	**Total Costs**	**# Routes**
1	0	63	372	375.04	32.3	407.34	4
2	0	87	479	586.79	75.34	662.12	5
3	0	105	607	413.46	36.01	449.47	7
4	0	42	213	215.39	11.87	227.26	3
5	0	45	230	304.44	24.17	328.61	3
Total	**0**	**342**	**1901**	**1895.12**	**179.69**	**2074.8**	**22**

To test the effect of collaboration among suppliers in a city logistics context, five random UCC locations around the city center are defined. Figure 8.6 outlines the geographic locations of all potential satellite locations (star symbols). As a larger vehicle is used to complete the first level-routes, the routing costs for stocking all opened UCCs are multiplied by 2, as proposed by Nguyen et al. (2012).

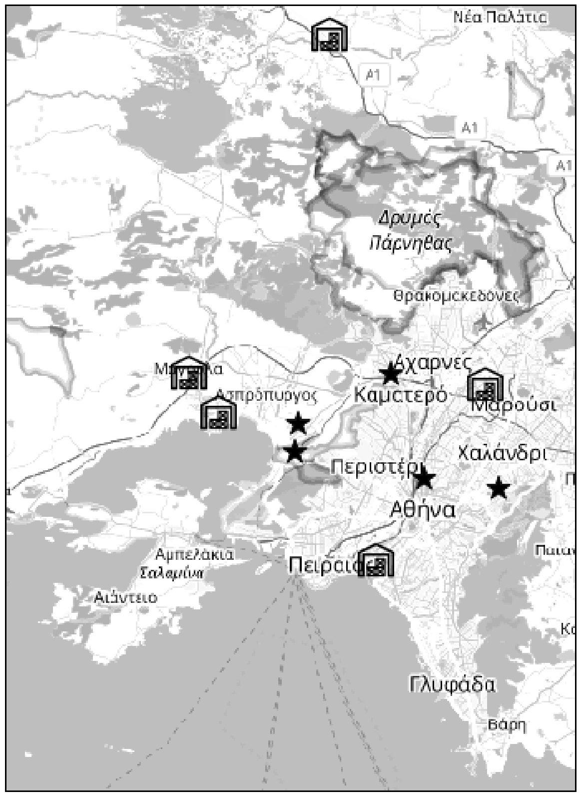

Figure 8.6: Location of central depots and and potential UCCs.

The ten most competitive 2E-LRP solutions are listed in Table 8.5. As can be seen, the best solution yields total costs of 1284.62, outperforming the current non-collaborative solution by over 38%. Moreover, the results suggest that a lower number of opened UCCs leads to the best overall 2E-LRP results. However, the stochastic costs seem to decrease with a higher number of opened UCCs, due to the fact that a higher number of satellite locations decreases the penalization costs of returning to the UCC in case of route failures.

Table 8.5: Overview of different 2E-LRP solutions

Sol	**# UCCs**	**Det Costs**	**Stoch Costs**	**First-level Costs**	**Total Costs**	**# Routes**
1	2	975.69	76.19	232.75	1284.62	20
2	2	1047	96.6	222.63	1366.23	21
3	2	1033.23	93.72	240.28	1367.23	20
4	2	1093.78	81.35	232.75	1407.88	20
5	3	1158.11	80.03	240.19	1478.33	20
6	4	1302.81	81.99	247.58	1632.38	21
7	4	1332.76	49.89	254.74	1637.4	22
8	4	1341.67	55.27	241.11	1638.06	22
9	4	1438.87	68.47	241.62	1748.96	22
10	5	1556.02	68.69	251.1	1875.81	22

CHAPTER 9

QUANTIFYING HORIZONTAL COLLABORATION CONCEPTS IN URBAN FREIGHT TRANSPORTATION

A promising supply chain management approach in the creation of efficient and sustainable logistics and transportation processes is that of horizontal collaboration (HC). The concept refers to different collaboration scenarios regarding coordinated practices based on joint decisions and shared resources among companies operating at the same level in the market. Especially in complex scenarios such as urban freight distribution, this leads to challenging optimization scenarios. The different degrees of collaboration discussed in this section incorporate the levels of complexity and decision-taking integration outlined in chapters 7 and 8. Highlights of this chapter include:

- the presentation of a metaheuristic algorithm based on Variable Neighborhood Search (VNS) and Biased Randomization (BR) to solve related optimization problems. With only minor modifications, this framework is able to solve the Location Routing Problem (fully-collaborative scenario), the multi-depot Vehicle Routing Problem (semi-collaborative scenario), and the capacitated Vehicle Routing Problem (non-collaborative scenario). The frameworks competitiveness is shown on a range of computational experiments (Quintero-Araujo et al. 2017*b*).

- a detailed result analysis that compares the different scenarios regarding monetary and ecological costs in freight distribution planning. Significant cost savings in terms of distance and CO_2 emissions are reported with increasing collaboration levels (Quintero-Araujo et al. 2017*b*).

- the proposal of a simheuristic algorithm to include stochastic input variables in the analysis and comparison of HC concepts. The outlined approach allows for quantifying collaboration scenarios according to additional decision-taking dimensions such as the expected solution reliability under different degrees of customer demand variability (Quintero-Araujo et al. 2016, 2017*c*)[1,2].

As depicted in Figure 9.1, the different horizontal collaboration scenarios outlined in this chapter involve all decision-taking problems discussed in previous sections. Depending on the collaboration degree, companies need to address the VRP (non-collaborative case), the MDVRP (semi-collaborative case), or the LRP (fully-collaborative case). The Inventory Routing Problem (IRP) is a typical example of vertical collaboration between subsequent actors in a value creation chain.

9.1 Metaheuristic solving approach

The following sub-section describes the generic BR-VNS algorithm to address the problem settings arising with different HC stages outlined in chapter 6.3. Subsequently, a range of computational experiments show the potentials of the algorithm in quantifying HC scenarios from a monetary and environmental standpoint.

9.1.1 Algorithm description

As a general approach for solving the distinct optimization problems modeling the considered HC scenarios, a hybrid metaheuristic algorithm that combines BR techniques with VNS (BR-VNS) is proposed. The BR-VNS approach is outlined in Figure 9.2. With minor modifications,

[1]The work put forward by Quintero-Araujo et al. (2016) is published in the SCOPUS indexed conference proceedings of the Spanish National Conference on Metaheuristics and Evolutionary and Bio-inspired Algorithms (MAEB) 2016 in Salamanca, Spain. Its findings were presented by the IN3-researcher Carlos Quintero-Araujo. As co-author of this publication, the student was mainly responsible for the literature review, experiment design, and analysis of results.

[2]The work put forward by Quintero-Araujo et al. (2017*b*) is published in the SCOPUS indexed journal Progress in Artificial Intelligence. As co-author of this publication, the student was mainly responsible for the algorithm development, experiment design, and analysis of results.

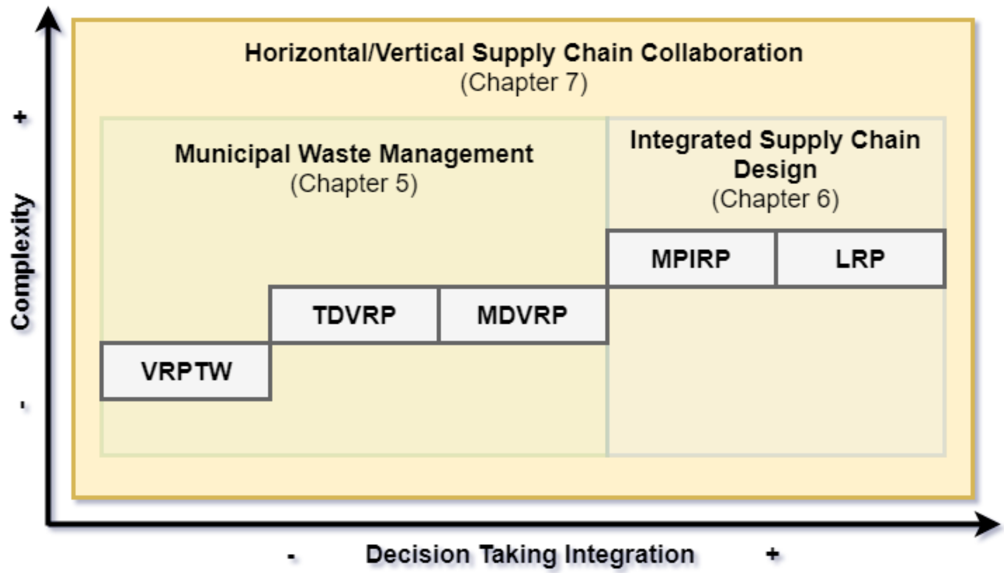

Figure 9.1: Complexity and decision-taking integration of central problem settings addressed in chapter 9.

it can solve the three problem settings associated with the alternative scenarios: the fully-collaborative one (LRP), the semi-collaborative one (MDVRP), and the non-cooperative one (VRPs).

BR techniques are applied at two stages of the algorithm: *(i)* the generation of customer-to-depot allocation maps; and *(ii)* the subsequent planning of delivery routes. On the one hand, 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-to-depot allocation maps are randomly generated following an iterative round-robin process. At each iteration, a different depot chooses the next customer to serve according to the geometric distribution parameter β. On the other hand, delivery routes are constructed using a biased randomized version of the Clarke-and-Wright savings heuristic.

During the construction of feasible solutions, upper- and lower bounds (UB/OB) concerning the number of facilities to be opened are computed by considering the aggregated customers' demands and depots' capacities. Then, different random combinations of n depots ($LB \leq n \leq UB$) are generated. After that, initial customers-to-depots allocation and

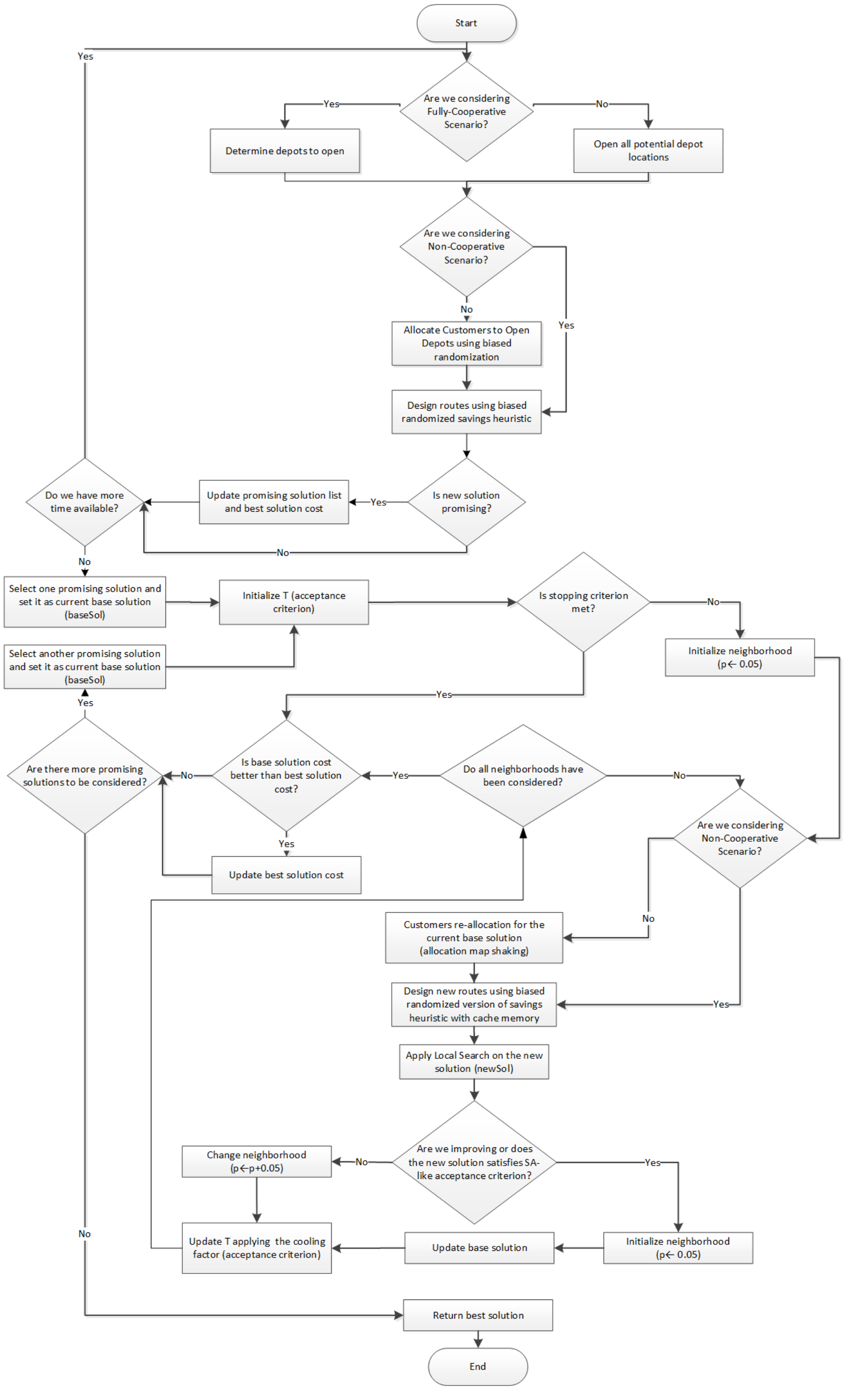

Figure 9.2: Flowchart of the BR-VNS Algorithm.

delivery-route planning are generated. This process is repeated multiple times to quickly generate a list of random — but promising by construction — initial solutions. From these initial solutions, the most promising ones are stored within a set of $baseSols$. Each potential solution is then further improved using a VNS framework.

In particular, the proposed VNS shaking procedure consists in randomly exchanging the depot allocation of a percentage p of all potential customers. In order to consider different neighborhood structures, this percentage is increased at each iteration. In particular, p takes ascending values in the set $\{0.05, 0.1, ..., 0.95\}$. Since the shaking procedure aims at exchanging customers among depots (i.e., modifying of allocation maps), this procedure is not considered in the non-cooperative scenario.

