Optimization of empty container movements in intermodal transport

Acknowledgements

This doctoral thesis is the result of four years of research at Hasselt University and constitutes the end of my life as a student. I am well aware that this thesis could not have been established without the support of many people in various ways. To all those people, I would sincerely like to express my gratitude.

First of all, I would like to thank all members of the jury. I am grateful to the external jury members for their effort in reading my thesis, their valuable comments and their presence during both the private and public defence. My thanks go to the internal jury members for their continuous guidance, useful remarks and numerous suggestions they made during the regular Ph.D. committees. Special thanks go to Prof. Dr. An Caris, my direct supervisor and invaluable guide throughout these four years. An, I have no idea how I would have managed this without you. You were always available when a problem came up and together we found a solution to all issues. I hope we can continue our fruitful cooperation in the future. Finally, I would like to thank my promoter, Prof. Dr. Gerrit K. Janssens, for giving me the opportunity to perform academic research under his supervision, for his guidance and for repeatedly drawing my attention to the overall picture of my thesis. Gerrit, I appreciate your confidence in my research skills and your trust in giving me the freedom to determine the main direction of my research myself.

Besides the people directly involved in my Ph.D. research, many other people deserve my gratitude. I would like to thank my colleagues of the research groups Logistics and Business Informatics and of the Transportation Research Institute (IMOB) for the stimulating and enjoyable working environment and for all pleasant activities, both in and out of the office. Kristel, thank you for all the administrative support during these four years.

Many thanks go to my family and friends, for showing their interest in my research and for their continuous effort in helping me to forget all work-related issues. I would like to thank my parents, for giving me the opportunity to perform university studies, for supporting my choice to prepare a Ph.D. and for all the support and help throughout the years which I too often took for granted. Finally, I am indebted much gratitude to An, my girlfriend and greatest believer. An, I can always rely on you and you are always able to put a smile upon my face, even when things do not go as planned. Thank you.

Kris Braekers
September 10, 2012

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List of symbols used in Chapters 4 to 7

General problem

P = length of planning period

N_{gen} = set of n nodes for the general problem (indices g, h)

A_{gen} = set of feasible arcs for the general problem

N_{PIC} = set of origins (shippers) of outbound loaded containers that have to be picked up and transported directly to the closest terminal

N_{DEL} = set of destinations (consignees) of inbound loaded containers that have to be delivered from the closest terminal

N_S = set of empty containers supplied by a consignee

N_D = set of empty containers demanded by a shipper

N_T = set of container terminals with container depot (index r)

N_{VD} = the vehicle depot

V = set of vehicles (index v)

K = number of vehicles available

k = a particular number of vehicles

M = a large number

$[a_g, b_g]$ = time window of node g

l_g = time to pickup / drop off a container at node g

d_{gh} = distance between nodes g and h

t_{gh} = travel time between nodes g and h

Empty container allocation problem

N_{orig} = set of origins (index g)
N_{dest} = set of destinations (index h)
A_{alloc} = set of possible empty container allocations
sup_g = number of empty containers available at origin g
dem_h = number of empty containers demanded at destination h
c_{gh} = cost of an empty container allocation from origin g to destination h
y_{gh} = number of empty containers allocated from origin g to destination h

Routing problem of sequential approach

N_{seq} = set of n nodes (indices i, j)
A_{seq} = set of feasible arcs
$[a_i, b_i]$ = time window of node i
l_i = time to pickup / drop off a container at node i
d_i = distance traveled to perform the task at node i
s_i = time required to perform the task at node i
d_{ij} = distance between nodes i and j
t_{ij} = travel time between nodes i and j

$$x_{ij} = \begin{cases} 1 & \text{if a vehicle travels from node } i \text{ to node } j \\ 0 & \text{else} \end{cases}$$

t_i = time epoch at which a vehicle arrives at node i

Integrated problem

N_{int} = set of n nodes (indices i, j)

N_L = set of nodes for each loaded container transport task
A_{int} = set of feasible arcs
$\hat{d}_{ij}$ = distance between nodes i and j
$\hat{t}_{ij}$ = travel time between nodes i and j

All other symbols have the same meaning as those used for the routing problem for the sequential approach.

Solution representation and local search operators

$\boldsymbol{x}$ = decision vector, solution
$\boldsymbol{x_b}$ = current best decision vector (hierarchical objective function)
$f(\boldsymbol{x})$ = objective vector corresponding with decision vector $\boldsymbol{x}$
S = set of mutually non-dominating solutions found by the bi-objective algorithm
z_v = the number of nodes visited by vehicle v
p = a percentage of the number of routes in the solution, used during one of the route reducing operators
et_i = earliest arrival time at node i
et_{n+1} = earliest arrival time at the vehicle depot
lt_i = latest arrival time at node j
lt_0 = latest departure time at the vehicle depot
ct_i = the core time (sum of all travel, service and unavoidable waiting times) after node i
ct_0 = total core time of a route
sl_{1i} = slack variable, indicating how much the arrival time at node i may be shifted backwards in time without introducing extra waiting time after node i
sl_{2i} = slack variable, indicating how much the latest departure time at the vehicle depot will increase at most when the latest arrival time at node i increases
Δd = change in distance traveled as a result of a local search move
k_{opt} = optimal (minimal) number of vehicles required for a problem instance
k_{init} = number of vehicles used in the initial solution

k_{cur} = number of vehicles used in the current solution

k_{min} = lowest number of vehicles for which a solution is found

Deterministic annealing algorithm

n_{it} = number of iterations of the deterministic annealing algorithm

m = number of local search operators

T = deterministic threshold value

T_{max} = maximum threshold value

ΔT = threshold reduction parameter

n_{imp} = number of iterations without improvement after which the search is restarted from the current best solution

i_{last} = number of iterations since the last improvement of the best solution was found

r = random number between 0 and 1

Time window partitioning

ω = set of subnodes (indices v, w)

Ω = set of feasible arcs between subnodes

$\delta(v)$ = original node of subnode v

$wait_{vw}$ = unavoidable waiting time between subnodes v and w

LB_v = lower bound on the number of vehicles

LB_d = general lower bound on total distance traveled

$LB_{d(k)}$ = lower bound on distance traveled when k vehicles are used

Wilcoxon matched-pairs signed-ranks test

θ_D = median of the differences scores

T = Wilcoxon statistic

$\sum R+$ = sum of all ranks with a positive sign

$\sum R-$ = sum of all ranks with a negative sign

n = the number of non-zero difference scores

z = normal approximation of the Wilcoxon T statistic

Time-dependent algorithm

N_{td} = set of n nodes (indices i, j)

A_{td} = set of feasible arcs

$A_{ij}(t)$ = arrival time function, earliest arrival time at node j when leaving node i at time t

$A_{ij}^{-1}(t)$ = inverse of arrival time function, latest time to leave node i in order to arrive at node j at time t

$\tau_{ij}(t)$ = travel time between locations i and j when leaving location i at time t

$\hat{\tau}_{ij}(t)$ = sum of travel, service and waiting times between nodes i and j when leaving node i at time t

$\hat{\tau}_{ij}^{min}$ = least possible duration of traversing link (i, j)

t_0^* = optimal departure time of a vehicle at the vehicle depot

Chapter 1

Introduction and problem statement

1.1 Introduction

Ever since the introduction of containers about fifty years ago, containerization of freight transport has been rising. Advantages of transporting freight by containers include the standardization of shipments and handling equipment, faster loading and unloading operations and reduced security and damage issues. Driven by these advantages, productivity gains within the sector and the increasing international division of labor, container trade grew at an average annual rate of 8.2% between 1990 and 2010. Total container trade volume in 2010 was estimated at 140 million twenty-foot equivalent units (TEU). (UNCTAD, 2011)

Due to the ease of loading and unloading containers onto vessels, trains and trucks, containerization has also contributed considerably to the emergence of intermodal transport (Dejax and Crainic, 1987). Intermodal transport is defined as the transport of freight by a combination of at least two modes of transport, without handling the goods during transfers. The largest part of the transport, the main-haulage, is carried out by one or more sustainable modes of transport like barge, train or ocean-going vessel. The initial and final part are generally performed by truck and are denoted as pre- and end-haulage or drayage operations. (Macharis and Bontekoning, 2004)

As a consequence of the containerization process, shipping lines and transportation companies are facing a number of complex planning problems such as container fleet sizing, decisions about container ownership and leasing and empty container repositioning (Dejax and Crainic, 1987). Especially the latter problem, empty container repositioning, is considered as highly challenging. Due to the natural imbalance of trade, over time certain areas develop a surplus of containers while other areas face a deficit. On a global level, these imbalances require the repositioning of empty containers between seaports. Drewry Shipping Consultants estimated that 20% of all maritime container movements are empty container movements (Boile et al., 2006). Song and Carter (2009) note that recently trade imbalances are becoming still more prominent. Total costs of maritime empty container repositioning in 2009 were estimated at 20 billion USD (UNCTAD, 2011).

Empty container repositioning takes place in the hinterland of seaports as well. Inbound loaded containers are transported from seaports to their final consignees by barge, train, truck or a combination of these modes. Vice versa, outbound loaded containers are transported from shippers to the port. Due to imbalances in container flows on an individual customer level, empty containers have to be repositioned between consignees, shippers, intermodal container terminals, inland container depots and the port. (Boile et al., 2008) For these continental empty container flows estimates are even higher than for maritime empty container flows, ranging from 40 up to 50% of all continental container movements (Crainic et al., 1993b; Konings and Thijs, 2001; Branch, 2006).

As opposed to loaded container transports, empty container movements do not generate revenues. Although empty container movements cannot be avoided completely, minimizing these costly activities would considerably reduce operating costs of shipping lines and transportation companies. Empty container repositioning is therefore one of the longstanding and ongoing issues in containerized transport. Furthermore, minimizing empty container movements would reduce external effects of transport such as congestion and air pollution, which makes the empty container repositioning problem relevant from a social point of view as well.

Throughout the years there has been a concentration of container shipping activities through mergers, acquisitions and alliances as well as a trend towards the use of larger and more economical vessels. This has lowered costs for shipping containers between seaports. At the same time, the inland part of an intermodal (maritime) transport accounts for an increasing portion of the total cost. Estimates range between 40 and 80% (Notteboom, 2004). A similar trend may be observed for the empty container repositioning problem itself. According to Le (2003) and Lopez (2003) shipping lines have mainly focused on minimizing costs of empty container repositioning on a global level. Certain levels of success in optimizing empty container movements in the maritime transit segment are attained by using surplus ship slots for empty container repositioning. In the past, less attention has been paid to the inland transport segment or empty container management on a regional level. Recently, attention for the inland transport segment has been increasing. Notteboom and Rodrigue (2005) define a new phase in port development, port regionalization, which indicates the ports' growing acknowledgement of the importance to increase their integration with inland freight distribution systems. Due to the large share of the inland transport segment in total costs, many shipping lines currently consider this segment as the most vital area to reduce costs (Notteboom and Rodrigue, 2005). As a result, inland container transportation and especially the optimization of costly and non-revenue generating empty container repositioning movements, constitutes an important and highly relevant field of research.

1.2 Problem statement

This thesis focuses on the empty container repositioning problem in the hinterland of a major seaport. The problem situation may be described as follows. When a ship arrives at the port, loaded containers have to be delivered to their final consignees at different inland locations. These transports are performed by a combination of barge or rail transport with road transport or directly by road transport. Following their delivery at a consignee's site, containers are unloaded and become available to be picked up and moved away. These empty container transports are often performed by another vehicle (Crainic et al., 1993b; Veenstra, 2005). Vice versa, empty containers have to be delivered to shippers in the hinterland. After they have been loaded, these containers are picked up by another vehicle and transported either directly to the port or to an inland intermodal terminal from which they are transported to the port by rail or barge.

Several options regarding empty container repositioning are available. When empty containers become available at a consignee, they may either be returned to the port for global empty repositioning, they may be transported to a container depot at the port or at an inland location in expectation of future requests for empty containers in the hinterland, or they may be moved directly to shippers which are located in the same region and demand empty containers. This last option is known as a street turn (Jula et al., 2006). Consequently, empty containers demanded by shippers come from a container depot at the port or at an inland location or they come directly from a consignee. Besides, empty containers may need to be repositioned among container depots, intermodal terminals and the port in order to overcome regional imbalances and to achieve cost reductions through mass transportation of containers by barge or rail (Crainic et al., 1993b).

In practice, empty container depots are often located nearby ports and most empty containers that become available at a consignee's site are directly transported back to the port. When a demand for empty containers arises in the hinterland, containers are subsequently transported back and forth again. (Crainic et al., 1993b) This leads to situations like in the Los Angeles/Long Beach region as described by Jula et al. (2003). In 2000, 1.130.000 empty containers became available in the hinterland at local consignees' sites, of which 94% were moved back empty to container terminals at one of the two ports. Meanwhile 550.000 empty containers were transported from the two ports to local shippers. Clearly, an opportunity for optimizing empty container flows exists in preventing some empty containers to be transported back to the port immediately. The objective of empty container management on a regional level is therefore to reposition empty containers efficiently in order to minimize costs, while fulfilling empty container demands.

1.3 Thesis outline

In this thesis, the optimization of empty container movements in intermodal transport is studied. The focus is on a regional level i.e. the repositioning of empty containers in the hinterland of a major seaport. Since loaded and empty containers are generally transported on the same network and using the same equipment, special attention is paid to methods which integrate empty container repositioning movements with loaded container movements. Regarding these loaded container movements, only full truckload transports of a single container type are considered. The outline of the thesis is shown schematically in Figure 1.1.

Since twenty years, an overwhelming growth in the number of papers published on empty container repositioning is observed. The majority of these papers studies the repositioning problem on a global level from different perspectives. In the last ten years, empty container repositioning on a regional level has received increased research attention as well. Unfortunately no detailed overview of this recent work is available. Chapter 2 remedies this shortcoming. Decisions related to empty container repositioning to be taken at the strategic, tactical and operational planning level are discussed. Existing literature is situated in a framework and described in detail. Although the main focus lies on empty container repositioning on a regional level, literature concerning repositioning on a global level is discussed as well. Research gaps

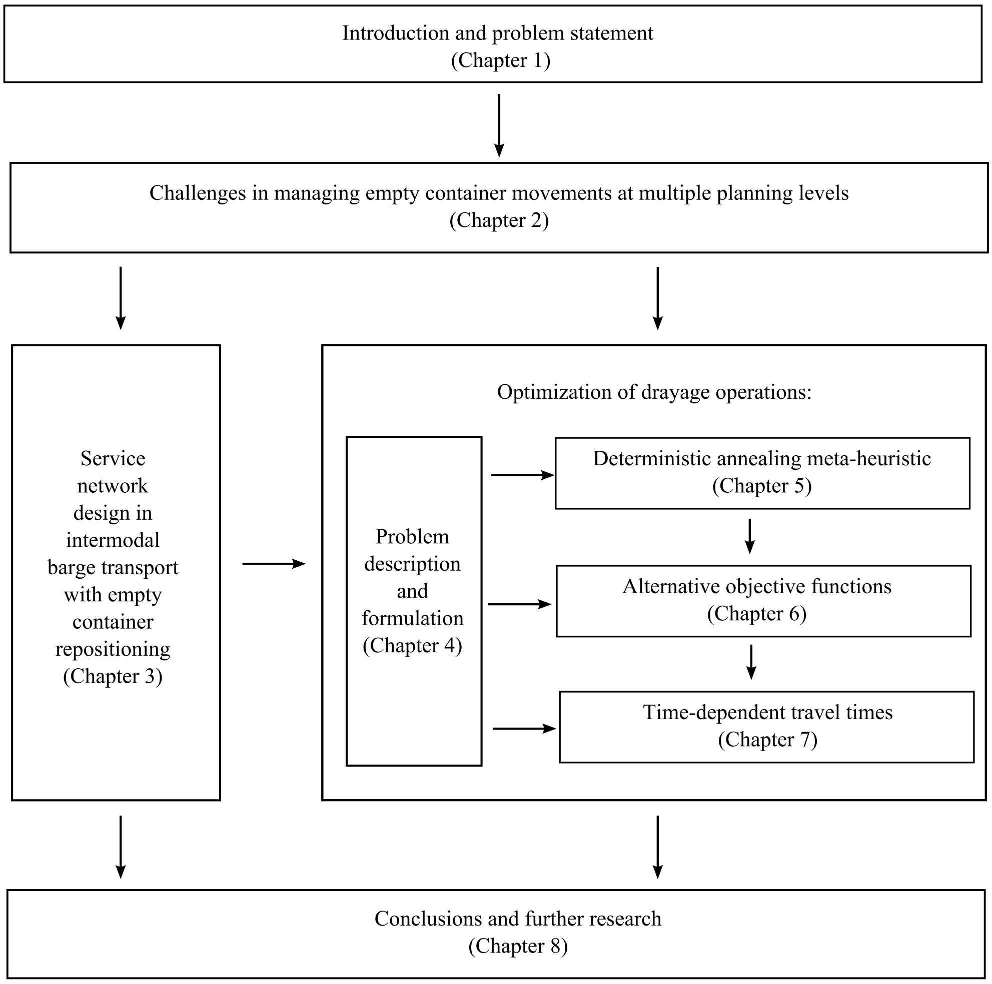

Figure 1.1: Outline of the thesis

and opportunities for further research are identified. In the following chapters, two of these research opportunities are studied in detail. The first is related to a tactical planning problem in barge transportation while the second is related to an operational planning problem in drayage operations. At both planning levels, opportunities for the integration of loaded and empty container movements are analyzed.

In Chapter 3, the transport of containers by barge between a seaport and a number of hinterland ports is investigated. Research on service network design for such intermodal barge transportation networks is scarce. Empty container repositioning in this context has received even less attention. A tactical planning model is proposed. This model may be used as a decision support tool to determine shipping routes, vessel capacity and service frequency when designing regular roundtrip barge services between a seaport and the hinterland. The versatility and flexibility of the model is demonstrated by applying it from the perspective of barge operators as well as from the perspective of shipping lines which arrange door-to-door transport activities. While barge operators are generally not concerned with empty container repositioning decisions, shipping lines are. A method to take these repositioning decisions into account when designing barge services is proposed.

While Chapter 3 is related to container transportation by barge between a seaport and a number of hinterland ports, Chapters 4 to 7 are concerned with the planning of container transports between hinterland ports or other (inland) container terminals and final customers. These transports are performed by truck and are called drayage operations. The focus lies on the operational planning of these activities.

Chapter 4 serves as an introductory chapter. The operational planning of drayage operations is discussed in detail. First, a traditional sequential solution approach is presented. An empty container allocation model determines the empty container transports that need to be performed in the service area of intermodal terminals. A vehicle routing problem is then solved to find efficient vehicle routes performing all loaded and empty container transports in the region during a single day. Second, an integrated planning approach is considered. Empty container allocation decisions are no longer made beforehand. Instead they are made simultaneously with vehicle routing decisions. Mathematical formulations for both solution approaches are presented. The primary objective is to minimize the number of vehicles used. The secondary objective is to minimize total distance traveled.

A deterministic annealing meta-heuristic is proposed in Chapter 5 to solve the sequential and integrated drayage problems. Four variants of this meta-heuristic are proposed and compared with each other. An experimental design is set up to demonstrate the advantage of an integrated approach over a sequential one. For the first time, this advantage is quantified and shown to be significant. Finally, the effect of implementing street turns is analyzed i.e. the effect of allowing direct transportation of empty containers between consignees and shippers, without an intermediate stop at a container terminal/depot. Results indicate that empty container repositioning costs may be reduced considerably by allowing street turns.

Chapter 6 considers alternative objective functions for the (integrated) drayage problem. Adaptations to the deterministic annealing meta-heuristic to take these alternative objective functions into account are discussed. Besides, the proposed meta-heuristic is compared with a recent solution method on a similar problem.

The assumption that travel times between two locations only depend on distance, is relaxed in Chapter 7. Instead it is assumed that travel times are a deterministic function of distance and time of day. In this way, hourly variations in travel times due to congestion may be taken into account. A time-dependent version of the deterministic annealing algorithm is presented to solve the problem. To the author's knowledge, no time-dependent version of the integrated drayage problem has been studied before.

Finally, general conclusions and opportunities for further research are presented in Chapter 8.

Chapter 2

Challenges in managing empty container movements at multiple planning levels

2.1 Introduction

Research on empty container management is mainly concentrated in the last twenty years. Especially during the last ten years, the amount of research has increased rapidly. Although numerous papers have addressed empty container repositioning from different perspectives, to our knowledge no detailed literature review describing all aspects of the problem is available. This chapter[1] provides an overview of the existing research on the topic (Figure 2.1). The main focus lies on empty container repositioning on a regional level, namely the hinterland of a seaport, although literature concerning repositioning on a global level is discussed as well.

Section 2.2 discusses several practical strategies which may reduce the need for empty container repositioning. Issues related to the modeling of the problem are described in Section 2.3. In the remainder of the chapter, the different planning models that are proposed in literature are reviewed. The scope from these models ranges from the strategic and tactical to the operational planning level. A classification according to these three planning levels is used. In Section 2.4 the decisions to be taken at each planning level are presented and an overview of the related planning models is

[1]This chapter is based on Braekers et al. (2011b).

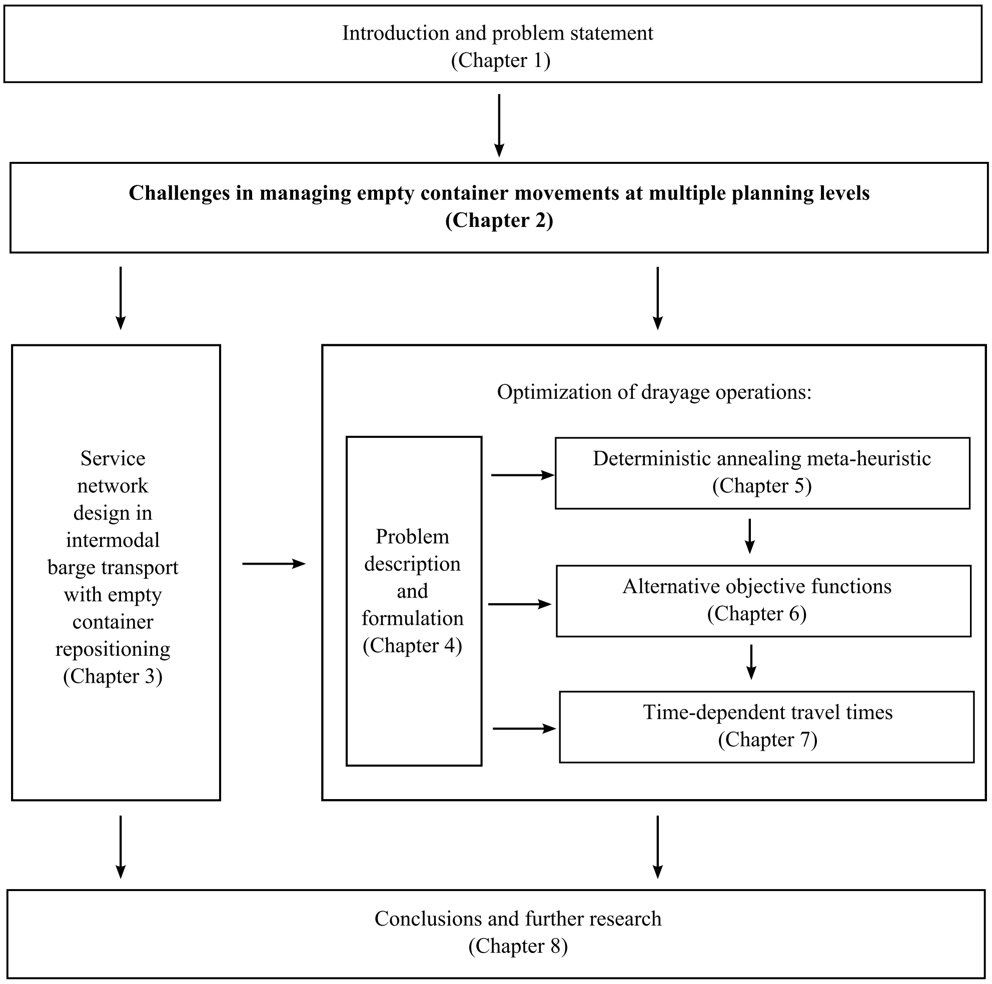

Figure 2.1: Outline of the thesis

given. In the following Sections (2.5 to 2.9) the planning models are discussed in detail. Models comprising elements of more than one planning level are discussed as well. Only models explicitly taking into account empty container repositioning are mentioned. For an overview of other planning models for (intermodal) freight transportation, the reader is referred to Crainic and Laporte (1997), Crainic (2002), Macharis and Bontekoning (2004), Crainic and Kim (2007) and Caris et al. (2008). Finally, research gaps and opportunities for further research are identified in Section 2.10.

2.2 Proposed solutions

Several practical strategies to address the empty container repositioning problem on a regional level are discussed in literature. Most authors assume transport of empty containers is carried out by trucks (Jula et al., 2003; Chang et al., 2006; Di Francesco et al., 2006). Especially strategies to reduce the number and length of empty movements are proposed. Examples are the use of inland container depots, street turns, container substitution, container leasing, foldable containers and internet-based systems. These strategies are described in following sections.

2.2.1 Inland depots

Container interchange can be defined as the transfer of a container from the responsibility of one party to that of another party (The Tioga Group, 2002). Chang et al. (2006) state that a system that facilitates container interchanges outside ports, called empty container reuse, is not only desirable but necessary. Jula et al. (2003) propose two approaches for empty container reuse, depot direct and street turn. The former is discussed in this section while the latter is discussed in Section 2.2.2.

The depot direct approach is similar to the system of Inland Depots for Empty Containers (IDEC) described by Boile et al. (2008). The idea is that empty containers could be temporarily stored at inland container depots instead of being moved back to the port immediately. When a demand for empty containers occurs, empty containers can be transported to the shipper and subsequently, when loaded, to the port. As a consequence, empty vehicle kilometers are reduced and costs of repositioning empty containers decrease significantly, as shown in Figure 2.2. (Boile et al., 2008)

Inland container depots offer additional benefits. They establish a neutral supply point for empty containers, facilitate the drop off and pickup of empty containers when terminals at ports are congested or closed and add buffer capacity to terminals at ports. (Jula et al., 2003)

Le (2003) states that currently empty containers are immediately shipped back to the port because shipping lines have their own container yard at the sea terminal and opening an inland depot would duplicate operating costs. According to Crainic et al. (1993b) and The Tioga Group (2002) this is not necessarily true. Container terminals at a port are operated by terminal operators on behalf of shipping lines but inland container depots are usually owned and operated by separate private firms. Only extra storage costs would be incurred but rising costs of land parcels and container operations at ports may offset these extra costs. (Le, 2003; Boile et al., 2008)

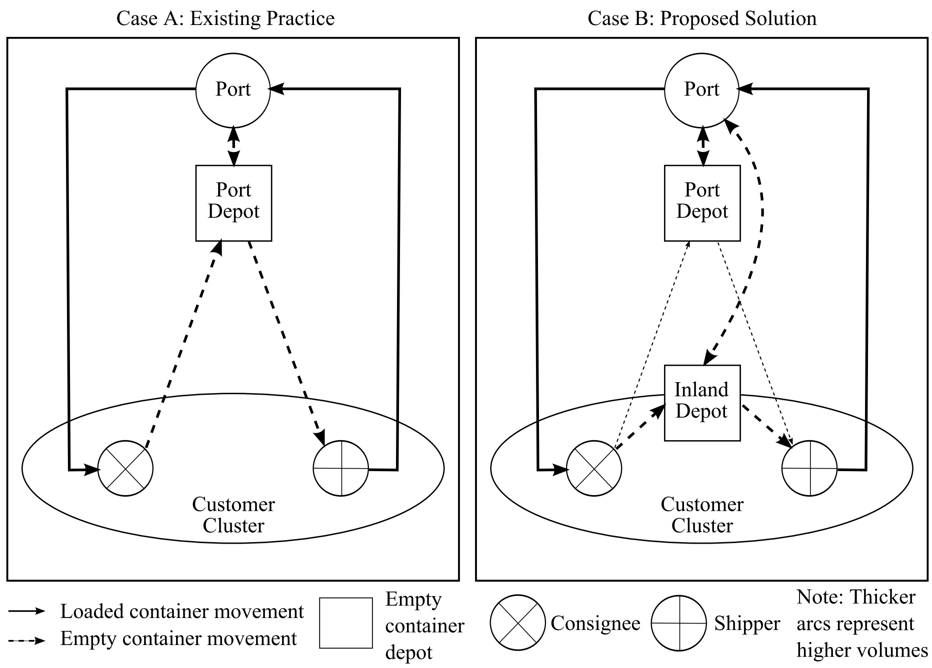

Figure 2.2: A system of inland depots (Boile et al., 2008)

2.2.2 Street turns

The second approach proposed by Jula et al. (2003) is the street turn approach (or triangulation (Le, 2003)). When using street turns, empty containers are moved directly from consignees to shippers, without an intermediate stop at a port or inland depot. This way, the number of empty container movements can be reduced, as is shown in Figure 2.3. Whereas for the import and subsequent export (situation a), two empty movements to and from terminals at ports are needed, for the street turn approach (situation b) only a single off-port empty movement is required. Street turns thus enable transportation companies to maximize their profits generated by trucking transportation requests (Deidda et al., 2008).

The approach offers several other benefits. External costs are reduced due to a reduction in empty movements. For each street turn two movements to and from terminals situated in the often highly congested port area are avoided, reducing external costs of congestion even further. Less container interchanges take place, saving shipping lines paperwork. Finally, empty container demands from export customers may be fulfilled sooner, decreasing container waiting times and increasing container utilization rates. (Jula et al., 2003; Dong and Song, 2009)

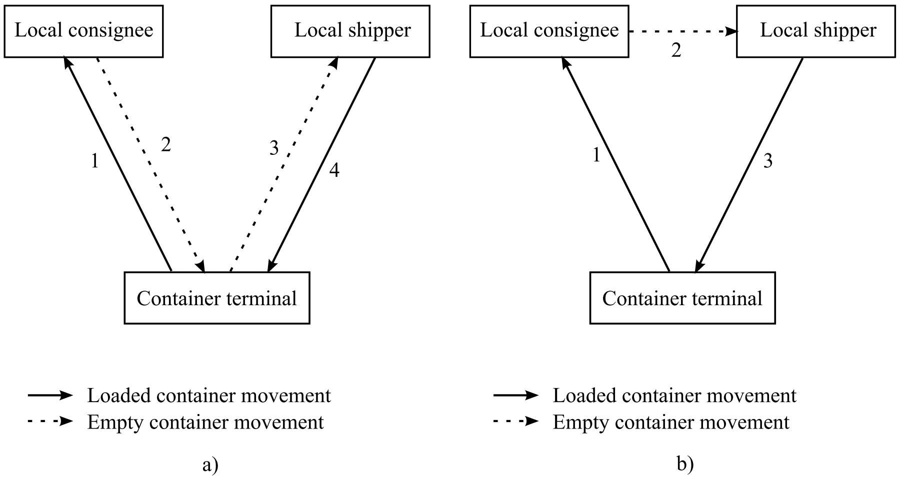

Figure 2.3: The street turn approach (Jula et al., 2003)

Although street turns are considered as highly desirable by all parties involved, they are hard to achieve. Due to the size of most problems, the existence of time windows and the need to model multiple resources, simply identifying options for street turns is a challenging task (Smilowitz, 2006).

Practical limitations for implementing street turns are: mismatches of time, location, container ownership or container type. Institutional barriers include: limited free time, managing repair charges, inspection and paperwork issues and a lack of a common or consistent procedure for interchange. Finally, commercial, insurance and liability issues, especially the responsibility for damages, play an important role in preventing street turns to be implemented on a large scale. (The Tioga Group, 2002; Jula et al., 2003).

2.2.3 Container substitution

A third approach to reduce empty container movements is container substitution (Chang et al., 2008). Containers come in several types and sizes. When substitution is allowed, empty container demands of one type may be fulfilled by the supply of empty containers of another type. For example, an empty container demand of two twenty-foot containers may be fulfilled by the supply of a single forty-foot container. This increases the flexibility of an empty container repositioning system and offers an opportunity to reduce costs. Certain rules concerning the substitution of each possible pair of container types have to be defined. These substitution rules may be symmetric or asymmetric. For example, a request of two containers of type a may be fulfilled by a single container of type b but not vice versa. According to Chang et al. (2008), a lack of well defined substitution rules prevents container substitution to be common practice.

2.2.4 Internet-based systems

Internet-based support systems offer detailed container status information to shipping lines, truckers and terminals. This allows better scheduling and coordination of container movements which may reduce congestion at port terminals (Le, 2003). A neutral Internet-based information exchange platform may facilitate empty container reuse and container sharing among shipping lines by using it as a 'virtual container yard'. Shipping lines may share information about their inventories of excess empty containers and their upcoming export loads. In this way empty containers and export loads may be matched. The required paperwork may be completed electronically and containers may be interchanged without being moved to a port or depot first. Although several efforts were made to set up such information exchange platforms, they have not been very successful in practice. A major issue is the willingness of shipping lines to share private business information. (The Tioga Group, 2002; Le, 2003; Theofanis and Boile, 2009)

2.2.5 Container leasing

Shipping lines have two possibilities to obtain containers, either ownership or leasing. Container leasing may reduce the need for globally repositioning empty containers by allowing shipping lines to hire containers at places where they have a shortage and to off-hire containers at points where they currently have a surplus. Furthermore, the opportunity to lease (and off-hire) empty containers may help to optimize regional repositioning decisions by facilitating containers to be introduced to or removed from the regional system in cases of respectively shortage and abundance.

The opportunity to save costs by container leasing is however greatly reduced by the terms and conditions of leasing arrangements. Leasing companies face deficits and surpluses on the same locations as shipping lines. They try to avoid this by imposing pickup and drop off charges which depend on the location. Leasing companies may also limit the number of containers that can be off-hired by a shipping line at a specific location each month. (Le, 2003; Di Francesco, 2007)

2.2.6 Foldable containers

Most literature on empty container management deals with reducing empty container movements. However, to some extent empty container movements are unavoidable (Konings and Thijs, 2001). Instead of avoiding movements, the concept of foldable containers focuses on reducing the cost of empty container movements. Folded containers need less transport capacity which reduces transport cost per container. They also provide opportunities for reducing storage and handling costs. Additional costs are incurred too. The folding and unfolding of containers requires extra time, manpower and equipment. Additional movements to places for folding and unfolding may be required. (Konings and Thijs, 2001; de Brito and Konings, 2006) Regardless of the extra costs, Konings (2005) and Shintani et al. (2010) show that foldable containers may substantially reduce costs in the total transport chain.

Although several types of foldable containers have been introduced in the past, neither one has been very successful. One of the main problems is skepticism about the technical performance and durability of these containers. Besides, the folding and unfolding is too complex and requires too much time, the purchase price is perceived as too high and the tare weight is much higher than for traditional containers. (Konings and Thijs, 2001; de Brito and Konings, 2006, 2008)

2.3 Modeling issues

In this section, several issues that complicate the modeling of the empty container repositioning problem are discussed. A first issue is the presence of uncertainty. Many sources of uncertainty exist. The number of empty containers available depends on uncertain parameters concerning demand for empty containers at ports for global repositioning, returning time of containers from consignees and results of container inspection on damages. (Olivo et al., 2005; Di Francesco et al., 2009) The demand for empty containers may be an uncertain parameter as well. Unexpected transportation requests may be made at the last moment by important customers. Finally, uncertainty may arise from network performance measures, such as transportation times and equipment failures (Dejax and Crainic, 1987; Cheung and Chen, 1998; Olivo et al., 2005; Crainic et al., 2007).

Another issue when modeling the empty container repositioning problem is to determine an appropriate planning horizon length. The operations of a company are expected to continue until far in the future or even infinity. Lam et al. (2007) propose to use average cost formulations in an infinite horizon framework. According to Crainic et al. (1993b), most models cover only a finite planning horizon consisting of several periods. A disadvantage of using a finite planning horizon to represent an infinite-horizon reality is that it creates distortions or end effects because of unrealistic ending inventories at the end of the planning period. These distortions should be minimized or even be excluded since they can affect the values of decision variables up to the first planning period. The use of models with a rolling planning horizon helps to reduce, but not eliminate, these distortions. (Hughes and Powell, 1988; Crainic et al., 1993b)

When deciding upon the length of the planning horizon, several factors have to be taken into account. First, the length of the planning horizon should be limited to a reasonable value to ensure computational tractability. Second, the availability of information concerning the supply and demand of empty containers should be considered. A longer planning horizon leads to more uncertain information, resulting in less reliable results. (Crainic et al., 1993b) Also the length of the longest transportation time in the system affects the choice of a proper planning horizon. The planning horizon should be at least as long as this transportation time. (Holmberg et al., 1998; Choong et al., 2002; Nilsson, 2002) Finally, Choong et al. (2002) empirically show that the length of the planning horizon may affect mode choice and repositioning costs in a multimodal network, as will be discussed in Section 2.7.

Finally, a characteristic of the empty container repositioning problem is that in all planning models decisions variables about container flows between two locations should be restricted to integer values. This requirement increases modeling complexity and augments computation times. Therefore, in some cases these integrality constraints are relaxed (Moon et al., 2010).

2.4 Overview of the planning levels

In addressing the empty container repositioning problem, several decisions have to be made. These decisions belong to different planning levels, namely a strategic, tactical and operational level, as shown in Figure 2.4. For each planning level, the main problem(s) to be solved is/are presented in the second column while the decisions related to these problems are indicated in the third column. A hierarchical relationship exists between the planning levels as indicated by the arrows. General policies are determined at the strategic level. These policies form the guidelines for decisions at the tactical level, while tactical decisions set the framework for operational and real-time decisions. The hierarchical relationship highlights differences in complexity and data requirements between decisions to be taken and prevents decisions to be represented by a single planning model. (Crainic et al., 1993b; Crainic, 2002) Principal decisions that have to be made at each planning level are discussed in the following paragraphs.