Once the solution structure of $baseSol$ has been transformed to create a new solution $newSol$, a local search procedure is applied to find the local minimum within the current solution neighborhood. The local search operator applied in the BR-VNS consists in improving delivery routes by exchanging customers among intra-company routes. Thus, $newSol$ is accepted as an updated $baseSol$ if the cost of the former is better than the one of the latter. Moreover, an acceptance criterion based on Simulated Annealing is applied. This criterion uses an initial temperature, T_0, and a 'cooling' constant, $coolingFactor$. This cooling constant is applied to reduce, at each iteration, the temperature T used in the acceptance criterion. Finally, the current $bestSol$ is updated whenever $newSol$ outperforms its current value. The entire procedure is repeated for each initial solution until a stopping criterion ($maxIter$) is met.

As the underlying optimization problem differs across the three HC scenarios considered in this work, small variations in the described algorithm must be adopted. In particular, the modifications are as follows:

- In the non-cooperative and semi-collaborative scenarios, the number of depots to be opened is no longer a decision variable but rather an algorithm input. Thus, *UB* and *LB* are set as the number of depots in the problem instance.

- 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, $nInit$, is set to 1.

- As the shaking operators aim at modifying customer-to-depot allocation maps, which is not allowed in the non-cooperative scenario, they are turned off in this scenario.

9.1.2 Computational experiments and analysis of results

In order to test the competitiveness of the BR-VNS algorithm for strategic location-routing decisions, it is applied to the well-known *Prodhon's instances* (Belenguer et al. 2011). This set constitutes a classical benchmark for the LRP. It includes a total of 30 instances, ranging from 5 to 10 potential facilities and from 20 to 200 customers. The solutions generated by the algorithm for these instances are compared to the ones provided in the recent LRP literature. Thus, Figure 9.3 shows a visual comparison of the BR-VNS algorithm against three state-of-the-art algorithms for the LRP: *(i)* a GRASP combined with integer-linear programming (GRASP+ILP) discussed in Contardo et al. (2014); *(ii)* a granular variable tabu neighborhood search (GVTNS) introduced by Escobar et al. (2014); and *(iii)* a sequential combination of Biased Randomization techniques with an Iterated Local Search (ILS) framework proposed by Quintero-Araujo et al. (2017*a*). The results achieved by the BR-VNS algorithm are comparable to the ones provided in these recent publications.

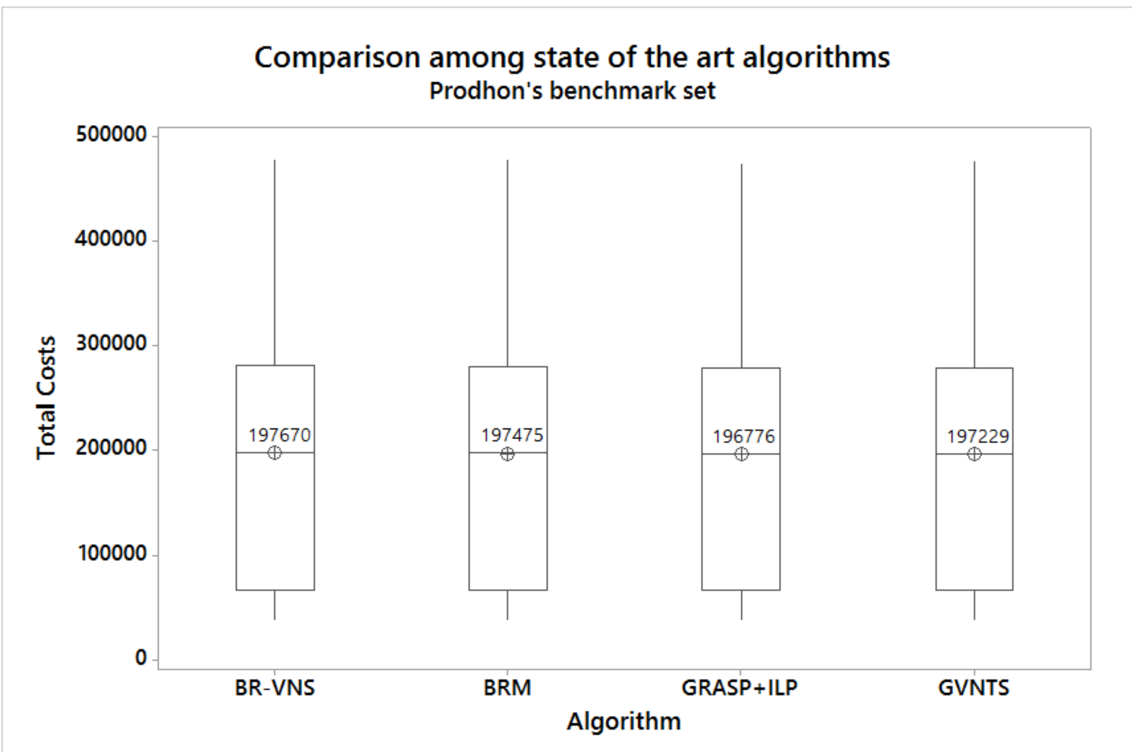

Figure 9.3: Visual comparison of different algorithms for the LRP.

In addition to the aforementioned Prodhon's instances, two additional benchmark sets were considered. The one proposed by Barreto (2004) contains a total of 17 instances, with 2 to 15 possible depot locations and 12 to 150 customers. The one introduced by Akca et al. (2009) includes 12 instances, with 5 depots and 30 to 40 customers. Each instance consists of a set of possible facility locations and numerous customers to be served by a homogeneous vehicle fleet. The objective for the LRP is to minimize the overall distribution costs, including opening costs, routing costs, and use of vehicles. In the non-cooperative and semi-collaborative scenarios, it is assumed that all possible facility locations are used. Then, in the non-cooperative case, customers are randomly assigned to the open depots. An estimation of the environmental impact is provided according to the load- and distance-based CO_2 emission calculations proposed in Ubeda et al. (2011). Thus, CO_2 emissions are hereby calculated according to travel distances and vehicle loads, as outlined in Table 9.1. This load dependency leads to asymmetric emission estimations for each established route, depending on the direction in which the delivery route is completed –the vehicle load on a given edge will be different depending on the direction of the route. Therefore, CO_2 emissions for each route are computed in both directions, and the one with the lowest value is selected.

Table 9.1: 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 a complement to the use of the aforementioned classical benchmarks, the algorithm is also tested in the more realistic scenario described in Muñoz-Villamizar et al. (2015). These authors discuss the impact of HC strategies in the context of city logistics. In their work, a total of 10 instances were considered. These instances represent different situations concerning customers' demands, with 3 depots supplying up to 61 clients scattered around the city of Bogotá (Colombia). The authors compare two scenarios, the non-cooperative and the collaborative ones. While the non-cooperative scenario is equivalent to the one described in this thesis, their cooperative scenario corresponds to the semi-collaborative setting, i.e., they do not consider a fully-collaborative scenario as defined in this work.

The BR-VNS algorithm 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. The reported results correspond to the best-found solution. After some quick fine-tuning process, the following values were selected for the parameters of the algorithm:

- $nIterSols = 300$
- $nInitSols = 2 + \lfloor nodes/100 \rfloor$
- $maxIter = 350$
- $routingIterationsRandomCWS = 150$
- $\alpha \in (0.05, 0.20)$
- $\beta \in (0.05, 0.80)$
- $T_0 = 50$
- $coolingFactor = 0.98$

Tables 9.2-9.4 show detailed results concerning opening, vehicle, routing, environmental and total costs in different HC scenarios. In the case of Prodhon's instances, a fixed vehicle cost of 1,000 units per used truck is applied, and the reported distances are multiplied by 100 and rounded up to the nearest integer in order to compute routing costs. Results for this set are summarized in Table 9.2, in which small-size instances refer to those with 20 customers and 5 potential locations, mid-size instances are the ones with 50-100 customers and 5 potential locations, and large-size instances refer to those with 100-200 customers and 10 potential locations.

Table 9.2: Summary of results for Prodhon's set

Type of instances	**Semi- vs Non-cooperative**		**Fully- vs Non-cooperative**	
	Gap total costs	**Gap CO_2**	**Gap total costs**	**Gap CO_2**
Small-size	-30.26%	-59.76%	-55.84%	-56.33%
Mid-size	-29.57%	-58.44%	-51.25%	-54.93%
Large-size	-15.90%	-66.60%	-68.11%	-59.29%
Average	-24.55%	-61.71%	-58.29%	-56.79%

Table 9.3: Comparing different HC scenarios - Barreto's instances

Instance	Non-cooperative scenario (NC)				Semi-cooperative scenario (SC)				Fully-collaborative 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 9.4: Comparing different HC scenarios - 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**

While the semi-collaborative scenario leads to an average reduction in total cost of about 24.55% (with respect to the non-cooperative one), this value increases up to 58.29% when considering the fully-collaborative scenario. Similarly, both the semi- and the fully-collaborative scenarios reported noticeable reductions in CO_2 emissions with respect to the non-cooperative one. For this benchmark set, the highest reduction in CO_2 is obtained with the semi-cooperative scenario. This is due to the fact that the fully-collaborative scenario aims at minimizing total costs, which might require opening fewer depots and thus employing larger routes.

The Barreto and Akca benchmarks do not envisage any fixed cost for the vehicle usage. For Barreto's set, reported results provide an average gap of 42.37% in total costs when comparing the semi-collaborative scenario against the non-cooperative one. This gap grows up to a 61.64% when the fully-collaborative scenario is considered. Regarding CO_2 emissions, the respective average gaps are 58.85% for the semi-cooperative scenario and 55.78% for the fully-cooperative one. Once more, emissions are lower in the semi-collaborative scenario than in the fully-cooperative one due to the fact that the former uses more depots and, hereby, shorter routes. The outcomes for the Akca's set are similar: the average gap in total costs is about 42.07% for the semi-cooperative scenario and about 55.37% for the fully-collaborative one; likewise, the average gaps related to CO_2 emissions are 55.77% and 52.74%, respectively. Figures 9.4 to 9.6 illustrate these gaps in a more visual way. As outlined in Figure 9.4, huge savings in opening costs are obtained when fully-collaborative concepts are applied. On the other hand, savings in distance-based routing costs are usually higher in the semi-collaborative scenario –which leads to a higher reduction in CO_2 emissions.

Apart from using classical benchmarks to compare different HC scenarios, the Bogotá dataset provided in Muñoz-Villamizar et al. (2015) is considered, which contains 10 instances based on real-life data. For the non-cooperative scenario, the presented approach was able to outperform the results reported in the aforementioned article, with an average gap of 4.93% (Table 9.5). Similarly, for the semi-collaborative scenario, the BR-VNS algorithm was also able to outperform the previously reported results, with an average gap of 4.81% (Table 9.6). Finally, three different HC scenarios are compared using the proposed algorithm (Table 9.7). Notice that both the semi-collaborative and the fully-collaborative scenarios render Significant distance savings in comparison to the non-cooperative one. In some instances (I1, I5, I8) the semi- and fully-collaborative scenarios yield the same routing distances, with a lower number of open depots in the latter scenario. In these instances, the solution of the semi-collaborative scenario only uses two out-of-the three depots given as inputs.

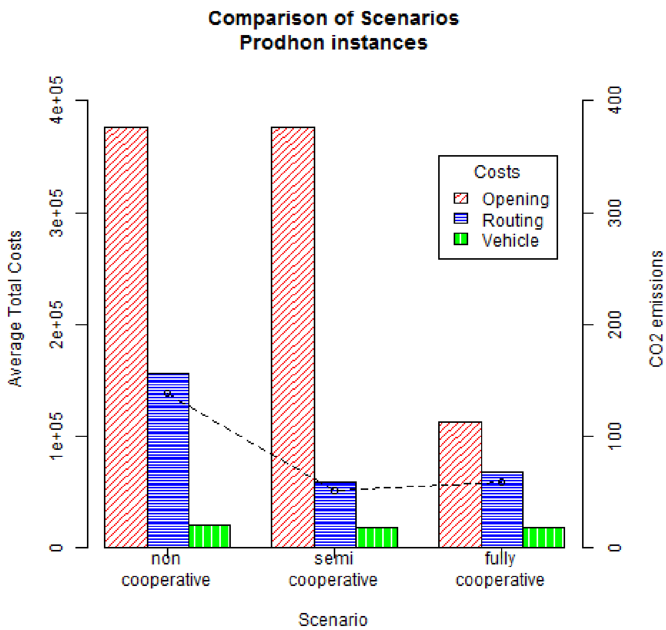

Figure 9.4: Summary of average results for Prodhon's instances

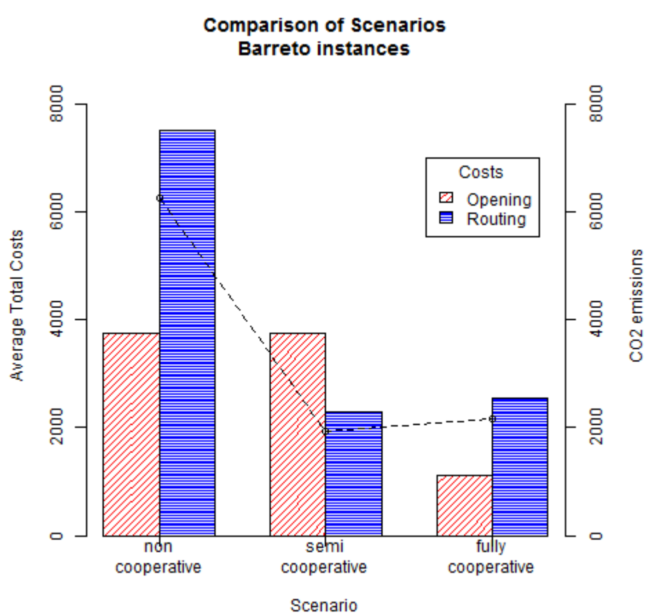

Figure 9.5: Summary of average results for Barreto's instances

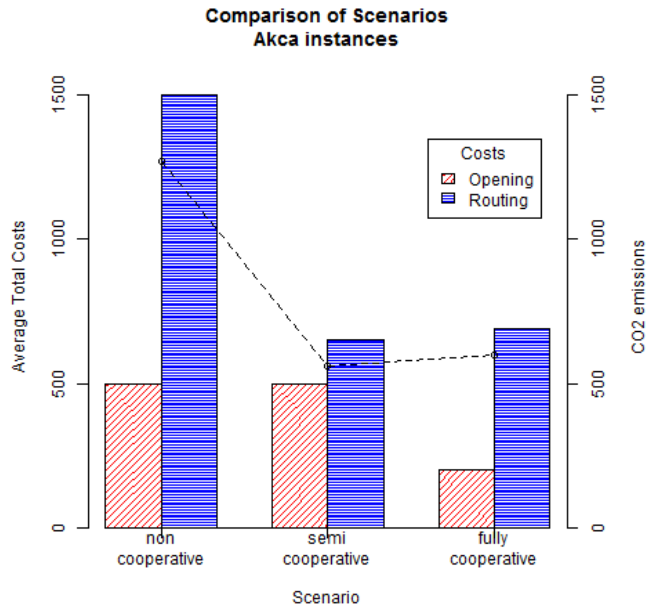

Figure 9.6: Summary of average results for Akca's instances

Table 9.5: Result comparison VRP

Instance	Muñoz-Villamizar et al. (2015)		Proposed approach		%-Gap
	km	Depots	km	Depots	km
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**

9.2 Including stochastic input variables in the assessment of HC concepts

In the following, a simheuristic algorithm for the multi-depot VRP (MDVRP) with stochastic demands arising in semi-collaborative HC scenarios is described. A detailed analysis of

Table 9.6: Result comparison MDVRP

Instance	Muñoz-Villamizar et al. (2015)		Proposed approach		%-Gap
	km	Depots	km	Depots	km
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**

Table 9.7: Result comparison LRP

Instance	Proposed approach non-cooperative (1)		Proposed approach semi-cooperative (2)		Proposed approach fully-cooperative (3)		Distance %-Gap	Distance %-Gap
	Distance	Depots	Distance	Depots	Distance	Depots	(1)-(3)	(2)-(3)
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**

results subsequently highlights the potentials of the approach in the quantification of HC agreements under demand uncertainty.