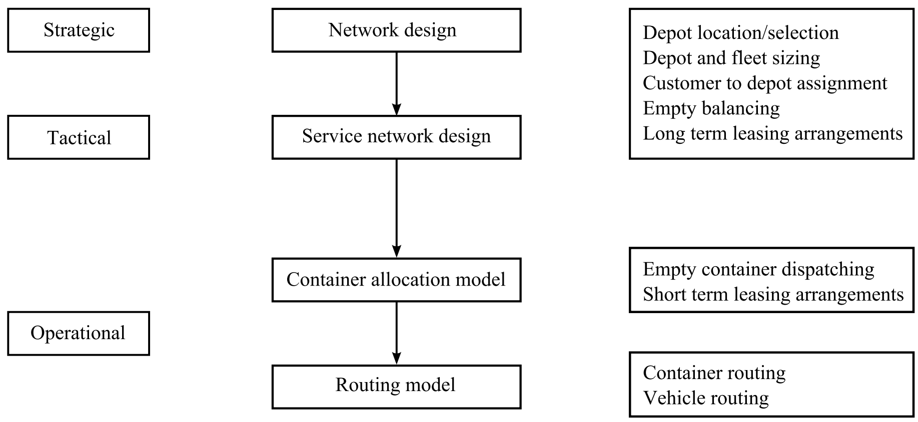

Figure 2.4: Overview of decisions for empty container repositioning (Crainic et al., 1993b; Lam et al., 2007)

Strategic planning typically involves long-term planning decisions such as large capital investments. Decisions at this level include designing the physical network by choosing locations of container depots and other facilities, depot and fleet sizing, acquiring resources, determining customer zones and defining broad service policies. (Crainic and Laporte, 1997; Nilsson, 2002; Lam et al., 2007)

Tactical planning aims to ensure an efficient and rational allocation of existing resources over a medium horizon (Crainic and Laporte, 1997). Most decisions at this level concern the problem of service network design. According to Crainic and Laporte (1997), Crainic (2000) and Wieberneit (2008), decisions at a tactical level include:

- service selection: the selection of routes on which services are offered and the frequency of these services;
- traffic distribution: specification of routes for the traffic of each origin-destination pair: services used, terminals passed through and operations performed at the terminals;
- terminal policies: consolidation activities that have to be performed at each terminal;

- empty balancing strategies: how empty vehicles, trailers and containers have to be repositioned in order to satisfy future requests;
- vehicle and crew planning: especially for less-than-truckload transportation in Europe, when vehicles and drivers are regarded as a single resource and vehicle tours have to be determined taking legal and social requirements into account.

Furthermore, customer zones have to be assigned to terminals. This assignment may be specified by container type and direction of movement. Empty container balancing flows between container terminals and depots should be indicated in the same way. However, the results should not be interpreted as decisions to be carried out in actual operations. They only give an indication of the magnitude of the balancing flows required over the following periods. Finally, to avoid the risk of empty container shortages, containers can be added to the system via long-term lease arrangements. (Crainic et al., 1993b; Nilsson, 2002; Lam et al., 2007)

The *operational planning* level is characterized by a highly dynamic environment. Firstly, the time factor plays an important role at this level. Secondly, the stochasticity inherent to the system, as discussed in Section 2.3, further compounds the dynamic aspect. Main issues of operational planning are the scheduling of services and the routing and dispatching of resources such as containers, vehicles and crews. Furthermore, the allocation of resources and the conclusion of short-term lease contracts belong to this planning level. (Crainic and Laporte, 1997; Lam et al., 2007)

Optimization of regional empty container repositioning at the operational level means making sure that demand for empty containers is satisfied at all locations and that the most efficient routes and transport modes are chosen. To account for the interactions between the different decisions to be made, Crainic et al. (1993b) note that ideally a single mathematical model should be developed. However, the authors state that, considering the available Operations Research techniques at that time, developing such a model is not feasible due to the complexity of the problem. Therefore, the operational planning problem is traditionally divided into two separate optimization problems, namely a container allocation and a vehicle routing model. The objective of the container allocation model is to determine the best distribution of empty containers among consignees, shippers, container terminals and container depots, while satisfying both known and forecasted demand. The vehicle routing model aims to minimize overall transportation costs of both loaded and empty containers and results in a list of movement orders which completely describe loaded and empty movements to be executed during the next period. (Crainic et al., 1993b)

As opposed to regional repositioning, operational decisions for globally repositioning empty containers generally do not include routing decisions. Empty containers are repositioned by using idle capacity on ships carrying loaded containers. Therefore, the remaining capacities for repositioning empty containers are introduced as constraints for each link in the container allocation model.

An overview of literature per planning level is given in Table 2.1. Papers dealing with decisions of several planning levels are mentioned as well. For the operational planning level, a distinction is made between regional container allocation models, global container allocation models and recent models that integrate container allocation and routing decisions. A difference is made between papers that propose a deterministic, stochastic and simulation model, although several papers may be placed in more than one category. Some papers continue work of a previous paper. In these situations, only the original paper is included in the table for clarity purposes but all papers are discussed in the following sections.

2.5 Planning models integrating strategic and tactical decisions

Crainic et al. (1993b) state that an integrated multilevel methodology may be designed to answer most questions of the strategic and tactical planning levels together. In order to do so, Crainic et al. (1989) introduce a class of problems called multimode multicommodity location(-allocation) problems with interdepot balancing requirements. Crainic et al. (1993a) define the general problem as follows: "to locate the empty container depots in order to collect the supply of empty containers available at customers' sites and to satisfy the customer demands for empty containers, while minimizing the total operation cost: the cost of opening and operating the depots, plus the transportation costs between customers and depots, and the costs generated by moving empty containers among depots to 'balance' the network." The authors state that this problem may be solved repeatedly because container shipping companies rather use available facilities than building their own depots. It is assumed that interdepot empty container movements are more efficient than empty container movements between depots and customers because transport can be consolidated for long distance movements, resulting in lower costs. Therefore, the very existence of interdepot movements is justified and the problem is differentiated from a classical location-allocation problem. (Crainic et al., 1989, 1993a)

A mathematical model for the multimode multicommodity location problem with interdepot balancing requirements has been described by Crainic et al. (1989). The

Table 2.1: Overview of planning models

		Deterministic	Stochastic	Simulation
Strategic		Boile et al. (2008)		Imai and Rivera (2001)
Tactical		Shintani et al. (2007) Maras (2008) Song and Carter (2009) Choong et al. (2002)		
Operational	Regional Container Allocation	Wang and Wang (2007) Olivo et al. (2005) Jula et al. (2003) Le-Griffin and Griffin (2010) Jansen et al. (2004)	Crainic et al. (1993b) Chu (1995) Chang et al. (2006)	
	Global Container Allocation	Shen and Khoong (1995) Moon et al. (2010) Feng and Chang (2008) Di Francesco et al. (2009) Erera et al. (2009)	Cheung and Chen (1998) Li et al. (2004) Song (2007) Song and Dong (2011) Yun et al. (2011) Chou et al. (2010)	Lai et al. (1995) Lam et al. (2007)
	Integrated Container Allocation & Routing	Erera et al. (2005) Baldacci et al. (2006) Deidda et al. (2008) Bandeira et al. (2009) Huth and Mattfeld (2009) Smilowitz (2006) Ileri et al. (2006) Zhang et al. (2009)	Huth and Mattfeld (2011)	
Strategic & Tactical		Crainic et al. (1989)		Gao (1997)
Strategic & Operational			Beaujon and Turnquist (1991) Du and Hall (1997) Song and Earl (2008)	Kochel et al. (2003) Dong and Song (2009)

model is a mixed integer program, combining binary location variables and a multicommodity network flow structure. Street turns are not considered in the model. Capacity constraints on depots and transport modes are not taken into account. Transportation and depot operating costs are assumed to be linear and demands are assumed to be deterministic.

Several solution procedures for the model are proposed in literature. Crainic et al. (1993a) note that although the proposed model has some characteristics of classical location models, the balancing requirements unveil a network structure that is favorable to efficient algorithmic developments. Crainic and Delorme (1993) discuss two dual-ascent procedures for solving the model which yield good solutions for random test cases. A tabu search heuristic is developed by Crainic et al. (1993c). The heuristic finds excellent, if not optimal, solutions in a reasonable amount of time and is favorable compared to the dual procedures of Crainic and Delorme (1993). Crainic et al. (1993a) propose a branch-and-bound procedure which takes advantage of the particular network structure of the problem, for example via special branching rules. Gendron and Crainic (1993) improve this branch-and-bound procedure by implementing it on a parallel computer. Two sources of parallelism are discovered, namely the exploration of the search tree and the decomposition of the problem by commodity. A branch-and-bound algorithm in which bounds are computed by a dual-ascent procedure is proposed by Gendron and Crainic (1995). The dual-ascent procedure is based on the one by Crainic and Delorme (1993). Results show that the algorithm outperforms all previous algorithms. Another parallel branch-and-bound procedure is described by Gendron and Crainic (1997). The authors propose a multiple-list implementation in which each process has its own local pool of subproblems. Finally, Bourbeau et al. (2000) further improve the existing parallelization strategies for branch-and-bound algorithms on the problem.

A capacitated version of the multicommodity location problem with interdepot balancing requirements is studied by Gendron et al. (2003a,b). Each possible depot location is characterized by a fixed and finite capacity. These capacities represent estimations for the number of empty containers that can be shipped through the corresponding depot within the planning horizon. Gendron et al. (2003b) use a sequential algorithm to solve the problem. A tabu search heuristic is proposed, for which an initial solution is generated by slope scaling. Gendron et al. (2003a) propose a parallel hybrid heuristic using variable neighborhood descent and slope scaling. Numerical experiments are performed in both papers. It is shown that the parallel solution approach yields better solutions than the sequential approach.

Another model concerned with both the strategic and tactical planning level is described by Gao (1997). The author proposes a multi-period mixed integer programming model for selecting the optimal set of inland intermodal container depots from a set of possible locations, while taking into account empty container repositioning needs. The considered network consists of a set of potential depot locations and supply and demand customers. Some depots and customers have the opportunity to bring empty containers in from outside the system or returning the excess of empty containers to the outside. A difference between the model of Gao (1997) and the class of models proposed by Crainic et al. (1989) is that the former is a multi-period model, while the latter is a single-period model. Gao (1997) notes that: ”In essence, balancing requirements imply repositioning empty containers from one location to another in preparation for expected demand in the latter depot in the subsequent time periods. A crucial pre-condition for permitting the modeling of balancing activities is a multiple-period modeling framework, because in a single-period model one cannot express the sequential behavior of the reallocation of container from an origin depot to a destination depot and then the use of the containers in the destination depot.” Therefore Gao (1997) states that, although Crainic et al. (1989) claim to do so, they do not take into account the balancing requirements, which are essential to the inland depot selection problem. The problem is formulated as a deterministic model without container substitution and street turns. Two decomposition algorithms are described. The model is applied to a real-life problem for a North American shipping company. Finally, a selected artificial depot procedure is formulated to include street turns and a simulation model is developed to account for uncertainty in empty container demand and supply.

2.6 Strategic planning models

While earlier papers integrate strategic and tactical decisions, recent research focuses on specific decisions of either the strategic or the tactical planning level. Strategic planning models are discussed in this section; tactical models in Section 2.7.

Boile et al. (2008) propose a system of inland depots for rationalizing empty container management on a regional level. The authors take a public-benefit perspective by considering transportation needs of multiple shipping lines. A strategic planning model is presented for determining optimal depot locations from an identified set of potential sites. No empty balancing flows between depots are considered due to the costs involved with these movements and due to agreements that may exist between terminal operators and depot owners for storing their empty containers. The problem is formulated as an inventory-based capacitated depot location problem with a long term (10 years) planning horizon. Empty containers are only transported by truck and street turns are not allowed. The model is applied on the Port of New York/New Jersey region in the United States. Results show that by implementing a system of inland depots a reduction of 49% in empty container kilometers may be achieved.

Imai and Rivera (2001) focus on the container fleet sizing problem for refrigerated maritime containers. First, the authors propose a mathematical model for the dry container fleet sizing problem with a relatively balanced demand between ports. Next, the model is extended for the case of refrigerated containers which have an extremely unbalanced demand. Finally, a simulation model is developed and used to find the best composition of owned and leased refrigerated containers. Scenarios with various trends of cargo demand are analyzed.

2.7 Tactical planning models

Service network design for a liner shipping company explicitly taking into account empty container repositioning is addressed by Shintani et al. (2007). Although service network design has received much attention in literature, service network design models taking into account empty container flows are rather scarce. Most authors deal with loaded and empty container flows separately, mainly due to the complexity of the problem. According to Shintani et al. (2007), this is only appropriate if all cargo demand is satisfied. If it is possible to forgo profitable cargo demand, because the revenue it generates is offset by the associated costs of empty container repositioning, separately dealing with both flows will lead to sub-optimization. The model of Shintani et al. (2007) determines a single shipping route by choosing an optimal set of calling ports and an associated calling sequence. Loaded and empty container flows are optimized together. The problem is formulated as a Knapsack problem and solved with a genetic algorithm-based heuristic. Results show that by taking into account empty container repositioning needs when determining a shipping route, less empty containers have to repositioned. As a result, vessel (un)loading times and operating costs are reduced. Therefore, ships can cruise at lower speeds which yields considerable fuel cost savings.

Maras (2008) investigates empty container repositioning in the context of service network design for barge transportation. The author adapts the model of Shintani et al. (2007) for service network design in maritime shipping. Maras (2008) considers the viewpoint of a logistic service provider or shipping company that wants to charter a single vessel to offer a roundtrip barge service between a fixed start and end port with eight intermediate ports. The objective is to find the profit maximizing route while taking both loaded container transports and empty container repositioning movements into account. Maras (2008) is able to find optimal solutions by using commercial software. The author finds the profit maximizing routes for five types of vessels for a single transport demand situation.

Song and Carter (2009) study general empty container balancing strategies for global repositioning like route coordination and container sharing. Route coordination refers to a single shipping line balancing its container flows across different service routes. Container sharing refers to pooling container fleets among different shipping lines. Results show that route coordination offers more opportunities to reduce repositioning costs than container sharing which may explain the reluctance of large shipping lines to join container sharing practices.

The effect of the planning horizon length on empty container management for an intermodal container-on-barge transportation network is studied by Choong et al. (2002). According to the authors, barge transportation offers the advantage that empty containers can be 'piggy-backed' onto loaded containers at a very low cost. There is however a trade-off with the relatively low speed of barge transport. Choong et al. (2002) adapt the deterministic single commodity model of Crainic et al. (1993b) which is discussed in Section 2.8.1. Storage capacities and multiple capacitated transport modes are included in the model. The authors consider two lengths for the planning horizon, namely 15 and 30 days. When comparing the results of the first 15 days of their 30-day model with the 15-day model, it appears that the length of the planning horizon has an effect on the results of these days. Total transport costs and holding costs are lowest for the 30-day model. Also the choice of transportation mode is affected. Truck usage is lower and barge usage is higher than with the 15-day model. The authors conclude that the use of a longer planning horizon on a rolling basis can produce better results for the empty container repositioning costs since it encourages the use of slower and cheaper modes.

2.8 Operational planning models

In Section 2.4 it is mentioned that the operational planning of empty container repositioning on a regional level may be divided into two subproblems, namely a container allocation problem and a vehicle routing problem, while generally only an empty container allocation model is used for planning global empty container repositioning movements.

The earliest models considering empty container allocation date from several decennia ago (Potts, 1970; White, 1972; Ermol'ev et al., 1976). However, the problem did not get much attention until the beginning of the nineties. In this thesis, a distinction is made between models for container allocation on a regional level and on a global level because some differences between these problems exist. On a regional level generally a large amount of allocation options are available to the decision maker: many shippers and consignees respectively demand and supply empty containers, containers are mostly transported individually (or per two) by truck and directly traveling between all pairs of locations is possible. On a global level fewer options are available: empty containers can only be repositioned when empty slots are available on ships, not all ports are connected directly to each other by a shipping route and shipping times are often determined by a fixed schedule. Regional container allocation models are discussed in the following section while global container allocation models are discussed in Section 2.8.2.

The vehicle routing subproblem for empty container repositioning on a regional level can be formulated as a full truckload Pickup and Delivery Problem with Time Windows (FT-PDPTW) as is shown in Chapter 4. No distinction has to be made between transporting loaded and empty containers when solving this problem. Related literature on this topic will be discussed in that chapter. In Section 2.8.3 of this chapter, recently proposed efforts to integrate empty container allocation decisions with empty and/or loaded container routing decisions are described.

2.8.1 Regional container allocation models

When modeling the empty container allocation problem on a regional level, several decisions or assumptions about the model have to be made:

- is the model deterministic or stochastic,
- is the model static or dynamic,
- is it a single commodity or a multicommodity model,
- are container substitution, container leasing and/or street turns allowed?

These decisions affect the model complexity and determine whether the model can be solved exactly or only approximately. The most realistic model would be a stochastic, dynamic, multicommodity model including opportunities for container substitution, container leasing and street turns. Formulating and solving such a model seems not feasible. To our knowledge no such model is described in literature. Several models, comprising some but not all elements, have been proposed. An overview of literature concerning models for regionally allocating empty containers is given in Table 2.2. For each reference it is shown which elements are taken into account and whether an exact, approximating or no solution method is proposed.

Table 2.2: Overview of regional container allocation models

Author(s)	Stochastic	Multicom.	Substitution	Dynamic	Street turns	Leasing	Solution
Crainic et al. (1993b)		•	•	•		•	none
Crainic et al. (1993b)	•						none
Wang and Wang (2007)		•		•			exact
Chu (1995)	•			•		•	approx.
Olivo et al. (2005)		•				•	exact
Di Francesco et al. (2006)		•	•	•			approx.
Di Francesco (2007)		•	•	•		•	exact
Jula et al. (2003)		•		•			exact
Chang et al. (2008)		•		•	•		approx.
Chang et al. (2006)	•						approx.
Le-Griffin and Griffin (2010)							exact
Jansen et al. (2004)					•		exact

Crainic et al. (1993b) offer a general framework for the allocation of empty containers. The authors describe a dynamic deterministic mathematical model for the single and multicommodity case. Space and time dependency of events, container substitution and relationships with partner companies are taken into account. Time steps of one day are proposed, with a planning horizon of 10 to 20 days. Street turns are not considered. Next, a stochastic model, dealing with uncertainties concerning demand and supply is described for the single commodity case. Since a multi-stage stochastic program with full network recourse would be intractable, Crainic et al. (1993b) formulate a two-stage restricted recourse model in which all decisions are made by the first-stage model at the beginning of the planning period. The second-stage model tracks down how the stocks of containers at the following periods fluctuate as a consequence of the random supplies and demands, but decisions are not re-optimized. Finally, Crainic et al. (1993b) propose to use a decomposition approach to solve the deterministic multicommodity model and a stochastic quasi-gradient method to solve their stochastic model, but no such methods are described. In a subsequent work, Abrache et al. (1999) develop a decomposition algorithm for the deterministic multicommodity problem. First, substitution links are excluded and all subproblems, one for each commodity, are solved. Next, subproblems are fused together and substitution links between them are made feasible. Several fusion strategies are proposed. Experimental results show that both global and progressive fusion methods are at least three times more efficient regarding computation time than general minimum cost flow algorithms.

A dynamic deterministic single commodity model, closely related to the one proposed by Crainic et al. (1993b), is described by Wang and Wang (2007). Three transport modes, road, rail and barge, are considered and for each of them lower and upper transport limits are imposed. Lower and upper storage limits at inland depots and ports are also included in the model. A small numerical experiment is performed.

Other mathematical models for empty container allocation are proposed by Chu (1995). First, a single and a multicommodity dynamic deterministic model are described. Interdepot movements and container leasing are accounted for. Street turns and container substitution are not considered. According to the author, the single commodity model can be solved by the network simplex method, while the multicommodity model can be solved by a decomposition method. Next, Chu (1995) formulates a two-stage and a multi-stage single commodity dynamic stochastic model. For solving these stochastic models, respectively a stochastic quasi-gradient approach and a network recourse decomposition method are proposed. Finally, by means of numerical experiments, it is shown that the multi-stage stochastic model offers better results than the dynamic deterministic model.

Olivo et al. (2005) develop a two-commodity deterministic model for empty container management on a continental or interregional level by formulating it as a minimum cost flow problem. Container substitution is not accounted for. The authors consider a dynamic multimodal network that consists of nodes for depots and macronodes which accumulate supply and demand for a regional zone. A distinctive characteristic of the proposed model is that hourly time steps are considered during a weekly, rolling horizon planning period. Most other models use time steps of one day. Olivo et al. (2005) claim that such small time steps are to be preferred in order for a model to be applicable in the real world. Hourly time steps offer the possibility for promptly adjusting decisions when unexpected new information, for example about equipment failures or traffic accidents, becomes available. The authors show that using hourly time steps does not lead to a computationally intractable model by applying their model as a real-world application in the Mediterranean basin.

Di Francesco et al. (2006) use a similar approach as Olivo et al. (2005) for the empty container allocation problem on a regional level. Time steps are one day with a rolling planning horizon of 15 days. Only company-owned containers are taken into account. Based on the work of Crainic et al. (1993b), the authors include the possibility of container substitution. First, the model is solved without substitution, balancing the network for each container type. In a second phase, better solutions are obtained by allowing substitution. Di Francesco (2007) continues the work by introducing the opportunity of short-term leasing containers into the dynamic deterministic model of Di Francesco et al. (2006).

Jula et al. (2003) describe several methods for modeling the depot direct and street turn approaches discussed in Section 2.2. Static as well as dynamic models are discussed. For both methods, four scenarios are modeled, namely a base scenario, a street turn scenario, a scenario involving street turns and inland depots and a multicommodity scenario. All proposed models are deterministic. Interdepot movements are excluded and the multicommodity models do not consider container substitution. The planning horizon is one eight-hour day, consisting of eight periods of one hour. The models are applied on the Los Angeles and Long Beach port area. Results show that costs from empty movements drop significantly when allowing street turns and using inland depots. (Jula et al., 2003) More simulations of the dynamic model including street turns and inland depots are performed by Jula et al. (2006).

Chang et al. (2006, 2008) and Ioannou et al. (2006) continue the work of Jula et al. (2003, 2006). The authors propose mathematical models for the static deterministic two-commodity and multicommodity allocation problem with container substitution. A branch-and-bound based algorithm is considered. To reduce computation times, Ioannou et al. (2006) and Chang et al. (2008) propose an approximation method which forces fractional variables to become integers. Comparing simulation results with those from Jula et al. (2003) shows that allowing for container substitution may result in a reduction of costs from empty container movements. Next, Chang et al. (2006) and Ioannou et al. (2006) propose a model for the static stochastic single commodity problem, without container substitution. First, the problem with stochastic demand is modeled as a two-stage stochastic program. Then, the problem with both stochastic demand and supply is modeled as a one-stage stochastic program. Finally, a Monte

Carlo simulation method is proposed to optimize the two-stage stochastic program.

Le-Griffin and Griffin (2010) study the use of short sea shipping within a regional port system along the west coast of the United States for repositioning empty containers. A regional port system is a network consisting of a major seaport and some secondary ports. The authors conclude that using short sea shipping in such a system could be an option to reduce repositioning costs and landside congestion.

A real-life application of the container allocation problem is described by Jansen et al. (2004). The authors describe an operational planning system taking repositioning aspects into account for the German company Danzas Euronet. However, the planning and repositioning problems are solved separately due to the large size of the problem. Repositioning of empty containers is modeled on a rail-road network as a minimum cost flow problem.

2.8.2 Global container allocation models

Two research directions can be distinguished concerning global container allocation models. One direction makes use of mathematical programming. According to Song and Dong (2011) these mathematical models often successfully capture the stochastic and dynamic nature of the problem, but they may give rise to some issues such as determining an appropriate planning horizon, ensuring computational tractability and ensuring robustness of the policy to uncertainties. An overview of literature on models using mathematical programming is presented in Table 2.3. All models consider multiple ports and multiple periods, while none considers container substitution. Table 2.3 shows for each model which modeling or solution approach is used and whether the model is stochastic, considers multiple commodities and/or considers container leasing.

A second research direction makes use of inventory theory to determine (near-) optimal empty container repositioning policies for shipping networks with a specific topological structure. These threshold policies have the advantage of being easy-to-operate and easy-to-understand. (Song and Dong, 2011) Table 2.4 gives an overview of literature on models using inventory theory. For each paper, it is shown which type of network is studied and whether stochastic demand, multiple commodities and/or container leasing are considered.

A more detailed description of the models in Tables 2.3 and 2.4 is presented in Sections 2.8.2.1 and 2.8.2.2. A paper by Chou et al. (2010) which combines inventory theory and mathematical programming is discussed as well.

Table 2.3: Overview of global container allocation models using mathematical programming

Author(s)	Stochastic	Multicom.	Leasing	Modeling/solution approach
Shen and Khoong (1995)			•	Network optimization
Cheang and Lim (2005)		•	•	Network optimization
Moon et al. (2010)		•	•	Genetic algorithms
Feng and Chang (2008)		•		Integer programming
Feng and Chang (2010)		•		Integer programming
Lai et al. (1995)	•	•	•	Simulation, two-step heuristic
Cheung and Chen (1998)	•		•	Quasi-gradient, hybrid approximation
Lam et al. (2007)	•		•	Dynamic programming
Di Francesco et al. (2009)		•		Multi-scenario model
Erera et al. (2009)				Robust optimization

Table 2.4: Overview of global container allocation models using inventory theory

Author(s)	Stochastic	Multicom.	Leasing	Network
Li et al. (2004)	•		•	Single port
Li et al. (2007)	•		•	Multiple ports
Song (2007)	•		•	Two ports
Song and Carter (2008)	•		•	Hub-and-spoke
Song and Dong (2008)	•			Cyclic routes
Song et al. (2010)	•			Two ports
Song and Zhang (2010)	•		•	Single port
Song and Dong (2011)	•			Multiple ports
Yun et al. (2011)	•		•	Single port

2.8.2.1 Mathematical programming

A decision support system based on network optimization is proposed by Shen and Khoong (1995). Leasing decisions are taken into account and a single container type is assumed. The decision support system is implemented on a rolling horizon basis. Two algorithms to minimize the impact of changes in the demand and supply of empty containers on decisions taken in previous periods are suggested. Cheang and Lim (2005) present a similar decision support system for the multicommodity problem.

Another deterministic multicommodity model for empty container repositioning between ports is described by Moon et al. (2010). Container purchasing and short term leasing options are included. A LP-based genetic algorithm and a hybrid genetic algorithm are proposed to solve the model.

To avoid capacity being lost on long-distance high-revenue links, Feng and Chang (2008) propose to partition the shipping network of a shipping line into smaller geographical regions and to reposition empty containers only within these regions. A deterministic multicommodity model for empty container repositioning within small geographical regions is proposed. Feng and Chang (2010) study a similar problem to maximize the profit of a specific shipping route using revenue management.

Other mathematical models explicitly take into account uncertainty concerning empty container demand and supply. Lai et al. (1995) use simulation and a two-step heuristic to minimize operational costs of repositioning empty containers between a single supply point in the Middle East and 11 demand points (ports) in the Far East. The situation where total demand exceeds total supply of empty containers is studied. The model accounts for both dynamic and stochastic issues. Two container sizes are considered but container substitution is not allowed. Short-term leasing is used to avoid shortages. Simulation results show a reduction in annual operating costs compared with current practice due to the introduction of safety stocks and a revised allocation priority.

A dynamic single commodity two-stage stochastic network is formulated by Cheung and Chen (1998). In the first stage, all parameters are assumed to be deterministic, while in the second stage empty container supplies and demands and ship capacities are stochastic variables. Decisions in stage one aim to minimize the costs of that stage and the expected costs of the second stage. A stochastic quasi-gradient method and a stochastic hybrid approximation procedure are proposed to solve the model.

Lam et al. (2007) formulate the container allocation problem for maritime transportation as a dynamic, stochastic programming model for obtaining an optimal average cost over an infinite planning horizon. A two-ports two-voyages and a multiple-ports multiple-voyages model are described. By using an average cost formulation over an infinite planning horizon, distortions from approximating an infinite horizon by a finite horizon are avoided. To solve the models, a simulation based approximate policy iteration algorithm is proposed.

Di Francesco et al. (2009) note that, in order to use stochastic models, a good knowledge of the random variable distributions is needed to avoid low quality solutions. To avoid using a stochastic model, the authors propose to use a set of scenarios representing different levels of the uncertain parameters. Weights attributed to these scenarios might represent probabilities but also subjective opinions.

Another way to account for uncertainty, proposed by Erera et al. (2009), is to use a robust optimization approach. An interval of possible values is determined for each uncertain parameter. The objective is to find a minimum cost recoverable solution for the repositioning problem while it is assumed that only a limited number of parameters take on their worst value. A recoverable solution is defined as a solution for which the repositioning plan may be transformed to a feasible solution for every joint realization of uncertain parameters by changing a limited set of decisions.

2.8.2.2 Inventory theory

Li et al. (2004) look at a single port with the objective of fulfilling empty container demand for export while minimizing the number of redundant empty containers. The empty container allocation problem is considered as a non-standard inventory problem with simultaneous positive and negative demand under a general holding cost function. Demand has to be satisfied, if necessary by leasing. An optimal policy (U, D) is derived for both the finite- and infinite-horizon problem. Empty containers should be imported when there are less than U, empty containers should be exported when there are more than D and no action should be taken when there are between U and D empty containers. Li et al. (2007) extend the work of Li et al. (2004) to the multi-port case. A heuristic algorithm is developed to reduce average costs when allocating empty containers between ports.

Song (2007) study a periodic review system with vessels performing shuttle services between two ports. Finite repositioning capacity is assumed. The objective is to minimize the total cost of container leasing, storage and repositioning. Optimal repositioning policies minimizing the expected discount cost or the long-run average costs are determined. Song and Carter (2008) extend this work to a hub-and-spoke transportation system using a dynamic decomposition procedure, while Song and Dong

(2008) study a threshold control policy for empty container management in cyclic shipping routes. The optimal control policy for a two-port service system without short term container leasing is determined by Song et al. (2010). Song and Zhang (2010) use a fluid flow model to determine the closed-form solutions for a threshold policy for a single port with stochastic demand.

A repositioning model with flexible destinations is described by Song and Dong (2011). The destination of empty containers being repositioned is chosen after they are loaded onto a ship. A threshold-type policy is presented. Simulation results show that the model with flexible destinations outperforms a traditional model with determined destinations in situations with unbalanced trade and medium container fleet sizes.

Yun et al. (2011) propose an (s, S) inventory policy to control the number of empty containers in a shortage region. Container demand is stochastic with a high and low demand season. When it is expected that less than s containers will be available, empty containers are repositioned from other regions up to an inventory level S. In case of shortages, empty containers are leased. Simulation is used to find the average cost rate which is to be minimized. An optimization tool is used to determine the near optimal policy.

Finally, a combination of inventory theory and mathematical programming is used by Chou et al. (2010). The authors present a mixed fuzzy decision making and mathematical programming model. In the first stage, the optimal quantity of empty containers at port is determined by a fuzzy backorder quantity inventory model. Container imports and exports are stochastic. In stage two, the optimal number of empty containers to be repositioned between ports is found by a mathematical programming model.

2.8.3 Integration of container allocation and routing decisions

Dejax and Crainic (1987) suggested that the independent consideration of container allocation and routing neglects possible synergies arising from an integrated view on these problems. As was already mentioned in Section 2.4, Crainic et al. (1993b) state that a single mathematical model comprising container allocation and routing decisions would be computationally intractable. Due to the continuous improvement of Operations Research techniques and computer capabilities, this opinion has changed. Recently, a number of attempts to integrate container allocation and vehicle routing decisions have been made. Erera et al. (2005) develop a mathematical model integrating the routing and repositioning decisions for tank container operators on a global level. The proposed model is formulated as a deterministic multicommodity network flow problem over a time-expanded network. A rolling planning horizon approach is used. A computational study has been conducted to show that the model can be solved by commercially available optimization software for real-life cases.

Other efforts to integrate container (or trailer) allocation and routing decisions focus on the empty container repositioning problem on a regional level. Baldacci et al. (2006) study the Multiple disposal facilities and multiple inventory locations Rollon-Rolloff Vehicle Routing Problem (M-RRVRP). The problem arises in the sanitation industry where tractors move trailers between customer locations, disposal facilities and inventory locations. Five types of trips are identified. For some trip types, the origin or destination of an empty trailer is not predefined. A set partitioning formulation is used and an exact solution method is proposed.

Deidda et al. (2008) propose a static, deterministic optimization model for implementing the street turn approach discussed in Section 2.2.2. They simultaneously address the allocation of empty containers between shippers, consignees and a port and the design of vehicle routes for transporting empty containers. Loaded container transports are not considered and vehicles, located at the port, have a capacity of two containers. Only distances traveled by vehicles that transport at least a single empty container are minimized, while distances traveled without a container are ignored.

A decision support system that simultaneously models the routing of loaded containers and the allocation and routing of empty containers is proposed by Bandeira et al. (2009). The routing problem is formulated as a Multiple Depot Vehicle Scheduling Problem. Street turns are not considered. The decision support system is decomposed into two interconnected models: a static model, responsible for the allocation and movement of containers, and a dynamic model which updates the future demands and supplies of loaded and empty containers.

Huth and Mattfeld (2009) describe mathematical models for the sequential and integrated planning of container allocation and vehicle routing for the swap container problem. Again a capacity of two containers is assumed. Containers are transported between hubs in a hub-and-spoke network in a dynamic, deterministic environment. No time windows are considered. The allocation problem is modeled as a multi-stage transportation problem while the routing problem is modeled as a generalization of the pickup and delivery problem. The authors propose two approaches to integrate both models: functional integration, which leads to hierarchical decision making between both models, and deep integration, which leads to a single new model. A Large Neighborhood Search (LNS) is used to solve the models. Results show the advantage of an integrated approach for this type of problem. Recently, a stochastic version of the problem is described by Huth and Mattfeld (2011).

Some integrated approaches for container allocation and vehicle routing taking time windows into account have been proposed as well. All these approaches assume a vehicle capacity of a single container. Smilowitz (2006) studies the routing and scheduling of loaded and empty trailers (or containers) between rail terminals, shippers, consignees and equipment depots. Trailer allocation decisions are made simultaneously with vehicle routing decisions by introducing flexible tasks for empty trailers demanded and supplied (origins resp. destinations are not predefined). Only allocations with a distance smaller than a threshold are considered as possible executions for a flexible task. The objective of the model is to both minimize fleet size and travel time. The model is solved by a branch-and-bound heuristic using column generation. This solution method is improved in subsequent work (Francis et al., 2007). Recently, dynamic versions of this problem are studied by Escudero et al. (2011) and Zhang et al. (2011a).

Another column generation approach embedded in a branch-and-bound framework for the integrated allocation and routing of trailers in drayage operations is proposed by Ileri et al. (2006). A heterogeneous fleet of drivers with different start and end locations is assumed. The objective is to minimize costs with company drivers having a different cost structure than third party drivers. When traveling between certain types of tasks, intermediate stops at empty trailer storage and supply locations are introduced to ensure that vehicles arrive at the starting location of a task appropriately (empty or with an empty trailer).

A similar problem, in the context of container transportation, is investigated by Zhang et al. (2009). Empty container allocations are integrated with routing decisions for vehicles with a single container capacity. A single container terminal and several vehicle depots with an empty container stock are considered. Vehicles are not required to return to their starting depot. The objective is to minimize total travel time. It is shown that the problem can be formulated as a multiple vehicle Traveling Salesman Problem with Time Windows (m-TSPTW) and multiple depots. A Reactive Tabu Search (RTS) algorithm is proposed to solve the problem. Zhang et al. (2010) extend this problem to a multiple depot, multiple terminal problem and solve it by a time window partitioning method. Finally, Zhang et al. (2011b) look at the single depot, single terminal problem for which the number of empty containers available at the depot is limited. Again an RTS algorithm is proposed. It seems that solving this problem is much more complex than solving the problems in Zhang et al. (2009) and Zhang et al. (2010) without a limit on the number of empty container available at the depots.

2.9 Planning models integrating strategic and operational decisions

Although the container fleet sizing (strategic) and the container allocation (operational) problem belong to different planning levels, they are closely related. A reduction of container fleet size saves capital investment and inventory costs, but increases the need for empty container repositioning, container leasing costs in case of shortages and even the risk of customer loss due to container unavailability. (Imai and Rivera, 2001; Dong and Song, 2009) Despite this relationship, Imai and Rivera (2001) state that it is more convenient to deal with both problems separately. In general, owned containers are kept in use for more than ten years. Taking into account future empty movements when determining the container fleet size is both practically impossible and useless according to the authors. This may be a reason for the fact that although for both problems a rich literature exists, the simultaneous consideration of both problems is only investigated by a few papers. (Kochel et al., 2003)

Beaujon and Turnquist (1991) present a first paper that investigates the combined consideration of both problems. The authors propose a non-linear optimization model to optimize vehicle fleet size and vehicle utilization decisions simultaneously. Du and Hall (1997) look at the fleet sizing and empty resource repositioning problem by building on inventory theory. The authors propose a decentralized repositioning policy and apply it to hub-and-spoke networks. The objective of the policy is to minimize the fleet size, while meeting a given allowed long-run stock-out probability. Kochel et al. (2003) propose a simulation optimization approach, based on genetic algorithms and evolutionary strategies, for the combined fleet sizing and allocation problem. Numerical experiments are presented to show the applicability of their approach. The problem of determining optimal control policies for empty container repositioning and fleet-sizing in a two-depot service system is considered by Song and Earl (2008). Short-term leasing options and uncertainties in travel and storage times are accounted for. It is shown that the optimal repositioning policy is of the threshold type (a lower and upper bound on inventory) and that the optimal fleet size and threshold values can be derived analytically.

While the previous papers focus on vehicle or container fleet management in inland transportation systems, Dong and Song (2009) consider the combined container fleet sizing and empty repositioning problem for a liner shipping system. As Kochel et al. (2003) do for the land transportation case, Dong and Song (2009) propose a simulation optimization tool, using genetic algorithms and an evolutionary strategy, that finds the optimal fleet size and optimal threshold parameters simultaneously.

2.10 Research gaps and opportunities for further research

Empty container management constitutes a broad domain of research, ranging from long-term strategic issues to day-to-day operational decisions. The last twenty years attention for the problem has grown, which has resulted in a large amount of recent publications, especially concerning operational issues. This chapter gives a detailed overview of the work done so far and creates a framework wherein the existing literature is situated.

Several opportunities for further research are identified in Table 2.5. Research on strategic and tactical aspects of the repositioning problem is rather scarce, especially for the global problem. An interesting research direction is the introduction of repositioning needs in service network design for maritime shipping, on which Shintani et al. (2007) already presented a first effort. Future research could also focus on container fleet sizing which is addressed by only a few papers. At the operational level of the global problem, most research has focused on optimizing operations of a single shipping line. Future research could identify cost saving opportunities from cooperation among shipping lines. Furthermore, global repositioning decisions obviously have an impact on the decisions to be taken on a regional level (e.g. the number of empty containers available at a port). However, to the author's knowledge no research has studied the interdependence between both problems.

Table 2.5: Opportunities for further research

	Global problem	Regional problem
Strategic/tactical level	Service network design with empty container repositioning	Multimodal (service) network design with empty container repositioning
	Container fleet sizing	
Operational level	Cooperation between shipping lines	Integration of allocation and routing
	Effect of decisions on regional decisions	

For the empty container repositioning problem on a regional level, several opportunities for further research exist as well. Transportation on a regional level takes place on a multimodal (road, rail, barge) network. However, most research has focused on a single transportation mode (road transport). Especially at the strategic and tactical decision level, designing physical and service networks which consider empty container repositioning decisions in a multimodal context could be further explored. At the operational level, recently promising efforts are made to integrate container allocation and vehicle routing decisions in drayage operations. Since these problems are often very complex, they can only be solved exactly for very small instances. Future work should focus on designing efficient heuristics and meta-heuristics for these problems.