9.2.1 Algorithm description

Regarding the MDVRP with stochastic demands, the solving approach consists of two main phases. First, different customer-depot allocation maps which are then routed using a biased-randomized version of the savings heuristic are created. This process is then integrated into a VNS framework to create a large number of allocation maps. Then, Monte Carlo simulation (MCS) to evaluate the behavior of the most promising allocation maps in a stochastic environment is applied.

To create different customer-depot allocation maps, a biased round-robin criterion is used.

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 $k \in V_d$ (set of depots), compared to serving it from the best alternative depot k^* (such that $\mu_i^k = c_i^{k^*} - c_i^k$, where $c_i^{k^*}, c_i^k$ are the corresponding allocation costs),

Next, the nodes are randomly assigned. Each depot iteratively selects 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 a geometric distribution of parameter α, with $0 < \alpha < 1$.

Once all customers have been assigned, the resulting customers-to-depot assignment map can be seen as a series of VRPs, which are then solved using the biased randomized version of the savings heuristic. In order to test different customer-depot allocation maps, the described procedure is integrated into a VNS framework. Thus, the deterministic counterpart of the stochastic problem is considered by using expected demands at each customer. After finding an initial solution (which is set as $currentBest$) and the corresponding allocation map, the latter is modified by applying a destroy-and-repair strategy, in which $p\%$ of customers are exchanged among the depots.

After each modification, the new allocation map is solved again by using the previously cited routing algorithm. Accordingly, the current best solution is updated when necessary. Furthermore, an acceptance criterion is included, which permits a base solution worsening in some cases. More specifically, base solutions are accepted when the last iteration from x to x^* was an improvement ($f(x) > f(x^*)$), and the difference between the current base 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 VNS procedure is run for $pertubTime$ seconds, during which the m most promising (deterministic) solutions are defined. See Algorithm 15 for an overview over the applied approach.

Each of the most promising solutions obtained for the deterministic environment are then evaluated in a stochastic environment. Here, it is assumed that there is a positive correlation between high-quality deterministic solutions and high-quality stochastic solutions, which makes sense for stochastic environments with a moderate level of uncertainty (random variables with moderate variance). By simulating only the most promising deterministic customer-depot allocation maps, the computational effort is kept manageable. To test the behavior of each solution considering stochastic demands, random demands are repeatedly sampled using MCS. That is, during each of a total of $nIter$ simulation runs, the demand D_i

Algorithm 15: Generation 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
$initSol \leftarrow currentBest$
while *elapsed time < max time* **do**
  pertubate current map(p)
  $newSol$ ← solve map using randomized CWS
  if $newSol < currentBest$ *or acceptance criterion is met* **then**
    $newSol \leftarrow currentBest$
  end
end
return Set M of promising solutions for the deterministic problem

of each customer i is sampled from a probability function using the expected demands as mean and considering a demand variance $Var[D_i] = hE[D_i]$, with $h > 0$. In the numerical experiments a log-normal distribution is applied, but the approach allows for applying any other theoretical (e.g., Weibull, gamma, etc.) or empirical probability distribution.

The stochastic costs can be estimated via the simulation process. As vehicle capacities are limited, a higher-than-expected overall demand will lead to route failures. That is, the vehicle has to return to the depot to fill up its stock before continuing its route. Accordingly, route failures are penalized by adding additional costs for a round trip from the current customer to the depot and back. The expected variable cost is estimated by adding the costs of all round trip failures during each simulation run n and dividing it by the total number of simulation runs, i.e.:

$$expectedStochCosts = \frac{\sum_{n=0}^{nIter} RouteFailCost_n}{nIter}. \tag{9.1}$$

Route failures also affect the reliability of the solution. Thus, for each route, its reliability is estimated using the following formula:

$$RouteReliability = \left(1 - \frac{\sum_{n=0}^{nIter} RouteFailuresCount}{nIters}\right) * 100\% \tag{9.2}$$

This formula corresponds to the percentage of times that a route does not lead to a failure during the $nIter$ simulation runs. Therefore, the value obtained using this equation provides an idea of the robustness of a route when it faces different stochastic scenarios. The reliability of an entire solution (set of independent routes) can be obtained by simply multiplying the individual reliabilities of its routes.

The simheuristic approach described before allows for obtaining an estimate of the expected total cost by adding the deterministic and expected variable costs. At this stage, the use of short and long simulation runs is suggested. 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 time-consuming simulation with more runs, $nIterLong$. Finally, the presented framework returns a list of ranked solutions. See Algorithm 16 for a pseudo-code description of the simulation procedure.

Algorithm 16: Simulation of stochastic demands

```
Input: M; nIter; Var[d_i]
% Set of promising deterministic solutions, number of simulation runs (short and long),
  and 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 of elite solutions for the stochastic problem
```

Table 9.8: Chosen instances and their features

Instance	Depots	Customer	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

9.2.2 Computational experiments and analysis of results

In order to test the proposed paradigm and contrast collaborative versus non-collaborative scenarios, tests have been carried out on the benchmark instances proposed by Cordeau et al. (1997) for the multi-depot VRP. Particularly, ten representative instances of different sizes are chosen. Their features are summarized in Table 9.8. Each instance was transformed to fit the non-collaborative scenario by using a greedy distance-based heuristic (round robin process) which iteratively assigns each customer to its closest facility. The non-collaborative scenario was solved by using the routing algorithm proposed in Juan et al. (2011), whereas the collaborative case was solved by means of the biased-randomized VNS algorithm explained before. Both algorithms were implemented as Java applications and run on a Macbook Pro Core i5-2.4GHz processor with 8 Gb RAM. The following values were used for the different parameters during the test execution:

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

After analyzing the effects of HC in a deterministic environment, the analysis is extended to the stochastic environment, i.e., one in which uncertainty is present and, therefore, a

Table 9.9: Results in low demand variance scenario

	Non-collaborative		**Collaborative**		**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%	7.90%	3.83%
P02	511.64	97.72%	491.83	100.00%	4.03%	2.33%
P03	682.25	98.84%	671.41	100.00%	1.61%	1.17%
P05	790.29	99.57%	773.09	100.00%	2.22%	0.43%
P09	4113.53	97.93%	4047.19	98.56%	1.64%	0.64%
P10	3.914.09	99.30%	3902.52	98.51%	0.30%	-0.80%
P18	4.228.57	91.25%	3855.56	100.00%	9.67%	9.59%
P19	4.227.91	91.37%	3923.45	100.00%	7.76%	9.45%
P20	4.227.57	91.39%	4080.35	100.00%	3.61%	9.42%
P22	6.341.26	91.38%	5899.48	100.00%	7.49%	9.43%
Average					4.62%	4.55%

simulation-optimization approach — as the one introduced in the previous section — is required. Table 9.9 shows the results for a low-variance demand ($Var[D_i] = 5\%\ E[D_i]$). For each scenario, the expected total costs and the expected reliability of the best-found solution are included. The last two columns depict the improvements achieved by the collaborative scenario in terms of expected total cost and reliability. It can be seen that the collaborative scenario outperforms — in terms of total expected costs — the non-collaborative case in all considered instances. Additionally, the reliability of the solutions increases in the collaborative scenario, i.e., route failures occur less frequently. Similar results are shown in Table 9.10 and Table 9.11 for medium-variance demand ($Var[D_i] = 10\%\ E[D_i]$), and high-variance demand ($Var[D_i] = 15\%\ E[D_i]$).

Figure 9.7 shows box-plot graphics that summarize the distribution of the results for the different variance levels in Tables 9.9, 9.10, and 9.11 in order to find a general pattern. As can be seen, the higher the variance level the higher the savings obtained by using HC strategies instead of the non-collaboration ones. Similarly, and at least for the instances considered in this work, the HC scenarios seem to provide solutions with higher reliability levels than those obtained in the non-collaborative scenario.

Table 9.10: Results in medium demand variance scenario

	Non-collaborative		**Collaborative**		**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%	8.96%	4.93%
P02	514.17	97.03%	491.83	100.00%	4.54%	3.06%
P03	686.92	97.85%	671.41	100.00%	2.31%	2.20%
P05	802.23	97.84%	773.09	100.00%	3.77%	2.21%
P09	4178.24	96.08%	4083.71	99.97%	2.31%	4.05%
P10	3949.39	98.47%	3921.84	98.87%	0.70%	0.41%
P18	4294.17	88.68%	3855.62	99.99%	11.37%	12.75%
P19	4291.28	88.65%	3923.51	99.99%	9.37%	12.79%
P20	4292.20	88.67%	4080.35	100.00%	5.19%	12.78%
P22	6439.76	88.64%	5899.56	99.99%	9.16%	12.80%
Average					5.77%	6.80%

Table 9.11: Results in high demand variance scenario

	Non-collaborative		**collaborative**		**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%	9.99%	5.91%
P02	512.92	98.63%	491.83	100.00%	4.29%	1.39%
P03	690.49	97.04%	671.41	100.00%	2.84%	3.05%
P05	796.21	98.18%	773.09	100.00%	2.99%	1.85%
P09	4205.89	95.37%	4111.02	95.20%	2.31%	-0.18%
P10	3983.54	97.89%	3936.38	97.94%	1.20%	0.05%
P18	4336.48	87.32%	3855.88	99.94%	12.46%	14.45%
P19	4332.61	87.40%	3923.74	99.94%	10.42%	14.35%
P20	4337.97	87.11%	4080.45	99.97%	6.31%	14.76%
P22	6502.50	87.32%	5899.89	99.94%	10.21%	14.45%
Average					6.30%	7.01%

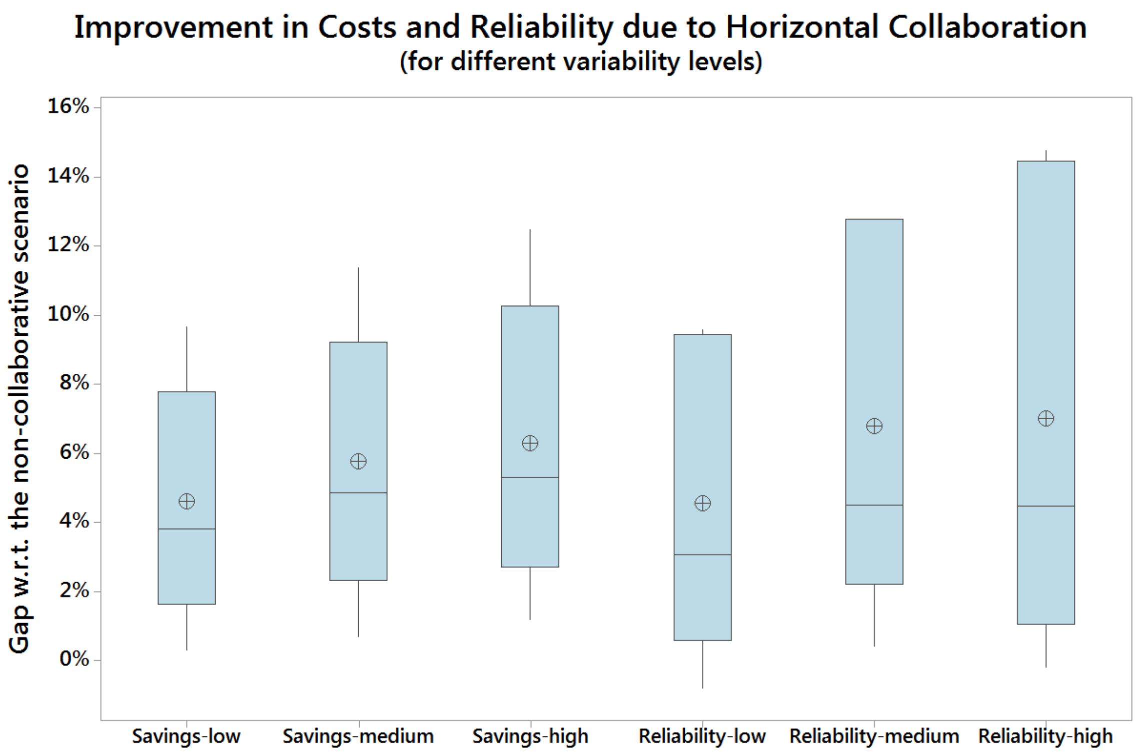

Figure 9.7: Improvement in costs and reliability w.r.t. the non-collaborative scenario

(III) CONCLUSIONS AND FUTURE RESEARCH

CHAPTER 10

FINAL CONCLUSIONS

10.1 Main research contributions

This thesis solidifies and extends the general simheuristic paradigm. In particular, it introduces and supports the use of the simulation-optimization framework as decision support tool in the creation of efficient and sustainable smart city logistics. Several research contributions according to the established investigation objectives can be identified:

- **Objective 1:** *Development of new simulation-optimization algorithms according to the general simheuristic framework.*

Various simulation-optimization procedures are developed according to the general simheuristic paradigm. Problem-specific algorithms for stochastic versions of different combinatorial optimization problems (COPs) are outlined. Special focus is put on solving frameworks to address different stages of urban freight transportation planning such as vehicle routing, customer clustering, facility location, and integrated supply chain design problems.