Technological developments (Internet-based platforms, foldable containers, ...) seem interesting options to facilitate and/or reduce the costs of empty container management. However, so far there has been little research on the potential savings of these technologies. Finally, most research takes the perspective of a single shipping line or transportation company. It could be worthwhile to investigate empty container management from a public-benefit perspective, for example by introducing external costs of transport in cost calculations or by showing the benefits of cooperation among shipping lines.

This thesis deals with empty container repositioning on a regional level. The focus is on two of the research opportunities described above. In Chapter 3, a tactical planning model for service network design in intermodal barge transportation is introduced. It is demonstrated how empty container repositioning decisions may be taken into account by this model. In Chapters 4 to 7, integration of container allocation and vehicle routing decisions in drayage operations is studied. A sequential and integrated planning approach are proposed and compared with each other. A deterministic annealing meta-heuristic is presented to solve both problems. This meta-heuristic is applied in several problem contexts: different objective functions and time-independent as well as time-dependent travel times are considered.

Chapter 3

Service network design in intermodal barge transport with empty container repositioning

3.1 Introduction

Loaded containers which arrive by maritime vessel at a seaport are distributed to their final customers in the hinterland of the port. Vice versa, loaded containers are transported from shippers' locations to the seaport prior to being exported. Both types of transport may be performed directly by road transport or by a combination of road transport with rail or barge transport. In the latter case, a transhipment at an inland intermodal container terminal is required.

This chapter[1] focuses on the transportation of containers by barge between a seaport and container terminals at a number of hinterland ports. During the last two decades intermodal barge transport has gained market share in Northwestern Europe, with annual growth figures up to 15% (Konings, 2003). Currently, barge transport plays an important role in the hinterland access of major seaports in this region. For the port of Antwerp in Belgium, the share of barge transport in the modal split rose from 22.5% to 34.8% between 1999 and 2009 (Port of Antwerp,

[1] This chapter is based on Braekers et al. (2012c).

2009). Although many interesting contributions to literature have been made, Caris et al. (2008) indicate several intermodal planning problems that need further research attention, like service network design for intermodal barge transportation.

Crainic and Laporte (1997) state that service network design is an important issue at the tactical decision level for intermodal transportation. It is involved with the selection of routes on which services are offered and the determination of characteristics of each service, particularly its frequency. State-of-the-art reviews on service network design in freight transportation are presented by Crainic (2000) and Wieberneit (2008). An overview of models for service network design in intermodal transportation may be found in Crainic and Kim (2007). Research on service network design specifically for intermodal barge transportation is scarce. Main decisions in the context of barge transportation include decisions on shipping routes, vessel capacity and service frequency. Additionally, it may be analyzed how and when empty container repositioning needs could be taken into account (Crainic, 2000).

Woxenius (2007) presents six different types of network design for intermodal transport. For geographical reasons, barge transportation is mainly based on a corridor network or line bundling design: a high-density flow along a artery with short capillary services to nodes off the corridor. Caris et al. (2012) consider service network design for such corridor networks in barge transport. The authors study advantages of cooperation between hinterland terminals and different bundling strategies for barge transportation in the hinterland of the port of Antwerp. The feasibility of hub-and-spoke networks in intermodal barge transportation is analyzed by Konings (2006). Groothedde et al. (2005) study the design of such a hub-and-spoke network for transporting palletized fast moving consumer goods by barge and road transport. Finally, empty container repositioning in the context of service network design for intermodal barge transportation is only studied by Maras (2008) (see Section 2.7).

In this chapter, a tactical planning model for service network design in the context of containerized barge transportation is proposed (Figure 3.1). A corridor network design is assumed. This means that vessels bundle freight of several ports located along a single waterway. The model may be used as a decision support tool for barge operators, logistic service providers or shipping lines that want to charter a vessel to offer regular roundtrip barge services between a number of ports located along a waterway. When considering a roundtrip service, vessel capacity and frequency of roundtrips have to be defined. For each service type (capacity and frequency) the model determines the optimal shipping routes (the ports to be visited) and the number of containers to be transported. The decision maker may use this information, together with information on other factors like customer preferences, to evaluate all

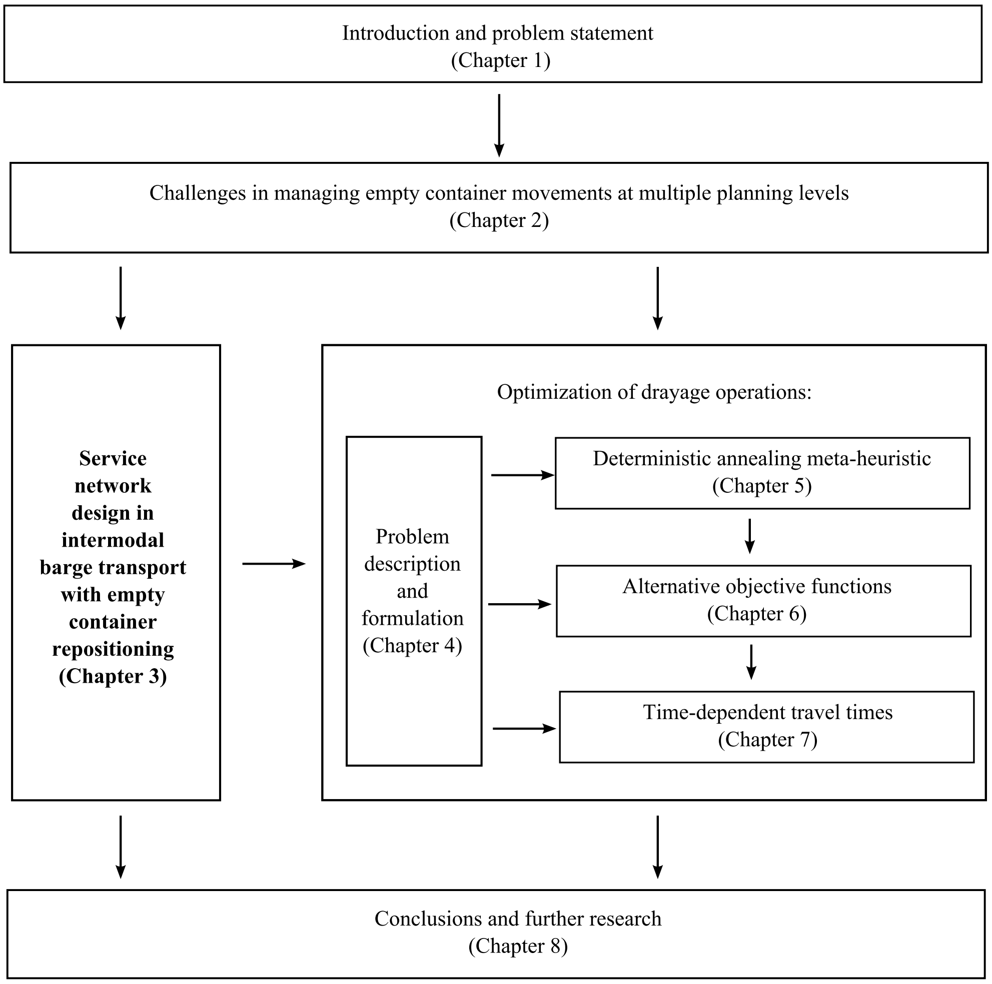

Figure 3.1: Outline of the thesis

possible types of service and choose the best among them. An application on the hinterland network of the port of Antwerp in Belgium is presented. The versatility and flexibility of the model is demonstrated by applying it in two different problem contexts.

First, the model is applied from the perspective of inland barge operators. Assuming transport demand is known and may be foregone, the objective of inland barge operators is to determine roundtrip barge services which maximize profits. Inland barge operators generally do not operate an own fleet of containers and are therefore not concerned with empty container repositioning needs. Second, the model is applied from the perspective of shipping lines which operate a fleet of containers. When containers are transported under the carrier haulage principle, door-to-door services are provided by shipping lines. Shipping lines arrange both the maritime and inland transport part. In that case, shipping lines are responsible for both the design of barge services and for empty container repositioning. In barge transportation, these repositioning movements are made by using excess capacity of container vessels (Choong et al., 2002; Maras, 2008). Hence, empty container repositioning needs may be taken into account when determining shipping routes.

The outline of the chapter is as follows. Section 3.2 describes the general framework of the model and how it is applied to the hinterland network of the port of Antwerp. In the following two sections (Sections 3.3 and 3.4), the application of the model for the two problem contexts described above is presented. Finally, conclusions and ideas for further research are discussed in Section 3.5.

3.2 Model framework and application

The tactical planning model is applied to the situation of the Albert Canal in Belgium. The Albert Canal connects the port of Antwerp with hinterland ports in Deurne, Meerhout, Genk and Liege. Vessels start their roundtrips at a port in the hinterland, travel to the port of Antwerp and finally return to the same hinterland port. In between, several other hinterland ports may be visited. In the port area of Antwerp, two clusters of sea terminals may be identified, one on the right river bank (RRB) and one on the left river bank (LRB). Both clusters are separated by three lock systems. The Albert Canal flows into the river Scheldt in the port area on the right river bank. This means that vessels coming from the Albert Canal have to pass a lock in the port area twice when visiting the cluster on the left river bank. Because traveling between both clusters may take two and a half hours, they are considered as separate nodes in the network. It is assumed that there is a central hub terminal at each river bank which the vessels may visit. This resembles the concepts proposed by Konings (2007) and Caris et al. (2011) to split barge services in a hinterland service and a collection/distribution service in the port area to avoid barges having to call at multiple terminals in the port area. If both hub terminals in the port of Antwerp are visited, the order of visiting should be free to choose since this may have an impact on the outcome of the model. In order to preserve the linear representation of the ports, a duplicate node is created for the terminal at the right river bank. All hinterland ports are duplicated as well to facilitate the formulation of the problem. The final

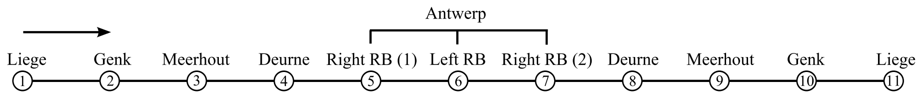

Figure 3.2: Network representation

network representation is shown in Figure 3.2. The port of Liege is represented by nodes 1 and 11, Genk by nodes 2 and 10, Meerhout by nodes 3 and 9, Deurne by nodes 4 and 8, Antwerp right river bank by nodes 5 and 7 and finally Antwerp left river bank by node 6.

A vessel starts its roundtrip at one of the hinterland ports and can only travel from a node to another node with a higher number. The end port should be the same as the start port and at least one of the river banks in Antwerp is visited during a roundtrip. Since distances on the Albert Canal are rather small, vessels may perform several roundtrips per week. Therefore, in this thesis, a service type is defined by the capacity of the vessel(s) and its/their weekly number of roundtrips.

A six day working week is assumed and transport demand is modeled as follows. Each day at each hinterland port a number of clients may request (loaded) containers to be transported from the hinterland port to one of the river banks in Antwerp. Similarly, each day other clients may request containers to be transported from one of the river banks of the port of Antwerp to a hinterland port. Transport demand between two hinterland ports is not assumed. When a service type is considered, the model determines in a preprocessing step which transport demand may be satisfied by which roundtrip(s). Finally, only a single container type is considered.

The fact that the model is formulated on a single line greatly facilitates the computational tractability of the model. Due to the use of a line network, the routing component of the problem reduces to the problem of selecting the ports to be visited since the order of visiting a given set of nodes is predefined. Hence, the number of possible shipping routes in a network of n nodes is equal to $\sum_{k=1}^{n} \binom{n}{k}$. In contrast, when a full network would be used, i.e. each node may be visited from each other node, the number of possible routes visiting a given set of nodes would increase dramatically since multiple visiting orders may be determined. The number of possible shipping routes in a network of n nodes then becomes $\sum_{k=1}^{n} k!\binom{n}{k}$. Especially when the number of nodes in the network increases, the number of possible shipping routes in a line network is only a small fraction of those possible in a full network. For example, for a line network with four nodes 15 shipping routes are possible instead of 64 in a full network while for a line network of ten nodes only 1023 possible shipping routes exist instead of 9864100. This analysis shows that it might not be straightforward to use the proposed modeling approach on a more general network in which the nodes are not all located along a single line.

Two other problem characteristics which influence the model formulation and solution complexity may be identified. The proposed model is able to deal with all combinations of both problem characteristics although the formulation and solution complexity will differ.

First, it could be assumed that each client has the same transport demand every week or it could be assumed that weekly transport demand is variable. The latter may occur when some clients have a weekly transport demand while others only demand containers to be transported every two or three weeks. When considering a constant weekly demand, roundtrips will be the same every week (since it is assumed that when the transport demand of a client is fulfilled in one week, it has to be fulfilled in all weeks). Therefore, it suffices to model only a single week. On the other hand, when demand varies over the weeks, the planning period has to be extended to take this into account. The planning period will be equal to a single demand cycle (each demand occurs at least once). Differences with the single week model are that roundtrips do not have to be the same each week. However, for customers with a weekly demand, the constraint that the demand of all weeks needs to be met if any, is still valid. Although the formulation of the model is very similar as for the constant weekly demand, solution complexity will be larger.

Second, the model formulation and solution complexity depend on whether only a single vessel is used to provide services or whether multiple vessels are employed. In all cases, it is assumed that transport demand may be fulfilled by only a single roundtrip of each vessel (the first after the demand was raised) which means transport demand cannot be transferred to a later roundtrip of the same vessel. When a single vessel is used, it is possible to establish a many-to-one relationship between transport demands and roundtrips, i.e. each transport demand can only be performed by a single roundtrip. When multiple vessels are used, this is not the case and solution complexity increases.

3.3 Perspective of barge operators

This section describes how the proposed model may be used by a barge operator. First, the model formulation is presented (Section 3.3.1). Next, random instances are generated and numerical experiments are presented in Section 3.3.2.

3.3.1 Model formulation

Based on forecasted transport demand for loaded and empty containers, barge operators provide roundtrips between a number of hinterland ports and the seaport on a fixed schedule. Roundtrips are planned with the objective to maximize profit. Barge operators do not manage an owned or leased fleet of containers. As a consequence, they are generally not concerned with empty container repositioning decisions. Empty containers are only transported when this is demanded by shippers or shipping lines. Since the model takes the viewpoint of a single company and the objective is to maximize profit, unprofitable transport demand may be turned down.

Revenues are generated by transporting loaded and empty containers. Freight rates for loaded containers are generally higher than for transporting empty containers. For each pair of ports, transport demand consists of the sum of the demand of several clients. Either all transport demand of a particular client is satisfied (during the total planning period) or all transport demand is turned down. Costs included in the model are daily charter and crew costs, distance-related fuel and maintenance costs, port entry costs and container handling costs at the ports. No costs for turning demand down are assumed. The major constraints are related to vessel capacity and maximum roundtrip duration. Maximum roundtrip duration of a vessel is determined by dividing the number of days per week (six) by the weekly number of roundtrips of the vessel.

First, the formulation of the model for the case with a single vessel and constant weekly demand is presented. Each transport demand may be fulfilled by only a single roundtrip and the length of the planning period is a single week. Next, it is discussed how the model may be adapted to situations with varying weekly demand or multiple vessels. The following notation is used:

$N = \{1, ..., 11\}$ = set of nodes (indices i, j, k)

c_i^e = entry cost at node i (€)

c_i^h = handling cost at node i (€/TEU)

t_i^m = sum of mooring and unmooring time at node i (h)

t_i^h = handling time at node i (h/TEU)

$L = \{(i, j) | i, j \in N, i < j, i \neq 5 \vee j \neq 7\}$

d_{ij} = distance between nodes i and j (km)

t_{ij} = travel time between nodes i and j (h)

f_{ij}^l = freight rate for loaded containers between nodes i and j (€/TEU)

$$f_{ij}^{e} = \text{freight rate for empty containers between nodes } i \text{ and } j \text{ (€/TEU)}$$
$$R = \{1, ..., r\} = \text{set of roundtrips}$$
$$Cap^{r} = \text{capacity of the vessel performing roundtrip } r \text{ (TEU)}$$
$$c_{char}^{r} = \text{charter and crew costs of the vessel performing roundtrip } r \text{ (€/day)}$$
$$c_{fuel}^{r} = \text{fuel and maintenance costs of the vessel performing roundtrip } r \text{ (€/km)}$$
$$t_{max}^{r} = \text{maximum duration of roundtrip } r \text{ (days)}$$
$$B = \{1, ..., b\} = \text{set of clients}$$
$$dem_{ij}^{bl} = \text{loaded container transport demand of client } b \text{ on link } (i,j) \text{ (TEU)}$$
$$dem_{ij}^{be} = \text{empty container transport demand of client } b \text{ on link } (i,j) \text{ (TEU)}$$
$$w_{ij}^{rb} = \begin{cases} 1 & \text{if transport demand of client } b \text{ on link } (i,j) \text{ may be performed} \\ & \text{by roundtrip } r \\ 0 & \text{else} \end{cases}$$
$$WNR = \text{weekly number of roundtrips of the vessel}$$
$$TNR = \text{total number of roundtrips of the vessel over the planning period}$$
$$M = \text{a large number}$$

The following binary decision variables are introduced:

$$a_{ij}^{rb} = \begin{cases} 1 & \text{if transport demand (loaded + empty containers) of client } b \\ & \text{on link } (i,j) \text{ is fulfilled during roundtrip } r \\ 0 & \text{else} \end{cases}$$
$$z_{i}^{r} = \begin{cases} 1 & \text{if node } i \text{ is visited during roundtrip } r \\ 0 & \text{else} \end{cases}$$
$$pre_{i}^{r} = \begin{cases} 1 & \text{if a node is visited before node } i \text{ during roundtrip } r \\ 0 & \text{else} \end{cases}$$
$$suc_{i}^{r} = \begin{cases} 1 & \text{if a node is visited after node } i \text{ during roundtrip } r \\ 0 & \text{else} \end{cases}$$

To simplify the formulation, additional variables are introduced:

$$D^{r} = \text{distance traveled during roundtrip } r \text{ (h)}$$
$$T_{hour}^{r} = \text{number of hours the vessel is used during roundtrip } r \text{ (h)}$$

T^r_{day} = number of days the vessel is used during roundtrip r (days)

x^r_{ij} = number of loaded containers transported on link (i,j) during roundtrip r (TEU)

y^r_{ij} = number of empty containers transported on link (i,j) during roundtrip r (TEU)

The problem (P3.1) is formulated as follows:

$$\text{(P3.1)}\max \sum_{r\in R}\sum_{(i,j)\in L}(f^l_{ij}x^r_{ij}+f^e_{ij}y^r_{ij})-\sum_{r\in R}c^r_{char}T^r_{day}-\sum_{r\in R}c^r_{fuel}D^r$$
$$-\sum_{r\in R}\sum_{i\in N}c^e_i z^r_i-\sum_{r\in R}\sum_{(i,j)\in L}(c^h_i+c^h_j)(x^r_{ij}+y^r_{ij}) \quad (3.1)$$

Subject to

$$x^r_{ij}=\sum_{b\in B}dem^{bl}_{ij}a^{rb}_{ij} \quad \forall r\in R,\forall(i,j)\in L \quad (3.2)$$

$$y^r_{ij}=\sum_{b\in B}dem^{be}_{ij}a^{rb}_{ij} \quad \forall r\in R,\forall(i,j)\in L \quad (3.3)$$

$$D^r=\sum_{i\in\{2,3,4,5\}}d_{i-1,i}pre^r_i+(d_{5,6}+d_{6,7})z^r_6$$
$$+\sum_{i\in\{7,8,9,10\}}d_{i,i+1}suc^r_i \quad \forall r\in R \quad (3.4)$$

$$T^r_{hour}=\sum_{i\in\{2,3,4,5\}}t_{i-1,i}pre^r_i+(t_{5,6}+t_{6,7})z^r_6$$
$$+\sum_{i\in\{7,8,9,10\}}t_{i,i+1}suc^r_i$$
$$+\sum_{i\in N}t^m_i z^r_i+\sum_{(i,h)\in L}(x^r_{ij}+y^r_{ij})(t^h_i+t^h_j) \quad \forall r\in R \quad (3.5)$$

$$24\times T^r_{day}\geq T^r_{hour} \quad \forall r\in R \quad (3.6)$$

$$T^r_{day}\leq t^r_{max} \quad \forall r\in R \quad (3.7)$$

$$2\times a^{rb}_{ij}\leq(z^r_i+z^r_j)w^{rb}_{ij} \quad \forall r\in R,\forall b\in B,\forall(i,j)\in L \quad (3.8)$$

$$\sum_{\substack{(i,k)\in L\\ i\leq j\\ k>j}}(x^r_{ik}+y^r_{ik})\leq Cap^r+(1-z^r_j)M \quad \forall r\in R,\forall j\in N \quad (3.9)$$

$$pre^r_1=0 \quad \forall r\in R \quad (3.10)$$

$$suc_{11}^r = 0 \qquad \forall r \in R \qquad (3.11)$$

$$2 \times pre_i^r \geq pre_{i-1}^r + z_{i-1}^r \qquad \forall r \in R, \forall i \in \{2,3,4,5\} \qquad (3.12)$$

$$2 \times suc_i^r \geq suc_{i+1}^r + z_{i+1}^r \qquad \forall r \in R, \forall i \in \{7,8,9,10\} \qquad (3.13)$$

$$z_5^r + z_7^r \leq 1 \qquad \forall r \in R \qquad (3.14)$$

$$pre_2^r = suc_{10}^r \qquad \forall r \in R \qquad (3.15)$$

$$pre_3^r = suc_9^r \qquad \forall r \in R \qquad (3.16)$$

$$pre_4^r = suc_8^r \qquad \forall r \in R \qquad (3.17)$$

$$pre_5^r = suc_7^r \qquad \forall r \in R \qquad (3.18)$$

$$a_{ij}^{rb} = \{0,1\} \qquad \forall r \in R, \forall (i,j) \in L, \forall b \in B \qquad (3.19)$$

$$z_i^r = \{0,1\} \qquad \forall r \in R, \forall i \in N \qquad (3.20)$$

$$pre_i^r = \{0,1\} \qquad \forall r \in R, \forall i \in N \qquad (3.21)$$

$$suc_i^r = \{0,1\} \qquad \forall r \in R, \forall i \in N \qquad (3.22)$$

The objective is to maximize profit (3.1). Revenues are generated by transporting loaded and empty containers. Four types of costs are considered. Charter and crew costs depend on the number of days a vessel is used. Fuel and maintenance costs are proportional to the total distance traveled. The number of nodes visited determines port entry costs while the number of loaded and empty containers transported determines handling costs. The number of loaded containers and the number of empty containers transported between two nodes are calculated by respectively constraints (3.2) and (3.3). Each roundtrip consists of three parts: a downstream part from the hinterland to the right river bank of the port of Antwerp, a possible visit of the left river bank and an upstream part back to the hinterland. Total roundtrip distances are calculated by constraint (3.4) while total roundtrip durations are calculated by constraints (3.5) and (3.6). Maximum roundtrip duration is imposed by constraint (3.7) and depends on the number of weekly roundtrips. Transport demand of a client can only be fulfilled by a specific roundtrip and containers can only be transported if both the origin and destination nodes are visited (3.8). Constraint (3.9) ensures that vessel capacity is respected. Constraints (3.10) to (3.13) make sure that variables pre_i^r and suc_i^r take on the appropriate values. The cluster on the right river bank of the port of Antwerp can only be visited once during each roundtrip (3.14) and the start and end port of a roundtrip should be the same (3.15 to 3.18). Finally, constraints (3.19) to (3.22) define the domain of the decision variables.

For problems with varying weekly demand, R represents the set of roundtrips performed by the vessel over the total planning period. Three extra constraints (3.23

to 3.25) are added to the model to ensure that the transport demand of a client is either fulfilled every week or never. In all three constraints $q = r - WNR$ i.e. q represents the roundtrip scheduled one week before roundtrip r.

$$a_{ij}^{rb} = a_{ij}^{qb} \qquad \forall r \in R, r > WNR, \forall (i,j) \in L, \; i \notin \{5,7\}, j \notin \{5,7\}, \forall b \in B \tag{3.23}$$

$$a_{5j}^{rb} + a_{7j}^{rb} = a_{5j}^{qb} + a_{7j}^{qb} \qquad \forall r \in R, r > WNR, \forall (7,j) \in L, \forall b \in B \tag{3.24}$$

$$a_{i5}^{rb} + a_{i7}^{rb} = a_{i5}^{qb} + a_{i7}^{qb} \qquad \forall r \in R, r > WNR, \forall (i,5) \in L, \forall b \in B \tag{3.25}$$

When considering a problem in which multiple vessels will be used to offer roundtrip services, R represents the set of roundtrips performed by all vessels. A transport demand dem_{ij}^{bl} may now be fulfilled by multiple roundtrips i.e. $\forall (i,j) \in L, \forall b \in B : \exists r, r' \in R : w_{ij}^{rb} = w_{ij}^{r'b} = 1$. Constraints (3.26), (3.27) and (3.28) are added to the model to ensure that each transport demand is satisfied by at most one roundtrip.

$$\sum_{r \in R} a_{ij}^{rb} \leq 1 \qquad \forall (i,j) \in L, \forall b \in B \tag{3.26}$$

$$\sum_{r \in R} (a_{5j}^{rb} + a_{7j}^{rb}) \leq 1 \qquad \forall (7,j) \in L, \forall b \in B \tag{3.27}$$

$$\sum_{r \in R} (a_{i5}^{rb} + a_{i7}^{rb}) \leq 1 \qquad \forall (i,5) \in L, \forall b \in B \tag{3.28}$$

3.3.2 Numerical experiments

In this section illustrative numerical experiments are presented. No real-life decisions or conclusions may be based on the results of these experiments. Numerical experiments are set up to show how the model may be used in practice to support the decision making process related to service network design in barge transportation. In order to use the model in practice, accurate cost and demand information is required. Furthermore, other factors like customer preferences on service frequency, may impact final decisions.

Three types of vessels with capacities of 100 TEU, 150 TEU and 300 TEU are considered. It is assumed that the first two types can make two or three roundtrips per week, while the largest vessel can make one or two roundtrips per week. Cost data are mainly based on a recent report commissioned by the Dutch government agency 'Rijkswaterstaat' of the Ministry of Infrastructure and the Environment (NEA, 2009). Other sources for time and cost data include Vacca et al. (2007), Promotie Binnenvaart Vlaanderen (2008), Konings (2009), Caris (2011) and personal communication. An overview of these data may be found in Appendix A. Ten instances of transport demand are generated randomly according to the following intervals:

- total weekly downstream demand for container transports: 300-600 TEU,
- total weekly upstream demand for container transports: 50-150% of downstream demand,
- percentage loaded containers of total transport demand: 70-80%,
- number of days per week with transport demand to/from a hinterland port: 2-6,
- daily number of clients with demand at a hinterland port: 0-3.

For all instances, transport demand is equally distributed over the two clusters in the port of Antwerp. The model is implemented in AIMMS and solved using CPLEX 12.0. Three scenarios are tested: (1) a single vessel and constant weekly demand, (2) a single vessel and varying weekly demand and (3) multiple vessels and constant weekly demand.

Results for the first scenario are shown in Table 3.1. Six different service types are considered as shown in the first row. They are indicated by the vessel capacity and the weekly number of roundtrips. For example, column 300/1 represents a vessel of 300 TEU sailing in a single roundtrip per week. The second row shows the average weekly profit over all instances. The third row indicates the percentage of possible roundtrips that are actually performed. In some situations, performing a roundtrip may not be profitable. This is especially the case when vessel capacity is large and the number of weekly roundtrips is high (and thus maximum roundtrip time is small). In such cases, there might not be enough time for loading and unloading sufficient containers in order to yield enough revenues to offset the costs. No roundtrip will be performed and the corresponding profit is zero. The following rows in Table 3.1 present average results over all instances for the roundtrips that are actually performed. The average percentage of the maximum roundtrip time that is used by a vessel during a roundtrip is shown in the fourth row. The fifth row presents the average capacity usage of the vessel when it enters and leaves the port area in Antwerp. Finally, the last two rows indicate the percentage of empty container transports and average computation time.

A first observation that can be made from Table 3.1 is that for each type of vessel the best results are obtained when the number of weekly roundtrips is low. A reason is that when the number of roundtrips is high, a lot of time is spent on sailing between ports which causes time available for loading and unloading containers to be limited as explained above. Offering more weekly roundtrips also involves higher

Table 3.1: Results for scenario one

Service types	300/1	300/2	150/2	150/3	100/2	100/3
Weekly profit (€)	15825	10485	12212	7990	10151	9595
Roundtrip services performed (%)	100.0	70.0	95.0	66.7	95.0	86.7
Available time used (%)	55.1	86.7	74.5	92.7	65.4	89.0
Vessel capacity used (%)	86.2	60.3	77.7	58.5	80.6	70.8
Weekly container transports (TEU)	517	506	443	351	306	368
Empty container transports (%)	4.3	9.5	6.3	10.5	2.9	10.5
Average computation time (s)	1.0	1.0	1.0	1.0	1.0	1.0

fuel and maintenance costs. For example, average profit is much higher for service type 300/1 than for 300/2. For service type 300/2 only 70.0 percent of the roundtrips are profitable, mainly due to limited time. For the roundtrips that are performed, average time used is high (86.7%) while the capacity of the vessel is not fully utilized at all (60.3%). In contrast, vessel capacity is used much more efficiently for service type 300/1. A second observation is that using a larger vessel seems to offer better results. This can clearly be seen when comparing service types 300/1, 150/2 and 100/3 which all have a weekly capacity of 300 TEU. The reasons are similar to those for the first observation. Finally, the portion of empty container transports in total container transport (2.9 to 10.5%) is much lower than the portion of empty container transport demand in total transport demand (20 to 30%). This may be explained by the fact that freight rates for empty containers are lower than for loaded containers.

Although the results favor using larger vessels and making less roundtrips, it should be taken into account that besides profit other factors will influence the final decision of a barge operator on the services to offer. Clients may prefer a larger frequency of roundtrips, so offering more roundtrips by smaller vessels may lead to a rise in transport demand or may justify higher freight rates.

Table 3.2 shows the results of the second scenario in a similar way as Table 3.1. The same transport demand instances as for scenario one are used but it is assumed that 30% of the clients request containers to be transported only every two weeks. The planning period is fixed at two weeks. Average weekly profits are much lower for this scenario. A reason is that total transport demand is lower since some clients only have a two-weekly demand and therefore some roundtrips might not be profitable anymore. As a result, the average number of roundtrips performed is much lower as can be seen from the third row in Table 3.2. When comparing results of the different service types, similar observations as for the first scenario may be made.

Table 3.2: Results for scenario two

Service types	300/1	300/2	150/2	150/3	100/2	100/3
Weekly profit (€)	19141	10627	13305	10008	11457	10825
Roundtrip services performed (%)	95.0	52.5	77.5	55.0	85.0	56.7
Available time used (%)	48.0	73.4	65.5	81.2	60.5	86.7
Vessel capacity used (%)	66.0	46.3	62.1	46.6	63.6	61.7
Weekly container transports (TEU)	410	316	322	257	238	232
Empty container transports (%)	8.7	8.9	12.1	11.3	11.5	10.8
Average computation time (s)	1.0	1.0	1.0	1.0	1.0	1.0

Table 3.3: Results for scenario three

Service types	300/1	300/1	300/1	300/1	300/1	150/2
	300/1	300/2	150/2	150/3	100/2	100/3
Weekly profit (€)	18003	17120	18115	17912	18713	18319
Roundtrip services performed (%)	75.0	36.7	60.0	45.0	83.3	62.5
Available time used (%)	43.3	61.7	56.3	58.1	47.5	59.2
Vessel capacity used (%)	66.9	82.7	74.9	68.2	69.7	68.2
Weekly container transports (TEU)	413	523	351	350	254	260
Empty container transports (%)	3.3	3.9	3.0	4.3	5.1	5.4
Average computation time (s)	1.0	1.0	1.0	1.0	1.0	1.0

In the third scenario multiple vessels are employed to offer roundtrips while transport demand is assumed to be constant over the weeks. Numerous types of service may be considered in this case. In total twenty-one service types with two vessels are analyzed. Table 3.3 gives an overview of the six service types which offered the best results in terms of profit (e.g. the first column represents a service type in which two vessels with a capacity of 300 TEU sail in a single roundtrip per week). On average, a vessel of 300 TEU with one weekly roundtrip and a vessel of 100 TEU with two weekly roundtrips offers the best results. However, the appropriate service type highly depends on the expected transport demand. For example, the abovementioned service type is only the best in four out of the ten instances.

3.4 Perspective of shipping lines

The tactical planning model may be applied from the perspective of shipping lines as well. When containers are transported under the carrier haulage principle, door-to-door services are provided by shipping lines. Currently the percentage of carrier haulage is on average about thirty percent of all maritime container transports. According to Notteboom (2004), shipping lines seek to increase the portion of carrier haulage on the European continent. They want to increase organizational control over hinterland transport since it is an important strategy to control the logistic chain and to generate cost reductions and additional revenues (Notteboom, 2007). Shipping lines that are successful in achieving cost reductions through better managing inland container logistics may have a competitive advantage. According to van den Berg and Langen (2011) shipping lines should be involved in the organization of barge and rail services in the hinterland, although they do not have to operate these services themselves. Instead, strategic partnerships with barge and terminal operators may be established (Notteboom, 2004; van den Berg and Langen, 2011). The tactical planning model, which is proposed in this chapter, may be applied by shipping lines or their strategic partners to develop regular roundtrip barge services.

Two main differences between the problem from the perspective of barge operators and the problem from the perspective of shipping lines are identified. A first difference is related to transport demand. Since it is assumed that the shipping line is responsible for the inland transportation part, they have to make sure that all loaded containers are transported from the seaport to their final destinations and from the shippers' locations to the seaport. Hence, all transport demand for loaded containers should be fulfilled by the shipping line. In case capacity of the chartered vessel(s) is not sufficient, alternatives have to be considered. Containers may be transported between hinterland ports and the port of Antwerp by barges of independent barge operators or they may be transported by truck. In this thesis, it is assumed that no capacity restrictions on these alternative transport options exist and that these transports are at least as fast as transporting containers by the chartered vessel(s). Finally, the cost of an alternative transport is assumed to be high compared with the cost of transporting a container by a chartered vessel. For clarity purposes, only alternative transportation of containers by truck is considered in the remainder of this chapter.

A second difference is related to container management. Shipping lines operate their own fleet of containers or have some long term leasing arrangements. They are responsible for efficiently managing this container fleet. To avoid empty container shortages at certain ports and empty container excesses at others, empty containers will have to be repositioned between ports. In barge transportation, these repositioning movements are generally made by using excess capacity of container vessels which transport loaded containers (Choong et al., 2002; Maras, 2008). Two options to plan empty container repositioning movements may be identified. The first option consists of planning barge services based on loaded container transport demand in a first step. The model described in Section 3.3 may be used for this purpose. Only the truck transportation option and the constraint that all transport demand has to be satisfied, should be added to the model. In a second step, empty container repositioning needs are determined. Based on information on excess capacity of the vessel(s), the same model may be used to find the most efficient way to perform these repositioning movements. Shipping routes and loaded container transports are assumed to be fixed during this step. A second option is to take empty container repositioning needs directly into account when planning barge services and loaded container transports. In the following paragraphs the model for this second option is described in detail. Both options are compared in Section 3.4.2.

Empty container repositioning needs may be included in the model by imposing balancing constraints at each port. These balancing constraints impose total container inflow to equal total container outflow for each port over the planning period. Besides, at any time sufficient empty containers should be available at each port for export purposes. This is accounted for by maintaining an inventory of containers at each port. Costs for storing containers at a port are taken into account. Each port has an initial inventory of containers at the beginning of the planning period. This initial inventory is modeled as a variable (i.e. the model decides the best value), although it may also be fixed to a certain value in advance. During the planning period, the stock of available containers at each port will fluctuate. At the end of the planning period, the inventory level should be equal to the initial inventory level. A distinction is made between regular ports and ports also acting as an empty container hub. The former have a rather limited storage space for containers which is modeled by imposing a maximum inventory level. The latter have no such restriction. Unless stated otherwise, only both terminals in the port of Antwerp are assumed to act as an empty container hub in this thesis. Finally, it is assumed that a loaded container arriving at a port is unavailable for three days. This ensures that there is enough time to transport the loaded container to its final customer, unload it and return it to the port empty. Similarly, three days before a loaded container transport takes place, an empty container should be available at the port of origin.

3.4.1 Model formulation

The formulation of the model is similar as in Section 3.3.1, although some adaptations are required. Only transport demand for loaded containers is considered. All demands should be satisfied, either by the chartered vessel(s) or by truck. Variable a_{ij}^{rb} is no longer a binary decision variable. Instead a_{ij}^{rb} is a continuous decision variable which indicates the fraction of transport demand of client b on link (i, j) that is fulfilled by roundtrip r. Similarly, the new continuous decision variable $\hat{a}_{ij}^{rb}$ indicates the fraction of transport demand of client b on link (i, j) which is fulfilled by truck at the same moment of roundtrip r. Auxiliary variable x_{ij}^{r} still indicates the number of loaded containers transported by the chartered vessel on link (i, j) during roundtrip r. Auxiliary variable $\hat{x}_{ij}^{r}$ represents the number of loaded containers transported by truck on link (i, j) (at the same moment of roundtrip r). The number of empty containers to be transported is a decision. As a result, dem_{ij}^{be} is no longer used. Integer decision variables y_{ij}^{r} and $\hat{y}_{ij}^{r}$ represent the number of empty containers transported on link (i, j) during roundtrip r respectively by the chartered vessel and by truck. The cost of a transport by truck on link (i, j) is indicated by $\hat{c}_{ij}$ and is expressed in €/TEU. Finally, the time that a container is unavailable before and after a loaded container transport is expressed in the number roundtrips and indicated by u (since three days of unavailability are assumed $u = 2$ if $WNR = 3$ and $u = 1$ otherwise).