The elaborated algorithms are flexible enough to be applied to a wider range of optimization problems under uncertainty. Especially SimGRASP and SimVNS are highlighted as two extensions to well-known metaheuristic procedures that can handle any kind of COP. On the one hand, SimGRASP is tested on the permutation Flow Shop Problem, the Vehicle Routing Problem, and the uncapacitated Facility Location Problem. In all cases it is shown that

SimGRASP constitutes a competitive and easy-to-implement framework to solve stochastic optimization problems in different environments. On the other hand, an even higher integration of simulation and optimization is achieved by SimVN through a stochastically-driven base solution from which new solutions are generated. The algorithms' performance and behavior is tested on stochastic versions of problem settings related to operational, tactical, and strategic problem settings arising in smart city logistics concepts. Even though the problem settings differ in their complexity and level of decision-taking integration, the proposed algorithm is able to find competitive solutions to large-scaled problem instances in only a few seconds or minutes.

- **Objective 2:** *Proposal of methodological extensions, definition of best-practices, and discussion of potential future applications of simheuristic paradigms.*

Simheuristics constitute a relatively new simulation-optimization approach that has been gaining increased attention in recent years. Research completed for this dissertation has directly supported the solidification and extension of the general framework. The following best practices in the creation of simheuristic algorithms are emphasized:

i It is shown that the performance of simheuristic results is directly related to the underlying optimization engine. The use of state-of-the-art metaheuristic procedures to ensure high-quality COP solutions is proposed.

ii The integration of two different simulation stages is highly recommended. By filtering promising solutions in a first (short) simulation phase, it can be avoided that a more extensive (long) set of simulation runs jeopardizes computational times.

iii Obtained simulation-optimization results show the potential of simheuristics regarding an additional risk analysis for further decision-taking insights. The creation of performance indicators such as the mean or standard deviation of expected results in order to rank created solutions along different dimensions is suggested. Tested scenarios include the evaluation of vehicle safety stocks, the effect of time-dependency in stochastic systems, customer allocation under different demand variance levels, and the location of facilities in complex environments. The completed risk and reliability analyses and their associated visualization — in the form of boxplots, radar charts, etc. — serve as illustrative examples for a wider range of potential applications.

Moreover, two major methodological extensions to the general simheuristic paradigm are proposed in this work. The importance of data preparation and continuous stakeholder involvement during the modeling process in real-life application scenarios is outlined. Additionally, an agent-based simheuristic framework that combines agent based simulation with metaheuristics is proposed. This represents a novel simulation-optimization approach to model and solve large-scaled optimization problems shaped by the complexity of stakeholder interaction in social networks.

- **Objective 3:** *Application of simheuristic algorithms to rich optimization problems (of theoretical and practical nature) related to urban freight transportation on operational, tactical, and strategic planning levels.*

Developed algorithms are applied to a range of stochastic problem settings related to urban freight transportation planning. On the one hand, smart urban waste management is supported. This includes the development of simheuristic approaches to optimize the operational task of waste collection in urban areas. The problem settings are formulated as rich vehicle routing problem extensions under the consideration of time-windows, capacity constraints, multiple depots, time dependency, driver-lunch breaks, and input uncertainty regarding waste levels and travel times. Numerical tests are completed on well-known academic benchmark settings with up to 2100 collection points and a large-scaled case study in the Catalan city of Sabadell with nearly 900 waste containers.

On the other hand, presented simheuristic algorithms are presented and tested on stochastic optimization problems with higher complexity derived from an increased level of decision-taking integration. This includes a simulation-optimization approach for the multi-period and stochastic Inventory Routing Problem arising in vendor managed inventory concepts, which combines vehicle routing and inventory replenishment decisions. Experiments are completed on theoretical benchmarks with up to 80 retail centers that are served from a central depot. Furthermore, the two-echelon Location Routing Problem is addressed. This problem setting occurs in the creation of urban consolidation centers, a concept that aims at reducing the negative externalities of freight transportation in cities. The proposed simulation-optimization procedure is tested on real-life data from a fast-moving goods supply chain with 100 delivery points in the Greek capital of Athens.

Finally, a simheuristic algorithm is proposed to support the development of horizontal collaboration concepts, which are based on joint decisions and resources of different supply chain actors operating on the same market level. Depending on the collaboration scenario, this involves the solution of COPs that differ in their operational, tactical, and strategic planning scope. Through various computational experiments, it is shown that simheuristics can be an important decision-support tool to assess any stage of collaboration agreements in different uncertainty scenarios.

- **Objective 4:** *Analysis of simheuristics as a decision support tool to generate managerial insights in the development of smart city logistics.*

Various research outcomes support the use of simheuristics as decision-support tool to generate managerial insights in the development of smart city logistics. In all discussed problem settings — regardless of their planning horizon, complexity, or decision integration —, simheuristics are able to provide results within a few seconds or minutes. Even large-scaled scenarios with several thousands of network nodes are solved within reasonable computational times, emphasizing the scalability of the simulation-optimization framework. Moreover, it is shown that the suggested algorithms are able to compete with exact solving approaches and state-of-the art academical and real-life benchmarks.

The main additional managerial insights through simheuristics are provided by their ability to account for uncertainty in a smart way. Apart from providing expected objective function values with regard to different levels of input variability, obtained simulation results are used for an additional risk and reliability analysis of obtained results. Examples outlined in this thesis include a reliability analysis of waste collection routes with different capacity safety stocks or stochastic travel times in time-dependent route planning, an analysis of expected routing and inventory costs with different demand variance levels, and a stock-out risk comparison between collaborative and non-collaborative supply chains. This information directly extends the decision-taking flexibility of urban freight transportation planners, as he or she is able to choose proposed solutions according to his or her utility function or risk adversity.

Furthermore, this thesis shows that simheuristic frameworks can support the analysis, quantification, and development of smart city logistics concepts. It is outlined how the paradigm can be used to evaluate different collaboration scenarios in urban freight transportation along monetary and environmental dimensions. This includes different levels of shared resources and joint decisions, including customer allocation, capacity sharing, or the creation of urban consolidation centers.

- **Objective 5:** *Comparison of developed optimization algorithms to state-of-the-art academic and real-life benchmarks.*

Whenever possible, the elaborated metaheuristic and simheuristic algorithms are evaluated against state-of-the-art benchmarks found in relevant academic publications. This underlines the competitiveness of the proposed solving frameworks in comparison to other algorithms put forward in the literature. Moreover, real-life data are used to show the applicability of developed paradigms in practical optimization scenarios.

The underlying Variable Neighborhood Search metaheuristic of the SimVNS algorithm proposed in the context of urban waste collection outperforms previously reported results for an extensive set of waste collection problem instances by over 2.5% on average. Likewise, the algorithm is compared to a GAMS implementation of an analytic problem formulation. Results outline superior modeling capabilities, scalability, and computational times of the developed metaheuristic. Regarding the case study in Sabadell, the proposed simulation-optimization algorithm improves current waste collection plans completed by the waste management service provider on a daily basis by over 10%. Moreover, collaborative waste collection in clustered urban areas is supported by showing that improved customer allocation yields potential operational cost savings of up to 30%.

For the Inventory Routing Problem addressed in the context of integrated supply chain design, it is shown that a multi-period planning horizon significantly outperforms the single period approach outlined in previous works. Moreover, the advantages of creating an individualized inventory replenishment matrices for each delivery point are emphasized. The potential benefits of creating urban consolidation centers on city borders are highlighted by solving the two-echelon Location Routing Problem. Computational experiments are completed on real-life data from a fast-moving goods supply chain in the Greek capital Athens. The application of the outlined simheuristic shows that up to 38% of routing costs can be saved through this city logistics concept.

Finally, the elaborated metaheuristic procedure to solve all optimization problems arising in the context of horizontal concepts is extensively compared to state-of-the-art algorithms found in relevant academic publications. Reported results suggest that the solving framework is generic enough to provide competitive solutions for the VRP, the MDVRP, and the LRP with only minor adjustments. Regarding the comparison of different supply chain collaboration degrees, the solving framework is able to quantify significant differences in terms of routing, facility location, vehicle usage, and external costs in the form of CO_2 emissions.

10.2 Potential future research lines

Various potential future research lines steam from this work. New simulation-optimization paradigms such as the proposed agent-based simheuristic framework could be tested. Additional insights on the behavior and performance of the established approach in different environments would allow a more detailed definition regarding the necessary steps and best-practices of this agent-based concept. A more detailed study of parallel and distributed computing systems for simheuristic paradigms could be especially (but not exclusively) interesting in this context.

Similarly, the elaborated simheuristic extensions to well-known metaheuristics such as SimGRASP or SimVNS could be explored in a wider range of application environments. While the proposed frameworks are thoroughly tested and applied to a range of stochastic optimization problems arising in the context of smart city logistics concepts throughout this dissertation, the presented algorithms are flexible enough to be applicable in other optimization settings such as flow shop scheduling, airline crew rostering, etc.

Research for this dissertation has led to the solidification of the general simheuristic framework, for example by showing that the use of a reduced simulation run can filter promising solutions to reduce the computational effort of a more detailed simulation phase. An interesting extension in this context would be a more focused study of different data analysis concepts to further improve the performance of simheuristic algorithms. This might include parameter fine-tuning algorithms, parallelization techniques, solution search predictions, or similar techniques.

Yet another interesting research area is the integration of machine learning techniques in simheuristic and metaheuristic approaches as natural approach for solving optimization problems with dynamic inputs. This makes the hybridization of simheuristics and machine learning a potential approach to deal with the increasing stochasticity and dynamism of real-world problems in complex environments such as urban freight transportation and logistics.

Finally, a more intensive investigation of simheuristics as "optimization-as-a-service" toolbox for real-life optimization settings would increase the applicability of the simulation-optimization paradigm. The methodological implications of applying metaheuristics in real-life settings are shown in this thesis through large-scaled case studies, which emphasize the importance of data preparation and a continuous stakeholder involvement for a successful implementation of the proposed approach. On the one hand, further research in the form of different case studies could be completed to test and improve the applicability of simheuristics in practical scenarios. On the other hand, more detailed research regarding the technical aspects of industrializing and implementing specialized simheuristic algorithms to provide their functionalities (e.g. regarding the development of smart city logistics concepts) to a wider audience would be of both theoretical and practical interest.

10.3 Summary of research output

The discussions and results presented in this work are based on numerous research outputs in the form of publications in ISI-SCI and SCOPUS indexed journals and the proceedings of peer-reviewed international conferences. Developed research dissemination includes:

- **Papers published in ISI-SCI indexed Journals**
  - ***(A1)*** **Gruler, A.**; Fikar, C.; Juan, A.; Hirsch, P.; Contreras, C. (2017): *Supporting multi-depot and stochastic waste collection management in clustered urban areas via simulation-optimization*. Journal of Simulation, 11(1): 11-19 (indexed in ISI SCI, 2017 IF = 1.218, Q3; 2017 SJR = 0.428, Q2). DOI: `https://doi.org/10.1057/s41273-016-0002-4`..
  - ***(A2)*** **Gruler, A.**; Quintero, C.; Calvet, L.; Juan, A. (2017): *Waste Collection Under Uncertainty: a simheuristic based on variable neighborhood search*. European Journal of Industrial Engineering, 11(2): 228-255. DOI: 10.1504/EJIE.2017.10003619 (indexed in ISI SCI, 2017 IF = 1.085, Q3; 2017 SJR = 0.595, Q1). DOI: `https://doi.org/10.1504/EJIE.2017.083257`.
  - ***(A3)*** **Gruler, A.**; Panadero, J.; de Armas, J.; Moreno-Perez, J.; Juan, A. (2018): *A Variable Neighborhood Search Simheuristic for the Multi-Period Inventory Routing Problem with Stochastic Demands*. Int. Transactions in Operational Research (indexed in ISI SCI, 2017 IF = 2.400, Q1; 2017 SJR = 1.071, Q1). DOI: `https://doi.org/10.1111/itor.12479`.
  - ***(A4)*** Quintero, C.; **Gruler, A.**; Juan, A.; Faulin, J. (2017): *Using Horizontal Cooperation Concepts in Integrated Routing and Facility Location Decisions*. Int. Transactions in Operational Research (indexed in ISI SCI, 2017 IF = 2.400, Q1; 2017 SJR = 1.071, Q1). DOI: `https://doi.org/10.1111/itor.12540`.

- **(A5)** Ferone, D.; **Gruler, A.**; Festa, P.; Juan, A. (2018): *Enhancing and Extending the Classical GRASP Framework with Biased Randomization and Simulation*. Journal of the Operational Research Society (indexed in ISI SCI, 2017 IF = 1.396, Q3; 2017 SJR = 1.002, Q1). DOI: `https://doi.org/10.1080/01605682.2018.1494527`.
- **(A6)** **Gruler, A.**; Panadero, J.; de Armas, J.; Moreno-Perez, J.; Juan, A. (**2018**): *Combining variable neighborhood search with simulation for the inventory routing problem with stochastic demands and stock-outs*. Computers and Industrial Engineering (indexed in ISI SCI, 2017 IF = 3.195, Q1; 2017 SJR = 1.463, Q1). DOI: `https://doi.org/10.1016/j.cie.2018.06.036`.