To take empty container repositioning into account, the inventory of containers at each of the six ports (Liege, Genk, Meerhout, Deurne, Antwerp RRB, Antwerp LRB) should be maintained. The following notation is used:

$$P = \{1, ..., 6\} = \text{set of ports (index } p)$$
$$\delta^-(p) = \text{index for the downstream node of port } p \text{ (e.g. } \delta^-(1) = 1, \delta^-(2) = 2)$$
$$\delta^+(p) = \text{index for the upstream node of port } p \text{ (e.g. } \delta^+(1) = 11, \delta^+(2) = 10)$$
$$c_p^s = \text{daily storage cost at port } p \text{ (€/(TEU} \times \text{day))}$$
$$inv_p^{max} = \text{maximum container inventory level at port } p$$
$$inv_p^r = \text{number of containers in inventory at port } p \text{ before roundtrip } r \text{ (TEU)}$$

The formulation of the problem (P3.2) with a single vessel and constant transport demand is as follows:

$$
\begin{aligned}
\text{(P3.2)}\min &\sum_{r\in R} c^r_{char} T^r_{day} + \sum_{r\in R} c^r_{fuel} D^r + \sum_{r\in R}\sum_{i\in N} c^e_i z^r_i \\
&+ \sum_{r\in R}\sum_{(i,j)\in L} (c^h_i + c^h_j)(x^r_{ij} + y^r_{ij}) \\
&+ \sum_{r\in R}\sum_{(i,j)\in L} \hat{c}_{ij}(\hat{x}^r_{ij} + \hat{y}^r_{ij}) \\
&+ \sum_{r\in R}\sum_{p\in P} 6 \times c^s_p inv^r_p / WNR
\end{aligned} \tag{3.29}
$$

Subject to

(3.4) to (3.18)

(3.20) to (3.22)

$$\sum_{r\in R}(a^{rb}_{ij} + \hat{a}^{rb}_{ij}) = 1 \qquad \forall (i,j)\in L, \forall b \in B \tag{3.30}$$

$$x^r_{ij} = \sum_{b\in B} dem^{bl}_{ij} a^{rb}_{ij} \qquad \forall r\in R, \forall (i,j)\in L \tag{3.31}$$

$$\hat{x}^r_{ij} = \sum_{b\in B} dem^{bl}_{ij} \hat{a}^{rb}_{ij} \qquad \forall r\in R, \forall (i,j)\in L \tag{3.32}$$

$$y^r_{ij} \le Cap^r z^r_i \qquad \forall r\in R, \forall (i,j)\in L \tag{3.33}$$

$$y^r_{ij} \le Cap^r z^r_j \qquad \forall r\in R, \forall (i,j)\in L \tag{3.34}$$

$$
\sum_{r\in R}\left[
\begin{array}{l}
\sum_{(j,\delta^-(p))\in L}\begin{pmatrix} x^r_{j,\delta^-(p)} + y^r_{j,\delta^-(p)} \\ +\hat{x}^r_{j,\delta^-(p)} + \hat{y}^r_{j,\delta^-(p)} \end{pmatrix} \\
+\sum_{(j,\delta^+(p))\in L}\begin{pmatrix} x^r_{j,\delta^+(p)} + y^r_{j,\delta^+(p)} \\ +\hat{x}^r_{j,\delta^+(p)} + \hat{y}^r_{j,\delta^+(p)} \end{pmatrix} \\
-\sum_{(\delta^-(p),j)\in L}\begin{pmatrix} x^r_{\delta^-(p),j} + y^r_{\delta^-(p),j} \\ +\hat{x}^r_{\delta^-(p),j} + \hat{y}^r_{\delta^-(p),j} \end{pmatrix} \\
-\sum_{(\delta^+(p),j)\in L}\begin{pmatrix} x^r_{\delta^+(p),j} + y^r_{\delta^+(p),j} \\ +\hat{x}^r_{\delta^+(p),j} + \hat{y}^r_{\delta^+(p),j} \end{pmatrix}
\end{array}
\right] = 0 \qquad \forall p \in P \tag{3.35}
$$

$$
\begin{aligned}
& inv_p^r + \sum_{(j,\delta^-(p))\in L} (x^v_{j,\delta^-(p)} + y^r_{j,\delta^-(p)} + \hat{x}^v_{j,\delta^-(p)} + \hat{y}^r_{j,\delta^-(p)}) \\
& \quad + \sum_{(j,\delta^+(p))\in L} (x^v_{j,\delta^+(p)} + y^r_{j,\delta^+(p)} + \hat{x}^v_{j,\delta^+(p)}\hat{y}^r_{j,\delta^+(p)}) \\
& \quad - \sum_{(\delta^-(p),j)\in L} (x^w_{\delta^-(p),j} + y^r_{\delta^-(p),j} + \hat{x}^w_{\delta^-(p),j} + \hat{y}^r_{\delta^-(p),j}) \\
& \quad - \sum_{(\delta^+(p),j)\in L} (x^w_{\delta^+(p),j} + y^r_{\delta^+(p),j} + \hat{x}^w_{\delta^+(p),j} + \hat{y}^r_{\delta^+(p),j}) \\
& \quad = inv_p^{r+1} \\
& \text{with } inv_p^{TNR+1} = inv_p^1, \\
& v = \begin{cases} r-u & \text{if } r > u \\ r-u+TNR & \text{else} \end{cases} \quad \text{and} \\
& w = \begin{cases} r+u & \text{if } r \le TNR-u \\ r+u-TNR & \text{else} \end{cases} \qquad \forall r \in R, \forall p \in P \quad (3.36)
\end{aligned}
$$

$$inv_p^r \le inv_p^{max} \qquad \forall r \in R, \forall p \in P \quad (3.37)$$

$$a_{ij}^{rb} \ge 0 \qquad \forall r \in R, \forall (i,j) \in L, \forall b \in B \quad (3.38)$$

$$\hat{a}_{ij}^{rb} \ge 0 \qquad \forall r \in R, \forall (i,j) \in L, \forall b \in B \quad (3.39)$$

$$y_{ij}^r \ge 0 \text{ and integer} \qquad \forall r \in R, \forall (i,j) \in L \quad (3.40)$$

$$\hat{y}_{ij}^r \ge 0 \text{ and integer} \qquad \forall r \in R, \forall (i,j) \in L \quad (3.41)$$

$$inv_p^r \ge 0 \text{ and integer} \qquad \forall r \in R, \forall p \in P \quad (3.42)$$

The objective of the model is to minimize total costs of fulfilling all transport demand for loaded containers and balancing the network by repositioning empty containers. The first four terms in objective function (3.29) indicate respectively charter and crew costs, fuel and maintenance costs, port entry costs and container handling costs, similar as in problem P3.1. The fifth term represents the cost of transporting loaded and empty containers by other means than the chartered vessel. The last cost term represents storage costs for containers at each port. These costs depend on container inventory levels and the time between two roundtrips which is indicated by $6/WNR$ i.e. the number of days per week divided by the number of roundtrips per week.

Revenues from transporting loaded containers are no longer considered since it is assumed that all transport demand should be fulfilled and hence revenues are constant. Revenues from transporting empty containers are not considered either since repositioning movements happen at the responsibility and expense of the shipping line itself. Constraints (3.4) to (3.18) and (3.20) to (3.22) are identical to those in the model in problem P3.1. Constraint (3.30) ensures that all transport demand is satisfied, either by the chartered vessel or by truck. The number of loaded containers transported on each link during a roundtrip is calculated by constraints (3.31) and (3.32). Constraints (3.33) and (3.34) indicate that empty containers may only be transported by barge between two nodes if both nodes are visited. Constraint (3.35) imposes container balancing at each port over the planning period while container inventories during the planning period are controlled by constraints (3.36) and (3.37). Finally, constraints (3.38) to (3.42) restrict the domain of the decision variables.

For problems with varying weekly demand, no changes have to be made to the formulation. When considering a problem in which multiple vessels will be used to offer roundtrip services, a small modification to the formulation is required. Since different vessels may arrive at ports at different moments during the day and week, it is no longer possible to take daily inventories into account. Hence all inventory-related parameters (c_p^s, inv_p^{max}), variables (inv_p^r) and constraints (3.36), (3.37) and (3.42) as well as the last term of objective function (3.29) are removed from the formulation. Constraint (3.35) still ensures container balancing over the total planning period.

3.4.2 Numerical experiments

Shipping lines have two options to plan empty container repositioning movements when organizing their own barge services. One option is to plan barge services based on loaded container transport demand in a first step and empty container movements separately in a second step. The second option is to plan barge services and empty container movements simultaneously by solving the model described in Section 3.4.1. In this section, numerical experiments are presented for both options. The same ten random problem instances as in Section 3.3.2 are used. All transport demands are assumed to be loaded container transport demands. Again three scenarios are tested: (1) a single vessel and constant weekly demand, (2) a single vessel and varying weekly demand and (3) multiple vessels and constant weekly demand.

Results for the first scenario are presented in Tables 3.4 and 3.5 for respectively separately and simultaneously planning barge services and empty container repositioning. Six service types are considered as shown in the first row. For each of them, the second row indicates average weekly costs. The third row shows the percentage of total transport demand which is satisfied by barge. The remainder is satisfied by road transport. Row four presents the percentage of available time used by the vessel on average. The capacity usage by loaded containers when entering and leaving the port area of Antwerp is shown in row five. The percentage of empty container transports in total transports is indicated in row six. Since for some instances computation times are much higher than for most other instances (especially for simultaneous planning), average computation times are not reported. Instead the median and maximum of computation times are shown in rows seven and eight. Finally, average cost reductions as a result of simultaneously planning barge services and empty container repositioning movements are indicated in the last row of Table 3.5.

Table 3.4: Results for scenario one: separate planning

Service types	300/1	300/2	150/2	150/3	100/2	100/3
Weekly cost (€)	109926	121358	121138	155636	145527	155019
Transports by barge (%)	63.6	64.4	57.2	39.4	38.3	37.3
Available time used by vessel (%)	72.3	98.1	94.0	93.0	76.3	95.9
Capacity used (loaded) (%)	97.1	59.4	90.1	55.7	95.2	75.6
Empty container transports (%)	30.9	32.7	33.6	31.4	33.8	32.7
Median of computation times (s)	1.0	1.0	1.0	1.0	1.0	1.0
Maximum computation time (s)	1.0	1.0	2.0	1.0	1.0	1.0

Table 3.5: Results for scenario one: simultaneous planning

Service types	300/1	300/2	150/2	150/3	100/2	100/3
Weekly cost (€)	108065	114590	118494	142900	138900	146784
Transports by barge (%)	66.9	66.7	58.5	49.4	44.6	43.4
Available time used by vessel (%)	74.1	98.6	93.8	99.7	83.8	98.7
Capacity used (loaded) (%)	92.7	52.3	85.2	46.3	88.9	62.7
Empty container transports (%)	29.4	31.3	32.7	30.6	32.1	31.2
Median of computation times (s)	1.0	1.0	1.0	1.5	2.0	2.0
Maximum computation time (s)	1.0	1.0	3.0	2.0	3.0	4.0
Average cost reduction (%)	1.7	5.6	2.2	8.2	4.6	5.3

Similar observations as for the problem from the perspective of barge operators may be made from Tables 3.4 and 3.5. For each vessel type, the service type with the lowest number of weekly roundtrips leads to the best use of available vessel capacity and lowest costs. A high number of weekly roundtrips generally results in situations with inefficient capacity usage due to time constraints. Average time and capacity usage are higher than in Section 3.3.2 since in this section fractions of transport demand of a client may be satisfied by barge transport while the remainder of the transport demand is satisfied by road transport. The portion of empty container transports in total transports ranges around 30% which is considerably higher than in Section 3.3.2. This is a result of the container balancing constraints that are imposed. Besides, in Section 3.3.2 empty container transports were less interesting than loaded container transports, due to their lower freight rate. The fraction of transports performed by barge ranges on average between 43 to 67% of all transports. Finally, simultaneously planning barge services and empty container repositioning movements results in cost reductions of one to eight percent, mainly due to the fact that different shipping routes are chosen for both options.

A more detailed comparison of the solutions obtained from the perspective of barge operators (Section 3.3.2) and the solutions obtained from the perspective of shipping lines with simultaneous planning in this section, reveals that considerable differences between these solutions exist. For a given problem instance and service type, on average 68% of the ports visited in the former case are visited in the latter case as well. Vice versa the same percentage applies. Only 9% of all roundtrips are exactly the same for both cases, although this percentage greatly depends on the service type under consideration. For service type 300/1, 40% of all roundtrips are identical while none of the roundtrips are identical for service type 100/2. Comparing solutions regarding the number of loaded containers transported is not possible since in the model from the perspective from shipping lines, all transport demand for loaded containers should be fulfilled.

Average results for the second scenario are shown in Tables 3.6 and 3.7. The same transport demand instances as for scenario one are used but it is assumed that 30% of the clients have demand only every two weeks. Average weekly costs are lower for this scenario due to lower total transport demand. As a consequence, average percentage of transports by barge are slightly higher than for the first scenario. Other results are similar to those of scenario one.

Again twenty-one service types with two vessels are analyzed for the third scenario. Results of the six service types which offer on average the lowest costs are presented in Tables 3.8 and 3.9. Since two vessels are employed, a larger portion of total transports

Table 3.6: Results for scenario two: separate planning

Service types	300/1	300/2	150/2	150/3	100/2	100/3
Weekly cost (€)	76096	88854	88317	107456	100349	106475
Transports by barge (%)	72.5	73.1	62.1	47.9	47.9	45.2
Available time used by vessel (%)	64.4	88.3	84.0	86.3	73.4	86.1
Capacity used (loaded) (%)	80.5	46.0	72.5	45.9	84.9	63.2
Empty container transports (%)	30.1	33.3	34.7	31.8	35.3	33.1
Median of computation times (s)	1.0	1.0	1.0	1.0	1.0	1.0
Maximum computation time (s)	1.0	1.0	1.0	1.0	1.0	1.0

Table 3.7: Results for scenario two: simultaneous planning

Service types	300/1	300/2	150/2	150/3	100/2	100/3
Weekly cost (€)	72574	81790	82785	96400	95909	97883
Transports by barge (%)	76.6	78.7	67.9	59.9	51.9	54.5
Available time used by vessel (%)	66.0	92.6	89.4	95.5	79.2	97.4
Capacity used (loaded) (%)	78.5	42.7	72.5	41.9	79.3	57.3
Empty container transports (%)	29.3	31.8	33.0	30.6	32.7	32.0
Median of computation times (s)	1.0	2.0	4.0	5.5	15.5	7.5
Maximum computation time (s)	2.0	3.0	13.0	10.0	58.0	31.0
Average cost reduction (%)	4.6	8.0	6.3	10.3	4.4	8.1

are performed by barge compared with the first scenario. As a result, less costly road transports are required and weekly costs are on average lower than when a single vessel is employed. On the other hand, the percentage of empty containers in total transports increases compared with scenario one. This is caused by the fact that daily container inventories are not taken into account and only container balancing constraints over the total planning period are imposed in the third scenario. This offers more flexibility for empty container repositioning. Although the percentage of empty containers in total transport increases, the portion of these empty container transports which is carried out by costly road transportation is reduced drastically from 36 to 15%. Finally, average cost reductions from simultaneously planning barge services and empty container repositioning movements are much larger for the third scenario compared with scenarios one and two. The reason is as follows. When barge services are planned only based on loaded container transport demand, for some instances it is better not to perform all roundtrips of both vessels. If capacity usage during a roundtrip would be too small, it might be more cost-efficient not to make a roundtrip, thereby saving charter and fuel costs, while transporting containers by truck. In case empty container repositioning needs are taken into account, capacity usage of the vessels will be higher and performing these roundtrips might in some cases be cheaper than transporting all containers by truck.

Table 3.8: Results for scenario three: separate planning

Service types	300/1 300/2	300/1 150/2	300/1 150/3	300/2 150/2	150/2 150/2	150/2 150/3
Weekly cost (€)	122257	122892	123833	133714	125177	125049
Transports by barge (%)	85.1	79.3	78.8	75.2	76.3	74.8
Available time used by vessel (%)	70.5	64.1	74.6	81.4	80.0	86.7
Capacity used (loaded) (%)	63.8	74.7	64.4	67.6	77.4	72.8
Empty container transports (%)	45.6	45.5	45.3	45.7	45.2	36.5
Median of computation times (s)	1.5	2.0	2.0	1.0	1.5	2.5
Maximum computation time (s)	4.0	5.0	4.0	2.0	4.0	7.0

Table 3.9: Results for scenario three: simultaneous planning

Service types	300/1 300/2	300/1 150/2	300/1 150/3	300/2 150/2	150/2 150/2	150/2 150/3
Weekly cost (€)	105946	108486	108865	106238	111093	111233
Transports by barge (%)	93.7	87.0	88.2	90.8	82.5	83.0
Available time used by vessel (%)	76.9	73.9	82.6	88.4	81.8	89.5
Capacity used (loaded) (%)	53.3	66.8	51.7	58.1	69.0	58.6
Empty container transports (%)	44.4	44.4	44.5	44.4	44.4	35.7
Median of computation times (s)	3.0	7.0	9.5	7.5	18.5	13.5
Maximum computation time (s)	4.0	19.0	22.0	14.0	80.0	36.0
Average cost reduction (%)	13.3	11.7	12.1	20.6	11.3	11.1

As shown in the previous paragraphs, the proposed model may be used by shipping lines to determine the best service type and the corresponding shipping routes for a given demand scenario while taking empty container repositioning into account. A sensitivity analysis on costs and freight rates may be performed as well. Additionally, the model may be applied for supporting long term strategic decisions. For example, the effect of changes in the network and service network configurations on the hinterland transport chain may be analyzed, as explained in the following paragraph.

In the numerical experiments described earlier, it is assumed that empty container hubs are only located at both river banks in the port of Antwerp while all hinterland ports have a maximum storage capacity of twenty containers. The starting inventory at these hinterland ports is chosen by the model. Examples of strategic decisions that may be analyzed include increasing or reducing container storage capacity of hinterland ports and the establishment of an empty container hub at one of the hinterland ports. For example, for the instances used in this thesis, a decrease of the storage capacity at the hinterland ports to ten containers increases costs on average by 1.21%, while establishing an empty container hub at the hinterland port in Genk yields an average decrease in costs of 1.50%. To correctly interpret the magnitude of these changes, it is necessary to have information on the cost of implementing the decisions.

3.5 Conclusions and further research

Despite the growing role of barge transportation in the hinterland access of major seaports in Northwestern Europe, service network design for intermodal barge transportation has received little research attention so far. In this chapter, a tactical planning model for service network design along a single waterway is proposed. A corridor network design is assumed. The model may be used as a decision support tool for barge operators and shipping lines that want to offer roundtrip barge services between a major seaport and several hinterland ports. It allows to calculate optimal shipping routes for a given vessel capacity and roundtrip frequency. A case study on the hinterland network of the port of Antwerp in Belgium is presented. To demonstrate the versatility and flexibility of the model, it is applied in two different problem contexts.

From the perspective of barge operators, the objective is to maximize profits. Unprofitable transport demand may be foregone and empty container repositioning decisions are not taken into account. Numerical experiments for three scenarios are presented to indicate how the model may be used in practice. On average, profit is higher when larger vessels are used and less roundtrips are made. However, customer preferences should be taken into account when making final decisions on the services that will be offered.

From the perspective of shipping lines, the model may be used when containers are transported under the carrier haulage principle and shipping lines organize the maritime as well as the inland part of maritime container transports. Several authors indicate that shipping lines seek to increase the portion of containers transported in this way in order to gain organizational control of the inland transportation part and to reduce costs. In such a situation, shipping lines are responsible for both scheduling barge services and empty container repositioning. The proposed model is adapted to account for empty container repositioning by imposing container balancing constraints at each port. Experimental results indicate that shipping lines may reduce costs by simultaneously planning barge services and empty container repositioning movements instead of planning empty container repositioning movements in a post-optimization phase.

In the future, additional aspects of the problem may be introduced in the model to better reflect the decision making process in reality. At the moment, the model concentrates on a single corridor while often several waterways are connected to a seaport. In such a situation, the simultaneous optimization of repositioning decisions for the complete network may be required. Only a single decision maker, either a barge operators or a shipping line, is assumed by the model, although it may be expected that in reality port authorities and terminal operators may play a role in the decision making process as well. In some case, when certain ports are able to attract sufficient volumes on their own, even a direct service between a hinterland port and the seaport may be established. In addition, transport demand is assumed to be deterministic in the proposed planning model. Future research could focus on how uncertainty regarding transport demand could be taken into account. Reserving a portion of vessel capacity for unexpected increases in transport demand may be an opportunity. Similar to the concept of safety stock in inventory theory, the amount of capacity to be reserved should depend on the variability of transport demand. A direction for qualitative research may be identified as well. The effect of service frequency on transport demand may be investigated. At the moment, it is not clear how shippers will react to changes regarding this frequency. Finally, additional numerical experiments may be performed to analyze whether the model can still be solved efficiently for larger problem instances (increase in number of ports, vessels, clients or weeks).