- **Papers published in Scopus indexed Journals**
  - **(B1)** Quintero, C.; **Gruler, A.**; Juan, A.; De Armas, J.; Ramalhinho, H. (2017): *Using Simheuristics to promote Horizontal Collaboration in Stochastic City Logistics*. Progress in Artificial Intelligence (indexed in Scopus, 2015 SJR = 0.124, Q4). DOI: `https://doi.org/10.1007/s13748-017-0122-8`.
  - **(B2)** Ferone, D.; Festa, P.; **Gruler, A.**; Juan, A. (2017): *Combining simulation with a GRASP metaheuristic for solving the permutation flow-shop problem with stochastic processing times*. Proceedings of the 2016 Winter Simulation Conference, 2205-2215 (Indexed in ISI Web of Science and Scopus, 2015 SJR = 0.115). DOI: `10.1109/WSC.2016.7822262`.
  - **(B3)** Agustin, A.; **Gruler, A.**; De Armas, J.; Juan, A. (2016): *Optimizing airline crew scheduling using biased randomization: A case study*. Advances in Artificial Intelligence. CAEPIA 2016. Lecture Notes in Computer Science, vol 9868 (indexed in ISI Web of Science and Scopus, 2014 SJR = 0.339, Q2). DOI: `https://doi.org/10.1007/978-3-319-44636-3_31`.
  - **(B4)** Quintero, C.; **Gruler, A.**; Juan, A. (2016): *Quantifying potential benefits of Horizontal Cooperation in urban transportation under uncertainty: A simheuristic approach*. Advances in Artificial Intelligence. CAEPIA 2016. Lecture Notes in Computer Science, vol 9868 (indexed in ISI Web of Science and Scopus, 2014 SJR = 0.339, Q2). DOI: `https://doi.org/10.1007/978-3-319-44636-3_26`.
  - **(B5)** **Gruler, A.**; Juan, A.; De Armas, J. (2016): *Behavioral factors in City Logistics from an Operations Research perspective*. Smart Cities. Smart-CT 2016. Lecture

Notes in Computer Science, vol 9704 (indexed in ISI Web of Science and Scopus, 2015 SJR = 0.252, Q3). DOI: `https://doi.org/10.1007/978-3-319-39595-1_4`.

- ***(B6)*** **Gruler, A.**; Juan, A.; Contreras-Bolton, C., Gatica, G. (2015): *A Biased-Randomized Heuristic for the Waste Collection Problem in Smart Cities*. Applied Mathematics and Computational Intelligence. FIM 2015. Advances in Intelligent Systems and Computing, vol 730 (indexed in ISI Web of Science and Scopus, 2015 SJR = 0.252, Q3). DOI: `https://doi.org/10.1007/978-3-319-75792-6_19`.

- **Papers under review in ISI indexed Journals at the time of submitting this dissertation**
  - ***(C1)*** **Gruler, A.**; Perez, T.; Calvet, L.; Juan, A. (under review): *A Simheuristic Algorithm for Time-Dependent Waste Collection Management with Stochastic Travel Times*. Int. Transactions in Operational Research (indexed in ISI SCI, 2017 IF = 2.400, Q1; 2017 SJR = 1.071, Q1). ISSN: 0969-6016.
  - ***(C2)*** **Gruler, A.**; De Armas, J.; Juan, A.; Goldsman, D. (under review): *Modeling Human Behavior in Social Networks: a survey and the need for simheuristics*. Statistics and Operations Research Transactions (indexed in ISI SCI, 2017 IF = 1.344, Q2; 2017 SJR = 0.551, Q2). ISSN: 1696-2281.

- **Presentations in peer-reviewed international conferences**
  - ***(D1)*** **Gruler, A.**; Klueter, A.; Rabe, M.; Juan, A. (2017): *A simulation-optimization approach for the two-echelon location routing problem arising in the creation of urban consolidation centers*. 17th ASIM Dedicated Conference on Simulation. Kassel, Germany. September 20-22.
  - ***(D2)*** Raba, D.; **Gruler, A.**; Riera, D.; Gelada, J.; Juan, A. (2017): *Combining real-time information with a variable neighborhood search metaheuristic for the inventory routing problem*. 2017 Metaheuristics International Conference. Barcelona, Spain. July 4-7.
  - ***(D3)*** Ferone, D.; **Gruler, A.**; Festa, A.; Juan, A. (2017): *Introducing biased randomization in GRASP*. 2017 Metaheuristics International Conference, 1-3. Barcelona, Spain. July 4-7.
  - ***(D4)*** **Gruler, A.**; Fikar, C.; Juan, A.; Hirsch, P.; Contreras, C. (2015): *A Simheuristic for the Waste Collection Problem with Stochastic Demands in Smart Cities*.

16th ASIM Dedicated Conference on Simulation. Dortmund, Germany. September 23-25.

- ***(D5)*** **Gruler, A.**; Juan, A.; Steglich, M. (2015): *A Heuristic Approach for smart Waste Collection Management*. 2015 Metaheuristics International Conference. Agadir, Morocco. June 7-10.
- ***(D6)*** **Gruler, A.**; Fikar, C.; Juan, A.; Hirsch, P. (2015): *Un algoritmo basado en aleatorización sesgada para la recolección eficiente de residuos en ciudades inteligentes*. X Congreso Español de Metaheurísticas, Algoritmos Evolutivos y Bioinspirados. Mérida, Spain. February 4-6.

APPENDIX A

COVER PAGES OF PAPERS PUBLISHED IN ISI-JCR INDEXED JOURNALS

Combining variable neighborhood search with simulation for the inventory routing problem with stochastic demands and stock-outs

Aljoscha Gruler[a,*], Javier Panadero[a], Jesica de Armas[b], José A. Moreno Pérez[c], Angel A. Juan[a]

[a]*IN3-Computer Science Department, Open University of Catalonia, Castelldefels, Spain*
[b]*Department of Economics and Business, Universitat Pompeu Fabra, Barcelona, Spain*
[c]*Instituto Universitario de Desarrollo Regional, Universidad de La Laguna, Santa Cruz de Tenerife, Spain*

Abstract

Vendor managed inventory aims at reducing supply chain costs by centralizing inventory management and vehicle routing decisions. This integrated supply chain approach results in a complex combinatorial optimization problem known as the inventory routing problem (IRP). This paper presents a variable neighborhood search metaheuristic hybridized with simulation to solve the IRP under demand uncertainty. Our simheuristic approach is able to solve large sized instances for the single period IRP with stochastic demands and stock-outs in very short computing times. A range of experiments underline the algorithm's competitiveness compared to previously used heuristic approaches. The results are analyzed in order to provide closer managerial insights.

Keywords: Variable neighborhood search, metaheuristics, simheuristics, inventory routing, stochastic demands.

*Corresponding Author
Email addresses: `agruler@uoc.edu` (Aljoscha Gruler), `jpanaderom@uoc.edu` (Javier Panadero), `jesica.dearmasa@upf.edu` (Jesica de Armas), `jamoreno@ull.es` (José A. Moreno Pérez), `ajuanp@uoc.edu` (Angel A. Juan)

Preprint submitted to Computers & Industrial Engineering *June 27, 2018*

Figure A.1: Cover Page of Gruler et al. (2018*c*)

INTERNATIONAL TRANSACTIONS IN OPERATIONAL RESEARCH

Intl. Trans. in Op. Res. XX (20XX) 1–22
DOI: xx.xxxx/itor.xxxxx

A Variable Neighborhood Search Simheuristic for the Multi-Period Inventory Routing Problem with Stochastic Demands

Aljoscha Gruler[a,*], Javier Panadero[a], Jesica de Armas[b], José A. Moreno Pérez[c] and Angel A. Juan[a]

[a]*IN3 – Computer Science Department, Open University of Catalonia, Castelldefels, Spain*
[b]*Department of Economics and Business, Universitat Pompeu Fabra, Barcelona, Spain*
[c]*Instituto Universitario de Desarrollo Regional, Universidad de La Laguna, Tenerife, Spain*
E-mail: agruler@uoc.edu [A. Gruler]; jpanaderom@uoc.edu [J. Panadero]; jesica.dearmasa@upf.edu [J. de Armas]; jamoreno@ull.es [J. Moreno Pérez]; ajuanp@uoc.edu [A. Juan]

Received DD MMMM YYYY; received in revised form DD MMMM YYYY; accepted DD MMMM YYYY

Abstract

The inventory routing problem (IRP) combines inventory management and delivery route-planning decisions. This work presents a simheuristic approach that integrates Monte Carlo simulation within a variable neighborhood search (VNS) framework to solve the multi-period IRP with stochastic customer demands. In this realistic variant of the problem, our goal is to establish the optimal refill policies for each customer-period combination, i.e., those individual refill policies that minimize the total expected cost over the periods. This cost is the aggregation of both expected inventory and routing costs. Our simheuristic algorithm allows to consider the inventory changes between periods generated by the realization of the random demands in each period, which have an impact on the quantities to be delivered in the next period and, therefore, on the associated routing plans. A range of computational experiments are carried out in order to illustrate the potential of our simulation-optimization approach.

Keywords: multi-period inventory routing problem; stochastic demands; variable neighborhood search; metaheuristics; simheuristics.

Figure A.2: Cover Page of Gruler et al. (2018*b*)

Enhancing and Extending the Classical GRASP Framework with Biased Randomization and Simulation

Daniele Ferone[a], Aljoscha Gruler[a,*], Paola Festa[b], Angel A. Juan[a]

[a] *IN3-Dept. of Computer Science, Open University of Catalonia, Av. Carl Friedrich Gauss 5, 08860 Castelldefels, Spain*

[b] *Dept. of Mathematics and Applications, University of Napoli FEDERICO II, Via Cintia, 80126 Napoli, Italy*

Abstract

Greedy Randomized Adaptive Search Procedure (GRASP) is one of the best-known metaheuristics to solve complex combinatorial optimization problems (COPs). This paper proposes two extensions of the typical GRASP framework. On the one hand, applying biased randomization techniques during the solution construction phase enhances the efficiency of the GRASP solving approach compared to the traditional use of a restricted candidate list. On the other hand, the inclusion of simulation at certain points of the GRASP framework constitutes an efficient simulation-optimization approach that allows to solve stochastic versions of COPs. To show the effectiveness of these GRASP improvements and extensions, tests are run with both deterministic and stochastic problem settings related to flow shop scheduling, vehicle routing, and facility location.

Keywords: GRASP; Combinatorial Optimization; Stochastic Optimization; Biased Randomization; Simheuristics.

1. Introduction

Many real-life combinatorial optimization problems (COPs) from different areas related to supply chain management, transportation and logistics, telecommunications, finance, production, etc. are shaped by large problem sizes and inherent complexity through various problem constraints. Typically, this results in NP-hard problem settings which cannot be solved to optimality in reasonable computing times. In this context, metaheuristics have proven to be very efficient in finding

*Corresponding author

Email addresses: dferone@uoc.edu (Daniele Ferone), agruler@uoc.edu (Aljoscha Gruler), paola.festa@unina.it (Paola Festa), ajuanp@uoc.edu (Angel A. Juan)

Preprint submitted to Journal of the Operational Research Society *July 10, 2018*

Figure A.3: Cover Page of Ferone et al. (2018)

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

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

Aljoscha Gruler*

IN3 – Computer Science,
Multimedia and Telecommunications Department,
Open University of Catalonia,
Castelldefels, Spain
Email: agruler@uoc.edu
*Corresponding author

Carlos L. Quintero-Araújo

IN3 – Computer Science,
Multimedia and Telecommunications Department,
Open University of Catalonia,
Castelldefels, Spain
and
International School of Economics and Administrative Sciences,
Universidad de La Sabana,
Chía, Colombia
Email: cquinteroa@uoc.edu

Laura Calvet and Angel A. Juan

IN3 – Computer Science,
Multimedia and Telecommunications Department,
Open University of Catalonia,
Castelldefels, Spain
Email: lcalvetl@uoc.edu
Email: ajuanp@uoc.edu

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 A.4: Cover Page of Gruler et al. (2017*c*)

Journal of Simulation (2016)

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Supporting multi-depot and stochastic waste collection management in clustered urban areas via simulation–optimization

A Gruler[1], C Fikar[2], AA Juan[1,*], P Hirsch[2] and C Contreras-Bolton[3]

[1]Department of Computer Science – IN3, Open University of Catalonia, Av. Carl Friedrich Gauss 5, 08860 Castelldefels, Spain; [2]Institute of Production and Logistics, University of Natural Resources and Life Sciences, Gregor–Mendel-Straße 33, 1180 Vienna, Austria; and [3]DEI, University of Bologna, Viale Risorgimento 2, 40136 Bologna, Italy

Waste collection is one of the most critical logistics activities in modern cities with considerable impact on the quality of life, urban environment, city attractiveness, traffic flows and municipal budgets. Despite the problem's relevance, most existing work addresses simplified versions where container loads are considered to be known in advance and served by a single vehicle depot. Waste levels, however, cannot be estimated with complete certainty as they are only revealed at collection. Furthermore, in large cities and clustered urban areas, multiple depots from which collection routes originate are common, although cooperation among vehicles from different depots is rarely considered. This paper analyses a rich version of the waste collection problem with multiple depots and stochastic demands by proposing a hybrid algorithm combining metaheuristics with simulation. Our 'simheuristic' approach allows for studying the effects of cooperation among different depots, thus quantifying the potential savings this cooperation could provide to city governments and waste collection companies.
Journal of Simulation (2016). doi:10.1057/s41273-016-0002-4

Keywords: simheuristics; simulation–optimization; waste collection management; multi-depot vehicle routing problem; horizontal cooperation; stochastic demands

Figure A.5: Cover Page of Gruler et al. (2017a)

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Intl. Trans. in Op. Res. 00 (2017) 1–27
DOI: 10.1111/itor.12479

Using horizontal cooperation concepts in integrated routing and facility-location decisions

Carlos L. Quintero-Araujo[a,b], Aljoscha Gruler[a], Angel A. Juan[a] and Javier Faulin[c]

[a] IN3 – Computer Science Department, Open University of Catalonia, 08860 Castelldefels, Spain
[b] International School of Economic and Administrative Sciences, Universidad de La Sabana, Chia, Colombia
[c] Institute of Smart Cities, Department of Statistics and OR, Public University of Navarra, 31006 Pamplona, Spain
E-mail: cquinteroa@uoc.edu, carlosqa@unisabana.edu.co [Quintero-Araujo]; agruler@uoc.edu [Gruler];
ajuanp@uoc.edu [Juan]; javier.faulin@unavarra.es [Faulin]

Received 11 April 2017; received in revised form 9 August 2017; accepted 10 October 2017

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: (a) a noncooperative scenario in which all decisions are individually taken (each enterprise addresses its own vehicle routing problem [VRP]); (b) a semicooperative scenario in which route-planning decisions are jointly taken (facilities and fleets are shared and enterprises face a joint multidepot VRP); and (c) a fully cooperative scenario in which route-planning and facility-location decisions are jointly taken (also customers are shared, and thus enterprises face a general location routing problem). Our analysis explores how this increasing level of HC leads to a higher flexibility and, therefore, to a lower total distribution cost. A hybrid metaheuristic algorithm, combining biased randomization with a variable neighborhood search framework, is proposed to solve each scenario. This allows us to quantify the differences among these scenarios, both in terms of monetary and environmental costs. Our solving approach is tested on a range of benchmark instances, outperforming previously reported results.

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

Figure A.6: Cover Page of Quintero-Araujo et al. (2017*b*)

APPENDIX B

COVER PAGES OF JOURNAL PAPERS PUBLISHED IN SCOPUS INDEXED JOURNALS

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.

COMBINING SIMULATION WITH A GRASP METAHEURISTIC FOR SOLVING THE PERMUTATION FLOW-SHOP PROBLEM WITH STOCHASTIC PROCESSING TIMES

Daniele Ferone
Paola Festa

Dept. of Mathematics and Applications
University of Napoli FEDERICO II
Via Cintia
80126 Napoli, ITALY

Aljoscha Gruler
Angel A. Juan

Dept. of Computer Science
Open University of Catalonia – IN3
Av. Carl Friedrich Gauss 5
08860 Castelldefels, SPAIN

ABSTRACT

Greedy Randomized Adaptive Search Procedures (GRASP) are among the most popular metaheuristics for the solution of combinatorial optimization problems. While GRASP is a relatively simple and efficient framework to deal with deterministic problem settings, many real-life applications experience a high level of uncertainty concerning their input variables or even their optimization constraints. When properly combined with the right metaheuristic, simulation (in any of its variants) can be an effective way to cope with this uncertainty. In this paper, we present a simheuristic algorithm that integrates Monte Carlo simulation into a GRASP framework to solve the permutation flow shop problem (PFSP) with random processing times. The PFSP is a well-known problem in the supply chain management literature, but most of the existing work considers that processing times of tasks in machines are deterministic and known in advance, which in some real-life applications (e.g., project management) is an unrealistic assumption.

Figure B.1: Cover Page of Ferone et al. (2016)

A Biased-Randomized Heuristic for the Waste Collection Problem in Smart Cities

Aljoscha Gruler[1(✉)], Angel A. Juan[1], Carlos Contreras-Bolton[2], and Gustavo Gatica[2,3]

[1] Universitat Oberta de Catalunya,
Rambla Poblenou 156, 08018 Barcelona, Spain
{agruler,ajuanp}@uoc.edu
[2] Universidad de Santiago de Chile,
Av. Libertador Bernardo O'Higgins 3363, Santiago, Chile
{carlos.contrerasb,gustavo.gatica}@usach.cl
[3] Universidad Andres Bello, Sazié, Región Metropolitana, Santiago, Chile

Abstract. This paper describes an efficient heuristic to solve the Waste Collection Problem (WCP), which is formulated as a special instance of the well-known Vehicle Routing Problem (VRP). Our approach makes use of a biased-randomized version of a savings-based heuristic. The proposed procedure is tested against a set of benchmark instances, obtaining competitive results.

Keywords: Vehicle routing problem · Biased-Randomized heuristics
Waste collection problem · Smart Cities

Figure B.2: Cover Page of Gruler et al. (2018*a*)

Behavioral Factors in City Logistics from an Operations Research Perspective

Aljoscha Gruler(✉), Jesica de Armas, and Angel A. Juan

Department of Computer Science - IN3, Open University of Catalonia,
Av. Carl Friedrich Gauss 5, 08860 Castelldefels, Spain
{agruler,jde_armasa,ajuanp}@uoc.edu

Abstract. In the face of sharp urbanization around the world, metropolitan areas have started different initiatives and projects to make cities more efficient and sustainable. Hereby logistics and transportation activities have a major impact in the development of so called 'Smart Cities'. By addressing complex decision making problems through simulation and optimization, the Operations Research community has contributed to the development of sustainable city logistic systems. While technical and structural problems have been extensively discussed in the literature, many models neglect the importance of behavioral issues arising from risk aversion, stakeholder interaction and human factors that play an important role in the consolidation and optimization of logistical activities. This paper reviews existing work considering behavioral factors from an OR perspective. Simulation and optimization models to major problem settings in City Logistics are discussed and methodologies to conquer real-life urban L&T challenges are presented.

Figure B.3: Cover Page of Gruler et al. (2016)

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

Carlos L. Quintero-Araujo[1,2](✉), Aljoscha Gruler[1], and Angel A. Juan[1]

[1] IN3 - Department of Computer Science, Universitat Oberta de Catalunya,
Av. Carl Friedrich Gauss 5, 08860 Castelldefels, Spain
{cquinteroa,agruler,ajuanp}@uoc.edu
[2] International School of Economics and Administrative Sciences,
Universidad de La Sabana, Autopista Norte Km 7, Chía, Colombia

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).

Figure B.4: Cover Page of Quintero-Araujo et al. (2016)

Prog Artif Intell (2017) 6:275–284
DOI 10.1007/s13748-017-0122-8

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REGULAR PAPER

Using simheuristics to promote horizontal collaboration in stochastic city logistics

Carlos L. Quintero-Araujo[1] · Aljoscha Gruler[1] · Angel A. Juan[1] · Jesica de Armas[2] · Helena Ramalhinho[2]

Received: 20 December 2016 / Accepted: 8 March 2017 / Published online: 23 March 2017

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

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

Figure B.5: Cover Page of Quintero-Araujo et al. (2017*c*)

Optimizing Airline Crew Scheduling Using Biased Randomization: A Case Study

Alba Agustín[1], Aljoscha Gruler[2(✉)], Jesica de Armas[2], and Angel A. Juan[2]

[1] Public University of Navarra, Pamplona, Spain
albamaria.agustin@unavarra.es
[2] Open University of Catalonia, Barcelona, Spain
{agruler,jde_armasa,ajuanp}@uoc.edu

Abstract. Various complex decision making problems are related to airline planning. In the competitive airline industry, efficient crew scheduling is hereby of major practical importance. This paper presents a metaheuristic approach based on biased randomization to tackle the challenging Crew Pairing Problem (CPP). The objective of the CPP is the establishment of flight pairings allowing for cost minimizing crew-flight assignments. Experiments are done using a real-life case with different constraints. The results show that our easy-to-use and fast algorithm reduces overall crew flying times and the necessary number of accompanying crews compared to the pairings currently applied by the company.

Keywords: Biased randomization · Airline planning · Metaheuristics · Crew pairing problem · Crew scheduling

Figure B.6: Cover Page of Agustín et al. (2016)

Appendix C

Performance of BR-GRASP and SimGRASP for the PFSP

One of the most studied scheduling problems is related to the optimization of flow shop operations (Pinedo 2008). It consists of a set J of jobs which has to be processed by $m \in M$ machines. The machines sequentially perform the operations O_{ij} related to each job $i \in J$, whereby each operation requires a specific processing time. The permutation Flow Shop Problem (PFSP) is a special scheduling case, in which the order of processing the operations on the machines is the same for all jobs. The objective function of the problem setting typically consists of the minimization of the overall completion time (known as *makespan*) of processing all jobs on all machines. This NP-hard problem (Garey and Johnson 1990) has a wide range of applications in different sectors, including manufacturing, pharmaceuticals, or the telecommunications sector.

To test BR-GRASP and SimGRASP, the benchmarks for the deterministic PFSP presented by Taillard (1993) are used. The problem settings range from 20-500 jobs and 5-20 machines, with the objective of minimizing total makespan. These benchmark cases were later applied by Zobolas et al. (2009) and Juan et al. (2014*e*). While the former address the deterministic problem setting with a hybrid metaheuristic based on a Genetic Algorithm enriched with VNS, the later develop a simheuristic algorithm based on the combination of simulation and ILS. More specifically, the authors solve the PFSP with stochastic processing times (PFSPST), in which processing times p_{ij} of job i and machine j are formulated as stochastic variables.

For the deterministic problem setting, both the traditional GRASP metaheuristic and BR-GRASP were implemented with a maximum running time of 30 seconds. After some preliminary testing, the threshold parameter defining the size of the RCL was set to $\alpha = 0.7$, while the geometric distribution parameter β defining the biased randomization probabilities was set to 0.1. To allow a fair comparison to other simheuristic approaches for the PFSPST, the maximum running time was defined as $t_{max} = 0.03 \times \#jobs \times \#machines$ in the stochastic case.

The performance of the algorithms are outlined in Table C.1. Compared to the best known solutions (BKSs) for the deterministic PFSP variant as put forward by Zobolas et al. (2009), the traditional GRASP metaheuristic yields an average percentage gap of 1.8%. This gap is reduced to 1.63% when applying BR-GRASP. Concerning to the stochastic problem version, SimGRASP is compared to the SimILS approach discussed by Juan et al. (2014*e*). These authors present a generalized PFSPST benchmark set by creating stochastic processing times P_{ij} based on the deterministic processing time values as a mean, and modeling the stochastic processing times within a log-normal distribution with different variance levels k. The table reports results for a variance level of $k = 0.5$. As it can be seen, the obtained average gap over all instances lies at 0.37%.

Table C.1: Performance of BR-GRASP and SimGRASP for the PFSP

Instance	BKS (1)	GRASP (2)	BR-GRASP (3)	%-Gap (1)-(2)	%-Gap (1)-(3)	SimILS (4)	SimGRASP (5)	%-Gap (4)-(5)
tai007_20_5	1234	1236	1239	0.16	0.41	1240.1	1240.63	0.04
tai009_20_5	1230	1230	1230	0.00	0.00	1237.3	1237.73	0.03
tai010_20_5	1108	1108	1108	0.00	0.00	1113.9	1113.59	-0.03
tai011_20_10	1582	1586	1586	0.25	0.25	1587.9	1587.76	-0.01
tai013_20_10	1496	1501	1508	0.33	0.80	1503	1503.4	0.03
tai027_20_20	2273	2291	2284	0.79	0.48	2277.1	2277.04	0.00
tai036_50_5	2829	2829	2829	0.00	0.00	2829.8	2831.98	0.08
tai040_50_5	2782	2782	2782	0.00	0.00	2783.1	2782.99	0.00
tai044_50_10	3063	3102	3093	1.27	0.98	3067.8	3070.32	0.08
tai045_50_10	2976	3068	3053	3.09	2.59	2999.7	3025.96	0.88
tai046_50_10	3006	3075	3079	2.30	2.43	3018.3	3038.43	0.67
tai047_50_10	3093	3158	3150	2.10	1.84	3131.6	3138.33	0.21
tai052_50_20	3704	3846	3828	3.83	3.35	3726	3767.71	1.12
tai055_50_20	3610	3747	3737	3.80	3.52	3631.5	3679.19	1.31
tai062_100_5	5268	5268	5268	0.00	0.00	5271.1	5270.1	-0.02
tai067_100_5	5246	5250	5246	0.08	0.00	5256.4	5262.94	0.12
tai078_100_10	5617	5695	5672	1.39	0.98	5646.3	5662.14	0.28
tai082_100_20	6183	6434	6416	4.06	3.77	6249.7	6305.68	0.90
tai087_100_20	6268	6519	6488	4.00	3.51	6351.8	6400.66	0.77
tai094_200_10	10889	10917	10893	0.26	0.04	10895.2	10893.1	-0.02
tai097_200_10	10854	10914	10885	0.55	0.29	10878.2	10893.12	0.14
tai102_200_20	11203	11617	11580	3.70	3.37	11390.2	11452.68	0.55
tai103_200_20	11281	11671	11694	3.46	3.66	11462	11526.96	0.57
tai104_200_20	11275	11672	11631	3.52	3.16	11386.6	11480.78	0.83
tai105_200_20	11259	11581	11535	2.86	2.45	11375.3	11435.16	0.53
tai107_200_20	11360	11741	11679	3.35	2.81	11511.9	11556.31	0.39
tai108_200_20	11334	11678	11687	3.04	3.11	11497	11563.86	0.58
tai112_500_20	26520	27084	27048	2.13	1.99	26757.9	26867.79	0.41
tai113_500_20	26371	26858	26801	1.85	1.63	26559.4	26631.68	0.27
tai118_500_20	26560	27051	26990	1.85	1.62	26713	26802.02	0.33
Average				***1.80***	***1.63***			***0.37***

APPENDIX D

Performance of BR-GRASP and SimGRASP for the VRP

The Vehicle Routing Problem (VRP) is typically formulated on a graph $G = (V, E)$, whereby customer set $V = 0, 1, \ldots, n$ describes n clients with demand $d_i, i \in V \setminus \{0\}$, which have to be served by a set of vehicles located at the central depot $0 \in V$. Travel distances between any two nodes are described by a set E of weighted edges. Typically, the objective function consists of the minimization of overall travel distances or costs (Toth and Vigo 2014).

In order to compare BR-GRASP with the traditional GRASP metaheuristic implementation, threshold parameter α was set to 0.3, while the geometric distribution parameter β was set to 0.5 respectively. As test instances, the sets A and B of the well-known benchmark set for the capacitated VRP proposed by Augerat et al. (1998) are used. The algorithms running time for the deterministic case was set to 30 seconds for both algorithm implementations. All results are compared to the optimal results for the chosen instances elaborated in the work of Fukasawa et al. (2006). Furthermore, the VRP with stochastic demands (VRPSD) was used to evaluate the performance of the SimGRASP methodology. As performance indicator, the results obtained with the simheuristic based on a multi-start heuristic procedure discussed by Juan et al. (2013*b*) are used. As done in their paper, the deterministic demand levels d_i given by the benchmarks are turned into their stochastic counterpart by applying different variance levels k, whereby a variance level of $k = 0.25$ is used to obtain the results reported in this work. Computational running times are set to 10 seconds for the stochastic case.

As summarized in Table D.1, the traditional implementation of GRASP is on average

Table D.1: Performance of BR-GRASP and SimGRASP for the VRP

Instance	BKS (1)	GRASP (2)	BR-GRASP (3)	%-Gap (1)-(2)	%-Gap (1)-(3)	SimMultiStart (4)	SimGRASP (5)	%-Gap (4)-(5)
A-n32-k5	787.08	807.09	787.2	2.54	0.02	993.20	890.95	-10.30
A-n33-k5	662.11	687.91	662.11	3.90	0.00	815.40	750.63	-7.94
A-n33-k6	742.69	768.84	742.69	3.52	0.00	912.60	837.63	-8.21
A-n37-k5	664.8	707.81	685.26	6.47	3.08	795.00	734.44	-7.62
A-n38-k5	716.5	768.13	747.14	7.21	4.28	885.10	824.37	-6.86
A-n39-k6	822.8	863.08	835.25	4.90	1.51	1010.60	926.11	-8.36
A-n45-k6	938.1	1006.45	957.06	7.29	2.02	1184.30	1091.36	-7.85
A-n45-k7	1139.3	1199.98	1155.22	5.33	1.40	1502.00	1336.08	-11.05
A-n55-k9	1067.4	1099.84	1088.45	3.04	1.97	1408.40	1258.72	-10.63
A-n60-k9	1344.4	1421.88	1363.58	5.76	1.43	1795.70	1579.79	-12.02
A-n61-k9	1022.5	1102.23	1042.96	7.80	2.00	1330.60	1224.44	-7.98
A-n63-k9	1607	1687.96	1649.33	5.04	2.63	2203.70	1897.29	-13.90
A-n65-k9	1166.5	1239.42	1197.49	6.25	2.66	1555.30	1437.84	-7.55
A-n80-k10	1754	1860.94	1798.01	6.10	2.51	2328.40	2177.10	-6.50
B-n31-k5	676.09	681.16	676.09	0.75	0.00	855.70	757.60	-11.46
B-n35-k5	956.29	978.33	961.77	2.30	0.57	1255.50	1098.00	-12.54
B-n39-k5	549	566.71	553.27	3.23	0.78	695.90	621.34	-10.71
B-n41-k6	826.4	878.3	844.7	6.28	2.21	1103.20	1005.62	-8.84
B-n45-k5	747.5	757.16	754.23	1.29	0.90	904.60	828.04	-8.46
B-n50-k7	741	748.8	744.23	1.05	0.44	945.80	859.48	-9.13
B-n52-k7	745.8	764.9	755.85	2.56	1.35	944.40	848.71	-10.13
B-n56-k7	704	733.74	719.03	4.22	2.13	920.00	845.37	-8.11
B-n57-k9	1596	1653.42	1602.92	3.60	0.43	2199.70	1885.69	-14.27
B-n64-k9	859.3	921.56	903.43	7.25	5.14	1179.60	1064.53	-9.75
B-n67-k10	1024.4	1099.95	1086.01	7.38	6.01	1404.50	1247.67	-11.17
B-n68-k9	1263	1317.77	1305.32	4.34	3.35	1754.70	1515.88	-13.61
Average				***4.59***	***1.88***			***-9.81***

4.59% worse than the optimal solution. This gap can be significantly reduced to 1.88% by introducing a biased randomized edge selection process. When comparing the combination of a multi-start heuristic with simulation to the outlined SimGRASP algorithm, it can be seen that SimGRASP outperforms previous simulation-optimization approaches by -9.81%.

APPENDIX E

Performance of BR-GRASP and SimGRASP for the UFLP

The uncapacitated Facility Location Problem (UFLP) consists of defining the necessary number of facilities in order to serve a set of customers. Associated costs consist in the sum of the setup-costs for each facility and the costs for serving all customers. In this thesis, the NP-hard (Cornuejols et al. 1990) UFLP with deterministic and stochastic customer demands is solved (Wolf 2011).

The benchmark instances are the ones originally proposed by Ahn et al. (1988) in their work on the p-median problem, ranging from 10-1000 potential facility locations from which 500-3000 clients have to be served. The results of the traditional GRASP and BR-GRASP for the selected deterministic instances are listed in Table E.1. Both the threshold- and geometric distribution parameter were set to 0.3. The algorithm running times were set to 30 seconds per instance. As benchmark results, the work presented by Resende and Werneck (2006) is used. On the other hand, the stochastic UFLP is compared to the SimILS approach discussed by de Armas et al. (2017). As algorithm stopping criterion for the stochastic demand scenario, 300 seconds of running time are defined.

As for the previously presented problem setting, BR-GRASP outperforms the traditional GRASP implementation, with percentage gaps to the BKS by 2.72% and 4.07% respectively. When comparing SimGRASP to the SimILS for the UFLP with stochastic demands, an

Table E.1: Performance of BR-GRASP and SimGRASP for the UFLP

Instance	BKS (1)	GRASP (2)	BR-GRASP (3)	%-Gap (1)-(2)	%-Gap (1)-(3)	SimILS (4)	SimGRASP (5)	%-Gap (4)-(5)
500-10	798577	817829	810525	2.41	1.50	2804875.3	2962061.99	5.60
500-100	326805.4	337105	331548	3.15	1.45	1166560.96	1178299.6	1.01
500-1000	99169	99300	99382	0.13	0.21	196806.67	192601.25	-2.14
1000-10	1434185.4	1475360	1473421	2.87	2.74	5367175.13	5467900.1	1.88
1000-100	607880.4	635610	620130	4.56	2.02	2211856.7	2223186.38	0.51
1000-1000	220560.9	224157	224227	1.63	1.66	603844.02	637491.97	5.57
1500-10	2001121.7	2066830	2054635	3.28	2.67	7723274.25	7819403.63	1.24
1500-100	866493.2	913517	893552	5.43	3.12	3303763.47	3319480.69	0.48
1500-1000	334973.2	344566	343247	2.86	2.47	1112816.36	1101848.44	-0.99
2000-10	2558120.8	2651555	2653412	3.65	3.73	9634858.71	9995791.03	3.75
2000-100	1122861.9	1183304	1159781	5.38	3.29	4283233.52	4326248.99	1.00
2000-1000	437690.7	454544	449637	3.85	2.73	1533026.75	1517522.93	-1.01
2500-10	3100224.7	3203874	3182487	3.34	2.65	11625433.27	12181196.86	4.78
2500-100	1347577.6	1419451	1391502	5.33	3.26	5230296.48	5232375.46	0.04
2500-1000	534426.6	557839	546963	4.38	2.35	1862652.94	1847852.18	-0.79
3000-10	3570818.8	3732263	3670865	4.52	2.80	13678703.33	14168356.46	3.58
3000-100	1602530.9	1686475	1649050	5.24	2.90	6172594.29	6212876.89	0.65
3000-1000	643541.8	673503	659208	4.66	2.43	2302997.41	2288101.2	-0.65
Averages				***4.07***	***2.72***			***1.36***

average percentage difference 1.36% can be observed.

Appendix F

Creating a real-life distance matrix for vehicle routing problems with QGIS and other open-source software

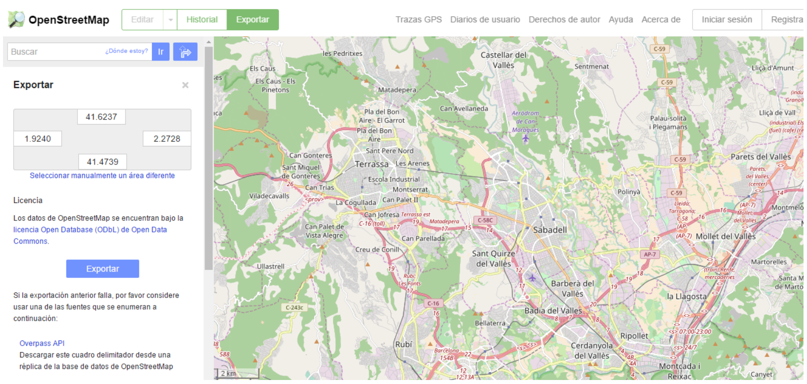
This report presents the use of the open source geographic information system QGIS to obtain a distance matrix between different locations based on real life information. All necessary tools and steps to create a routable network from OpenStreeMap (.osm) including the use of PostgreSQL databases, the PostgreSQL spatial database extensions PostGIS and pgRouting, and .osm file converter osm2po are described. The main goal is the creation of a distance matrix based on a large data set of longitude/latitude locations in the medium-sized Catalan city of Sabadell, which is used as illustrative example throughout this report.

The data was obtained through a collaboration agreement between the Internet Computing & Systems Optimization (ICSO) and the company SMATSA, who is responsible for the collection of waste in the inner-city area of Sabadell (around 200.000 inhabitants). The problem setting involves the waste disposal vehicle routing in order to find efficient routes between 886 paper waste containers. A single depot and landfill are considered. A distance matrix between all points which are initially given as Longitude/Latitude (Long/Lat) locations is created.

OpenStreetMaps

OpenStreetMaps (OSM) provides a free editable map of the world. One of its main functions is the ability to download .osm data files of any selected area. These type of files are coded in XML, and contain geographic data in a structured/ordered format. In order to download an .osm file from a given area, look for the area of interest and export the file. Figure F.1 shows a screenshot of the process when downloading a .osm file of Sabadell. Note that .osm files are not routable. Thus, the data needs to be adopted in order to make meaningful routing networks and connections.

Figure F.1: Downloading the .osm file of Sabadell in OSM

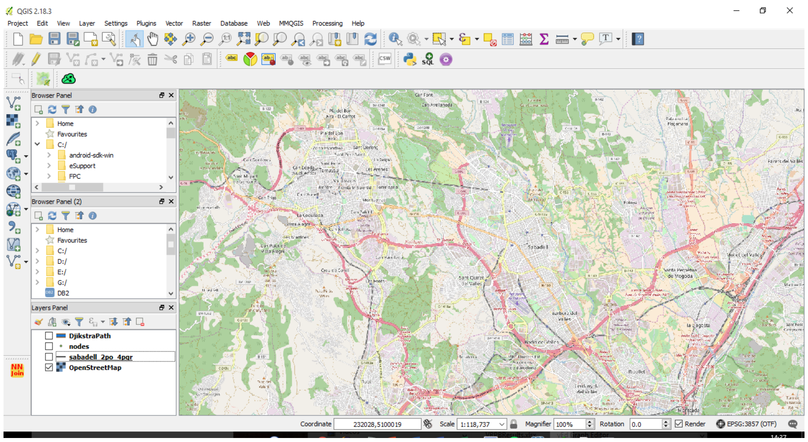


QGIS

QGIS is a free and open-source geographic information system (GIS). It enables users to create, edit, visualize, and publish geospatial information on any operating system. At the time of this report the latest QGIS version is 2.18, which is used in the following tutorial. Many QGIS features need to be imported through the use of different plug-ins, which are directly available from the software (in the "Plugins" tab). We will work with the plug-ins listed below. Furthermore, a screenshot from QGIS with the OSM layer can be seen in Figure F.2.

- DB Manager (allows the management of databases from within QGIS)
- OpenLayers (provides layers of different maps)
- NNJoin (finds closest point from a list A of points of each node of a list B of points)

Figure F.2: QGIS screen with enabled OSM layer



PostgreSQL

PostgreSQL (postgres) is an an object-relational database. It enables the creation and management of geospatial databases. Furthermore, QGIS offers the possibility of directly changing and working with postgres databases within QGIS. We will use postgres with the free database management tool pgAdmin (version 4). In order to create geospatial databases, the postgres extensions PostGIS and pgRouting need to be included in each new database which is supposed to allow location queries to be run in SQL. To these extensions run the SQL query shown in Figure F.3.

Figure F.3: SQL query to include PostGIS and pgRouting in a SQL database

SMATSA on postgres@PostgreSQL 9.6

```sql
CREATE extension postgis;
CREATE extension pgrouting;
```

osm2po

osm2po is a .osm file converter, which converts .osm files downloaded from OSM into routable data. The output of osm2po is a executable SQL query for PostGIS enables SQL databases. For this work we use the osm2po version 5.1.0. Download the .zip file and unzip the folder into a suitable location of your choice.

Get OSM data

First, the geographic information of the area of interest needs to downloaded from OSM. Export the .osm file (in our case *Sabadell.osm*) and save it in a folder of your choice.

Using osm2po to make routable PostGIS enabled SQL database

osm2po needs to be managed from the command prompt. Open the command prompt and type in the script outlined in Figure F.4. This reads the .osm file from a given destination (in this case *"C:/Users/-defaultuser0/OneDrive/PhD/GIS/Sabadell2/Sabadell.osm"* and create a new folder with the prefix "Sabadell" inside the osm2po folder. Inside the new folder there should now be an executable SQL file called *Sabadell_2po_4pgr.sql*. **Be careful**, as there are some issues with the newest version (5.1.0) of osm2po in creating this file. If the query runs correctly but does not return the SQL file, it is likely that the issue discussed and solved in has occurred.

Figure F.4: Script to convert .osm files into SQL file

```
C:\Users\defaultuser0\OneDrive\PhD\GIS\osm2po>java -Xmx1g -jar osm2po-core-5.1.0-signed.jar prefix=Sabadell
 "C:\Users\defaultuser0\OneDrive\PhD\GIS\Sabadell2\Sabadell.osm"
```

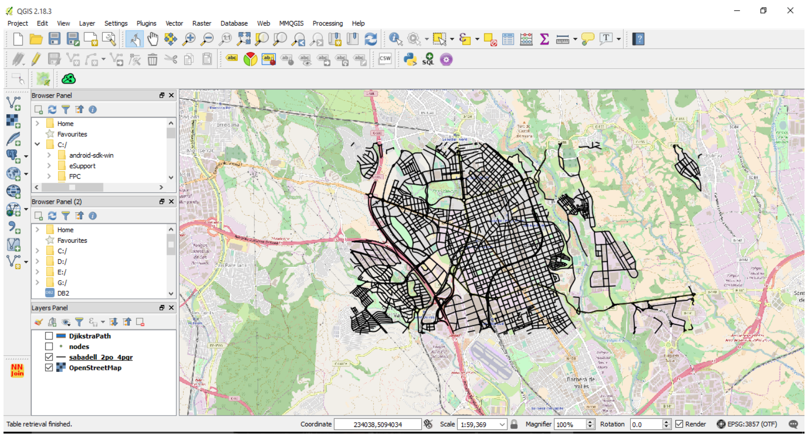
Run SQL file in pgAdmin and visualize output in QGIS

The executable SQL query can now be run in pgAdmin to create a table with all geographic ways in a PostGIS enabled database. The table includes the geographic information (i.e., length, start/end points, etc.) of the area exported as .osm file. The output can be directly visualized in QGIS by using the "Add PostGIS table" function. An example showing all ways of Sabadell included in the original .osm file over the OSM layer of QGIS can be seen in Figure F.5.

Obtaining network points

In order to make a routable network the geographic information of the start and end points of each way obtained in the previous step need to be saved in a separate file in which all nodes are stored. This can be done with the SQL query depicted in Figure F.6. As done before, the

Figure F.5: Illustration of geographic information table created with osm2po



nodes are imported to QGIS with the "Add PostGIS table" function. The output is highlighted in Figure F.7.

Figure F.6: Creation of nodes table with start and end points of ways obtained with osm2po

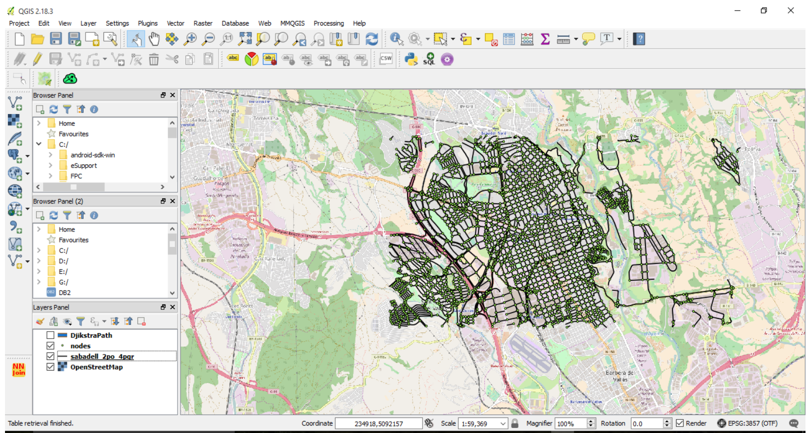
SMATSA on postgres@PostgreSQL 9.6

```
--drop table nodes;
create table nodes(
    id serial PRIMARY KEY,
    osm_id bigint,
    osm_name character varying,
    osm_source_id bigint, osm_target_id bigint, clazz integer,
    flags integer, source integer,  target integer);
alter table nodes add column geom geometry (PointZ, 4326);
select addgeometrycolumn ('nodes','the_geom',4326,'POINT',2, false);
insert into public.nodes(osm_id, osm_name, osm_source_id,
                             osm_target_id, clazz, flags, source, target, the_geom)
                             select font.osm_id, font.osm_name, font.osm_source_id,
                             font.osm_target_id, font.clazz, font.flags, font.source,
                             font.target,
                             st_geomfromtext('POINT('||font.x1||' '||font.y1||')',4326)
                             from sabadell_2po_4pgr as font;
```

Making a routable network topology and a first example

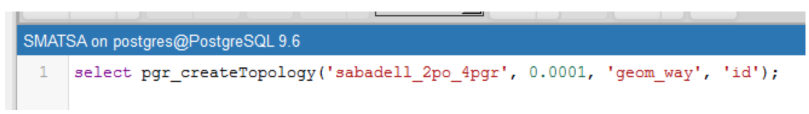
In order to make a routable network, the a topology of the ways table (*Sabadell_2po_4pgr* in our case) needs to be created. This can be done by running the SQL query described in Figure F.8. Finally, the real-life distance between different points in the network can be calculated and visualized. In order to directly do this in QGIS we use the DB manager plug in. In DB manager, connect to the postgre database and run the query seen in Figure F.9. This will

Figure F.7: QGIS file with nodes and ways



calculate the shortest path (using Djikstra's algorithm) between two given points (in this case 1 and 500) on the network. Load the output as new layer. On the one hand, the distance between the starting and end point (as sum of all distances between the traversed points) can be obtained in the attribute table. On the other hand, the new layer allows for visualizing the output as can be seen in Figure F.10.

Figure F.8: Creating a topology of ways



Create a geographic table of points

Given a set of long/lat locations (from which the resulting distance matrix is to be established), a geographic PostGIS table needs to be created. This is similar to the processes described before. A screen shot of an excel file with all locations can be seen in Figure F.11. These points can be imported into a PostGIS enabled SQL table as described later on. Once the table is created, it can be uploaded into QGIS with the "Add PostGIS layers" function. The resulting QGIS map is shown in Figure F.12 (the green points are the network nodes, the blue points are the uploaded points).

Figure F.9: Calculating the shortest path between two points on the network

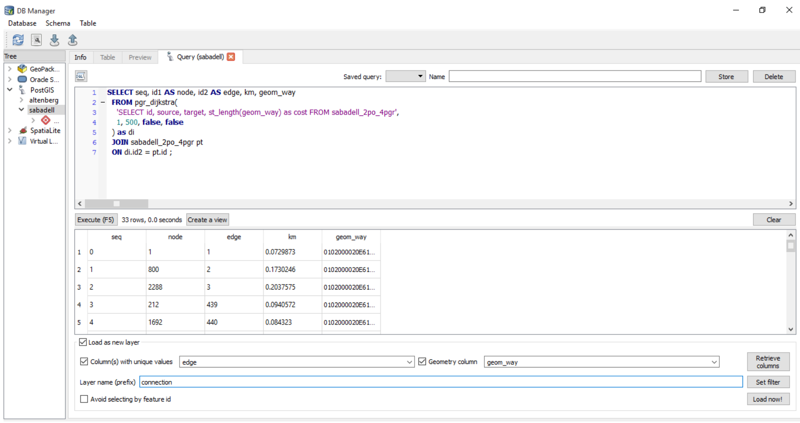


Figure F.10: Shortest path between two points on network

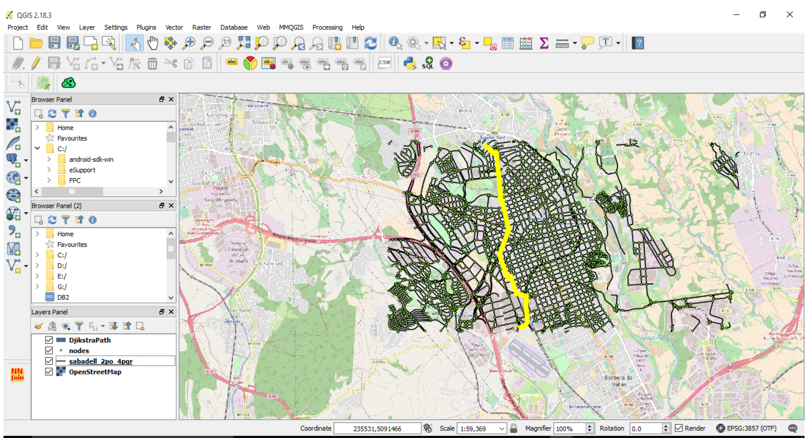


Figure F.11: Example of excel input with long/lat locations of different points

1	ID	Route	Latitude	Longitude
2	1	Landfill	41.58392	1.946886
3	3	PCL1	41.54628	2.108613
4	4	PCL1	41.54628	2.108613
5	5	PCL1	41.56178	2.099582
6	6	PCL1	41.56192	2.098295
7	7	PCL1	41.54722	2.119207

Figure F.12: Network nodes and imported point location layer

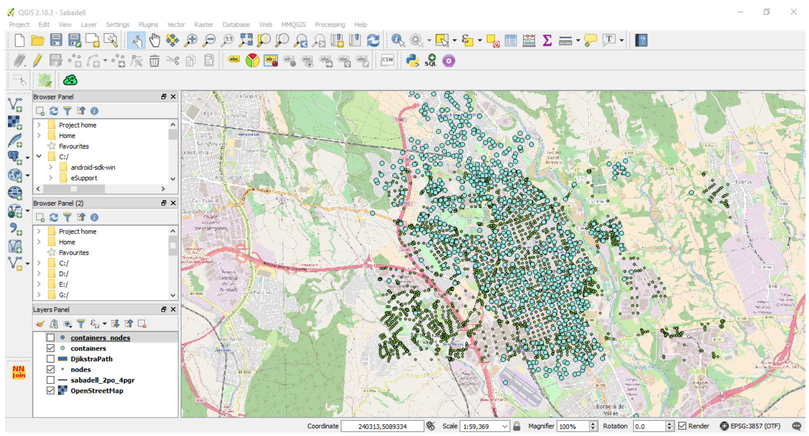
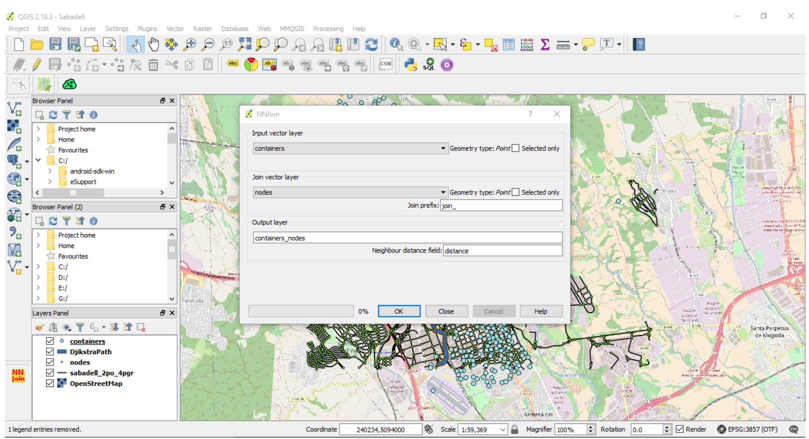


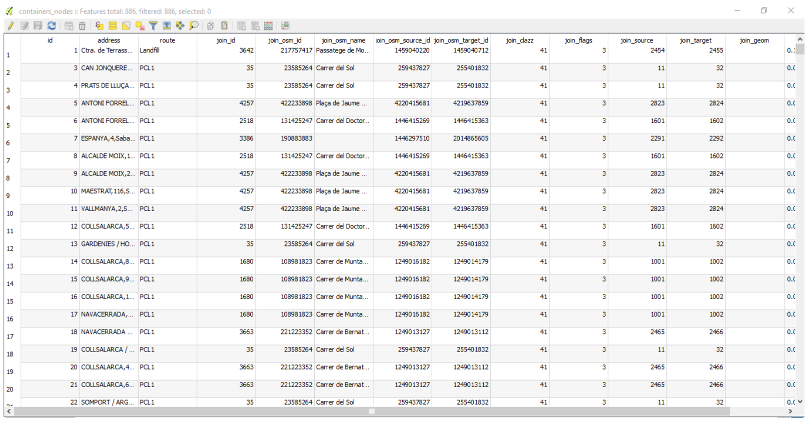
Figure F.13: Calculating the nearest neighbor of two point shapes with NNJoin



Calculating the nearest neighbor

Using the two point layers (of the containers and the network start/end points, respectively), we use the QGIS plug in NNJoin to calculate the nearest neighbors between all containers and the start/end points of the routable road network.A screen shot of the NNJoin interface can be seen in Figure F.13. The output is a new point-shapefile and the corresponding attribute table as seen in Figure F.14, which shows the nearest node of the routable network to the container point shapefile.

Figure F.14: Attribute table of NNJoin output



containers_nodes :: Features total: 886, filtered: 886, selected: 0

	id	address	route	join_id	join_osm_id	join_osm_name	join_osm_source_id	join_osm_target_id	join_clazz	join_flags	join_source	join_target	join_geom	
1	1	Ctra. de Terrass...	Landfill	3642	217757417	Passatege de Mo...	1459040220	1459040712	41	3	2454	2455		0.
2	3	CAN JONQUERE...	PCL1	35	23585264	Carrer del Sol	259437827	255401832	41	3	11	32		0.0
3	4	PRATS DE LLUÇA...	PCL1	35	23585264	Carrer del Sol	259437827	255401832	41	3	11	32		0.0
4	5	ANTONI FORREL...	PCL1	4257	422233898	Plaça de Jaume ...	4220415681	4219637859	41	3	2823	2824		0.0
5	6	ANTONI FORREL...	PCL1	2518	131425247	Carrer del Doctor...	1446415269	1446415363	41	3	1601	1602		0.0
6	7	ESPANYA,4,Saba...	PCL1	3386	190883883		1446297510	2014865605	41	3	2291	2292		0.0
7	8	ALCALDE MOIX,1...	PCL1	2518	131425247	Carrer del Doctor...	1446415269	1446415363	41	3	1601	1602		0.0
8	9	ALCALDE MOIX,2...	PCL1	4257	422233898	Plaça de Jaume ...	4220415681	4219637859	41	3	2823	2824		0.0
9	10	MAESTRAT,116,S...	PCL1	4257	422233898	Plaça de Jaume ...	4220415681	4219637859	41	3	2823	2824		0.0
10	11	VALLMANYA,2,S...	PCL1	4257	422233898	Plaça de Jaume ...	4220415681	4219637859	41	3	2823	2824		0.0
11	12	COLLSALARCA,5...	PCL1	2518	131425247	Carrer del Doctor...	1446415269	1446415363	41	3	1601	1602		0.0
12	13	GARDENIES / HO...	PCL1	35	23585264	Carrer del Sol	259437827	255401832	41	3	11	32		0.0
13	14	COLLSALARCA,8...	PCL1	1680	108981823	Carrer de Munta...	1249016182	1249014179	41	3	1001	1002		0.0
14	15	COLLSALARCA,9...	PCL1	1680	108981823	Carrer de Munta...	1249016182	1249014179	41	3	1001	1002		0.0
15	16	COLLSALARCA,1...	PCL1	1680	108981823	Carrer de Munta...	1249016182	1249014179	41	3	1001	1002		0.0
16	17	NAVACERRADA,...	PCL1	1680	108981823	Carrer de Munta...	1249016182	1249014179	41	3	1001	1002		0.0
17	18	NAVACERRADA ...	PCL1	3663	221223352	Carrer de Bernat...	1249013127	1249013112	41	3	2465	2466		0.0
18	19	COLLSALARCA / ...	PCL1	35	23585264	Carrer del Sol	259437827	255401832	41	3	11	32		0.0
19	20	COLLSALARCA,4...	PCL1	3663	221223352	Carrer de Bernat...	1249013127	1249013112	41	3	2465	2466		0.0
20	21	COLLSALARCA,6...	PCL1	3663	221223352	Carrer de Bernat...	1249013127	1249013112	41	3	2465	2466		0.0
	22	SOMPORT / ARG...	PCL1	35	23585264	Carrer del Sol	259437827	255401832	41	3	11	32		0.0

Figure F.15: Making a distance matrix based on the Djikstra algorithm between various points

SMATSA on postgres@PostgreSQL 9.6

```
SELECT * FROM pgr_dijkstraCostMatrix(
    'SELECT id, source, target, km AS cost, reverse_cost FROM sabadell_2po_4pgr',
    (SELECT array_agg(id) FROM nodes WHERE id < 10), false
);
```

Making a distance matrix with the Djisktra routing function of pgRouting and PostGIS

Finally, we can make a distance matrix in pgAdmin using the postgres extensions pgRouting and PostGIS. This can be done with the SQL query highlighted in Figure F.15. In this case, the distance in km is set ad costs (*km AS cost*), and a distance matrix of between the first 10 nodes is established.

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