Chapter 4

Optimization of drayage operations: problem description and formulation

4.1 Introduction

The previous chapter focuses on container transportation by barge from a major seaport to intermodal terminals at smaller hinterland ports. Chapters 4 to 7 focus on drayage operations (Figure 4.1)[1,2]. These operations relate to the full truckload container transport activities that take place on a regional scale around intermodal terminals. They are mostly performed by truck and often constitute a large part of the total cost of an intermodal transport (Smilowitz, 2006). An overview of the types of transport in drayage operations is given in Figure 4.2. Drayage operations include the pre- and end-haulage activities of intermodal transports which involve the transport of loaded containers from intermodal container terminals to final consignees (a) and from shipping customers to container terminals (b). Additionally, empty containers are repositioned since a customer is often either a consignee or a shipper but not both. Shippers request empty containers to be delivered while consignees request empty containers to be picked up. Container depots, often located at container terminals, may act as source and sink locations for these transports. As a result, empty containers are transported from container terminals/depots to shippers (c) and from

[1] Chapters 4 and 5 are based on Braekers et al. (2012b)

[2] An overview of the symbols used in Chapters 4 to 7 can be found at the beginning of the thesis.

consignees to container terminals/depots (d). To reduce empty container movements, empty containers may be transported directly from consignee to shippers (e) as well. This option is known as a street turn or triangulation (see Section 2.2.2). Finally, empty container balancing flows between terminals/depots may be needed (f). These balancing flows may sometimes be performed using modes of mass transportation (barge, rail), which is considered in the previous chapter.

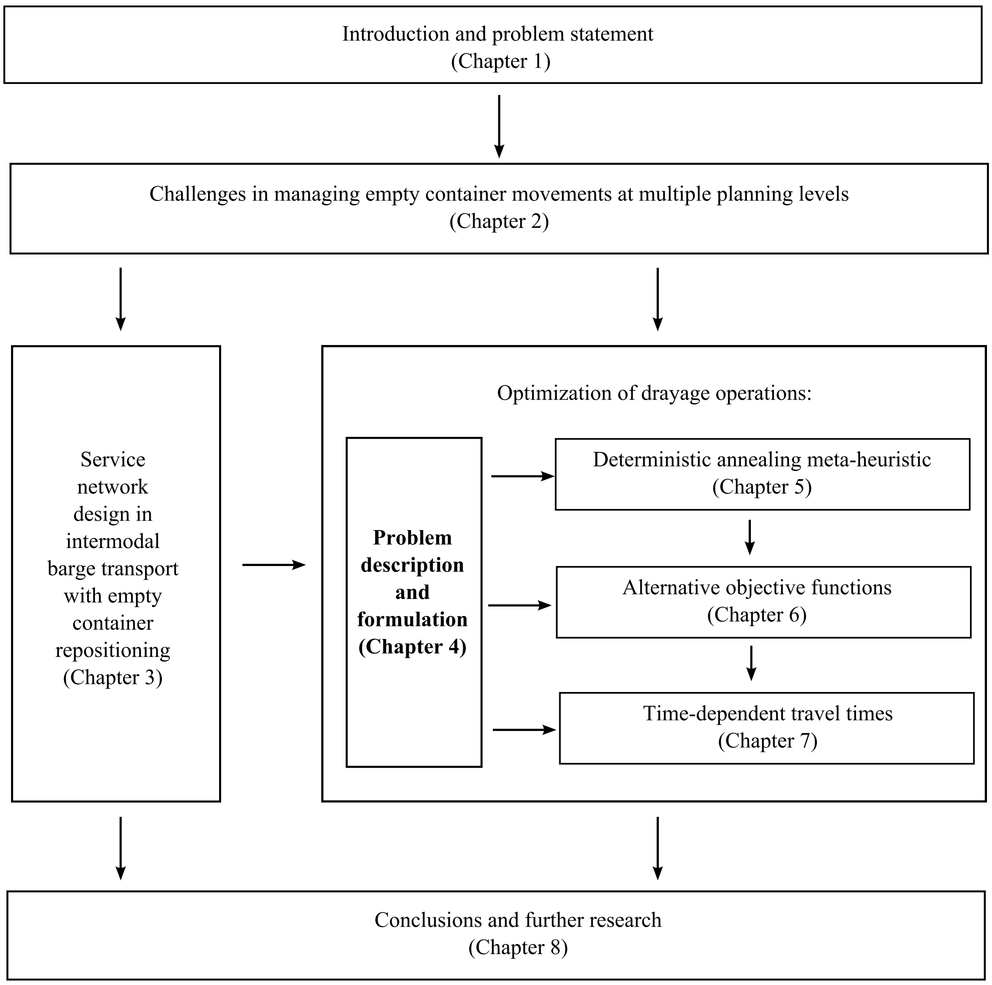

Figure 4.1: Outline of the thesis

The operational planning of drayage operations is studied. Special attention is paid to optimizing empty container movements since these are costly non-revenue generating activities. As discussed in Section 2.4, traditionally a sequential approach

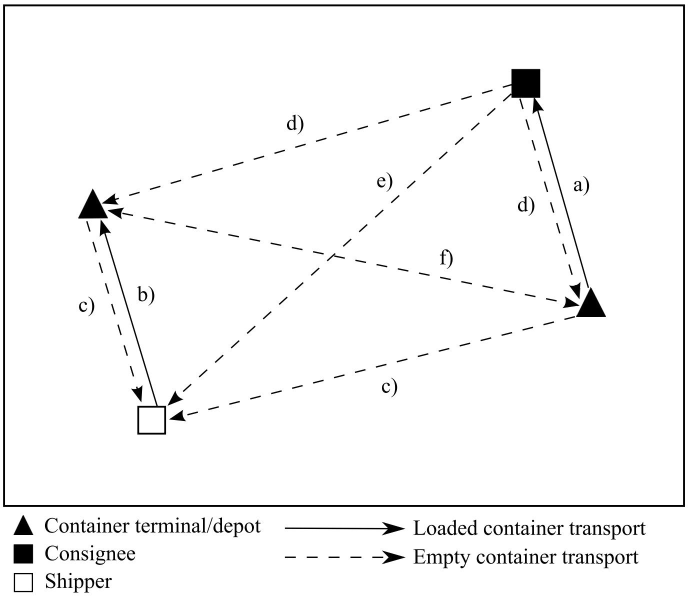

Figure 4.2: Overview of transports

is used for the operational planning of loaded and empty container movements in drayage operations. The problem is decomposed into two subproblems, an allocation and a routing problem. First, an empty container allocation model is used to determine the optimal repositioning of empty containers based on the locations of demand and supply in the region. Such an allocation model minimizes the total distance traveled by empty containers, without taking vehicle routing decisions into account. Next, a routing model is used to create efficient vehicle routes performing both loaded and empty container transport requests (Crainic et al., 1993b; Huth and Mattfeld, 2009). The objective is to minimize the number of vehicles used, distance traveled, traveling time, route duration or a combination of these. Such vehicle routing models are known to be very complex, especially when time windows are involved (Cordeau et al., 2007b). To solve problems of realistic size often meta-heuristics are used.

Recently, some efforts are made to integrate the allocation and routing subproblems in drayage operations described above. By using an integrated approach, thus considering empty container allocation and vehicle routing decisions simultaneously, drayage costs may be reduced. Since the origin or destination of empty container transports are not determined in advance, the resulting problem is even more complex. Although several papers have addressed this idea, the advantage of an integrated over a sequential approach for planning drayage operations, has not been quantified.

In this thesis both a sequential and an integrated approach are proposed and compared with each other.

This chapter serves as an introductory chapter for the following three chapters. Related literature is reviewed in Section 4.2. A detailed problem description is given in Section 4.3. Section 4.4 describes how both solution approaches are applied to the problem. For both the sequential and integrated approach, the routing problem can be formulated as an *a*symmetric *m*ultiple vehicle Traveling Salesman Problem with Time Windows (*am*-TSPTW).

In Chapter 5, a deterministic annealing meta-heuristic is proposed to solve this routing problem. A hierarchical objective function which first minimizes the number of vehicles and second the total distance traveled is used and the advantage of an integrated approach is quantified. The effect of considering street turns as an option to reduce empty container movements is analyzed as well. In Chapter 6, alternative objective functions are considered. First, the trade-off between the number of vehicles and total distance is analyzed by interpreting the problem as a bi-objective problem i.e. no priority is given to one of the objectives. In the second part of that chapter, it is shown how the algorithm presented in Chapter 5 may be adapted to accommodate the minimization of total route duration. This adaptation allows to benchmark the quality of the proposed algorithm by comparing it with a recently proposed solution method on a similar problem. Finally, in Chapter 7 the problem is extended to the case where travel times depend on the time of the day. A modified version of the algorithm is presented to solve the extended version of the problem.

4.2 Related literature

The operational planning of loaded and empty container movements in drayage operations is related to two different fields of research. First, the problem is related to the field of empty container management. Literature on this topic is extensively reviewed in Chapter 2. Regional empty container allocation models are described in Section 2.8.1, while papers concerning the integration of empty container allocation and vehicle routing decisions in drayage operations are discussed in Section 2.8.3.

Second, the problem is related to the field of vehicle routing. Routing problems in drayage operations can be classified as full truckload pickup and delivery problems (Erera and Smilowitz, 2008; Srour, 2010). The routing problem of the sequential approach may be modeled as a deterministic Full Truckload Pickup and Delivery Problem with Time Windows (FT-PDPTW). It differs from the Vehicle Routing

Problem with Backhauls and Time Windows (VRPBTW) since empty containers may be transported directly between customers (street turns). Jula et al. (2005) and Wang and Regan (2002) show that a FT-PDPTW may be transformed to an *a*symmetric *m*ultiple vehicle Traveling Salesman Problem with Time Windows (*am*-TSPTW) by collapsing each transport request into a single node. Section 4.4.2 shows how the integrated problem may be formulated as an *am*-TSPTW as well. In the following paragraphs, literature on FT-PDPTW and *(a)m*-TSPTW is discussed.

Gronalt et al. (2003) develop four savings based heuristics for a FT-PDPTW. Goods are transported between distribution centers or depots. Vehicles are based at different depots and may perform several routes during the planning period. A FT-PDPTW with multiple vehicle depots and additional weight constraints in the context of log truck scheduling is studied by Gronalt and Hirsch (2007). Different variants of the tabu search meta-heuristic are proposed to solve the problem. A tabu search heuristic for a FT-PDPTW with heterogeneous products and vehicles where the pickup points of goods to be delivered to customers are not predefined is proposed by Currie and Salhi (2004). The objective is to minimize total costs, including a fixed cost per vehicle used. Imai et al. (2007) introduce a full truckload pickup and delivery problem in the context of an intermodal terminal. They propose a Lagrangian relaxation-based heuristic. Caris and Janssens (2009) extend this problem to a FT-PDPTW by including time window constraints at customer locations. The problem is solved by a local search heuristic. In a subsequent work, a deterministic annealing algorithm is proposed (Caris and Janssens, 2010). The effect of the introduction of an appointment-based access control system at a port on full truckload drayage operations with time windows is studied by Namboothiri and Erera (2008). Mes et al. (2007, 2010) propose an agent-based approach for a dynamic version of the FT-PDPTW.

For early references on the *m*-TSPTW, the reader is referred to Desrochers et al. (1988). More recently, Wang and Regan (2002) use a time window partitioning method to solve an *am*-TSPTW. The authors iteratively solve an under- and over-constrained version of the problem. Jula et al. (2005) present an exact dynamic programming approach for solving small instances of the *am*-TSPTW. An insertion heuristic is proposed to solve large problem instances. Lower bounds on the number of vehicles for the *(a)m*-TSPTW are presented by Desrosiers et al. (1988) using Lagrangian relaxation, and by Mitrović-Minić and Krishnamurti (2006) using precedence graphs.

The Multiple Depot Vehicle Scheduling Problem with Time Windows (MDVSPTW), which is equivalent to a FT-PDPTW with multiple vehicle depots, is studied by Mingozzi et al. (1995), Desaulniers et al. (1998) and Hadjar and Soumis (2009). Currently, problems up to 900 tasks can be solved to optimality. However, since the problem is applied in the context of urban bus scheduling, time windows are assumed to be small (maximum 30 minutes) while in our problem time windows up to four hours are considered.

4.3 Problem description

In this section, the problem under study is described in detail. The problem is to create efficient vehicle routes performing all loaded and empty container transport requests in a region during a single day. It is assumed that a single vehicle depot and one or more container terminals with a container depot are located in the region. Both the container terminals and the vehicle depot are opened during the whole planning period P. Empty containers can be stored at each container terminal and sufficient empty containers are available at each terminal. Balancing flows between terminals are not considered. A homogeneous fleet of vehicles with a single container capacity is assumed. All vehicles start and end their route at the vehicle depot. When a vehicle arrives early at a location, waiting is allowed at no cost. The service time to pickup and drop off containers is constant and the same for loaded and empty containers.

Loaded container transport requests represent transports from a shipper to a container terminal (pickup customer, outbound loaded container) and from a container terminal to a consignee (delivery customer, inbound loaded container). For each transport, the terminal to be used is predefined (the closest one is used) so that for all loaded container transports the origin and destination are known in advance. Hard time windows are imposed on these transport requests.

For empty container transports, either the origin or the destination is not defined in advance. A shipper may request an empty container to be delivered before a specific point in time. The origin of this empty container is irrelevant for the shipper and is chosen by the decision maker. On the other hand, a consignee will have an empty container available after unloading an inbound loaded container. This container becomes available at a certain point in time and should be picked up before the end of the day. The destination of the empty container is determined by the decision maker. Empty containers can thus be transported from consignees to a container terminal, from a container terminal to a shipper or directly from a consignee to a shipper.

Different objective functions could be proposed for this problem. The main goal of solving the problem is to compare a sequential and integrated planning approach.

It is expected that using an integrated approach will lead to a reduction in the total distance traveled and might even lead to a reduction in the number of vehicles necessary to perform all transport requests (Braekers et al., 2009). Therefore a hierarchical objective function which first minimizes the number of vehicles and second the total distances traveled will be used. Using a hierarchical objective function instead of a weighted objective function which minimizes total costs, has the advantage that no fixed cost per vehicle used and no cost per kilometer traveled need to be determined. Priority is given to minimizing the number of vehicles used, as is common in vehicle routing literature (Bräysy and Gendreau, 2005a; Jozefowiez et al., 2008; Gendreau and Tarantilis, 2010). Total distance is used as the secondary objective instead of total duration of the vehicle routes for several reasons. Total route duration includes travel times, container pickup and drop off times and waiting times. On the one hand travel times are assumed to be proportional to distance, so the effect on travel times of using an integrated instead of a sequential approach is the same as on total distance. On the other hand no large effect of using an integrated approach on pickup and drop off times and waiting times is expected. Furthermore, total distance better reflects the social interest of reducing the external effects of freight transport. Finally, from the perspective of the growing advocacy of internalizing external costs of transport, the objective to minimize total distance will stay a priority for transportation companies.

In Chapter 6 two alternative objective functions will be considered: a bi-objective function to analyze the trade off between the number of vehicles and total distance and the objective to minimize route duration in order to compare our algorithm with an existing method proposed by Zhang et al. (2010).

Problems the closest related to the one described in this section are studied by Smilowitz (2006) and Zhang et al. (2009, 2010). A detailed description of these papers can be found in Section 2.8.3. The main difference between our problem and the one of Smilowitz (2006) is the fact that Smilowitz (2006) limits the number of feasible allocations by imposing a maximum distance on them. Differences between the problem of Zhang et al. (2009, 2010) and our problem include:

- multiple vehicle depots are considered,
- container depots are located at vehicle depots rather than at container terminals,
- when a vehicle delivers a loaded container to a consignee it has to wait at this location until the container is unloaded and can be picked up, while in this thesis it is assumed that the vehicle may leave for another task and an empty container that becomes available at the consignee's location may be picked up

by any vehicle,

- the objective function (minimize travel times in Zhang et al. (2009) and minimize route durations in Zhang et al. (2010))

Finally, Smilowitz (2006) and Zhang et al. (2009, 2010) do not make a comparison between their integrated planning method and a sequential method.

4.4 Problem formulation

The general problem described in the previous section can be defined on a graph $G_{gen} = (N_{gen}, A_{gen})$ with node set N_{gen} (indices g, h) and arc set $A_{gen} = \{(g,h)|g,h \in N_{gen}, g \neq h\}$. The node set N_{gen} consists of six different subsets, i.e. $N_{gen} = N_{PIC} \cup N_{DEL} \cup N_S \cup N_D \cup N_T \cup N_{VD}$ with:

N_{PIC}: a node for the origin (shipper) of each outbound loaded container that has to be picked up and transported directly to the closest terminal

N_{DEL}: a node for the destination (consignee) of each inbound loaded container that has to be delivered from the closest terminal

N_S: a node for each empty container supplied by a consignee

N_D: a node for each empty container demanded by a shipper

N_T: a node for each container terminal (with container depot)

N_{VD}: a node for the vehicle depot

For each node, its location and its time window $[a_g, b_g]$ are known. An overview of the values and meaning of these time windows can be found in Table 4.1. For nodes where a container should be picked up by a vehicle ($N_{PIC} \cup N_S$), the time window indicates the time interval in which this pickup should begin. For nodes where a container should be dropped off ($N_{DEL} \cup N_D$), the time window indicates the time interval that this drop off should be finished. For the remaining nodes ($N_T \cup N_{VD}$), the time window indicates the opening time of the terminal/depot (which is the whole planning period P). It can be noted that the nodes related to empty containers supplied (N_S) and demanded (N_D) have a one-sided time window to facilitate an efficient planning of empty container movements. Finally, it is assumed that these time windows allow at least a single feasible solution to the problem.

The distance d_{gh} and travel time t_{gh} between all pairs of nodes are assumed to be constant and proportional to the Euclidean distance between these nodes. The

Table 4.1: Overview of time windows

Node set	Value	Meaning
N_{PIC}	$[a_g, b_g]$	Container pickup should begin
N_{DEL}	$[a_g, b_g]$	Container delivery should be finished
N_S	$[a_g, P]$	Container pickup should begin
N_D	$[0, b_g]$	Container delivery should be finished
N_T	$[0, P]$	Terminal opening time
N_{VD}	$[0, P]$	Depot opening time

service time for picking up or dropping off a container at a node is denoted by l_g. The maximum number of vehicles available is K and M is a very large number.

In the following sections, the sequential and integrated solution approaches are described in detail. To make this discussion more clear, a small example is shown in Figure 4.3 to demonstrate how a solution is found by the two solution approaches. Figure 4.3(a) shows the problem situation. The network consists of a vehicle depot, two container terminals with an empty container depot, a single loaded container delivery customer, a single empty container supply location and a single empty container demand location. No time windows and a single vehicle are considered in this example. Parts (b), (c) and (d) of Figure 4.3 are discussed throughout Sections 4.4.1 and 4.4.2.

4.4.1 Sequential approach

When solving the problem sequentially, empty container allocations are determined before vehicle routes are created. This may lead to a suboptimal solution but reduces the complexity of the vehicle routing problem. The allocation model is discussed in Section 4.4.1.1. This model results in a set of empty container transports that need to be performed. In a second step, the routing problem is solved for loaded and empty container transports together. This problem is described in Section 4.4.1.2.

4.4.1.1 Empty container allocation problem

Based on known demand and supply locations, the best distribution of empty containers is determined by an empty container allocation model (Crainic et al., 1993b). The objective is to minimize the total distance traveled by empty containers.

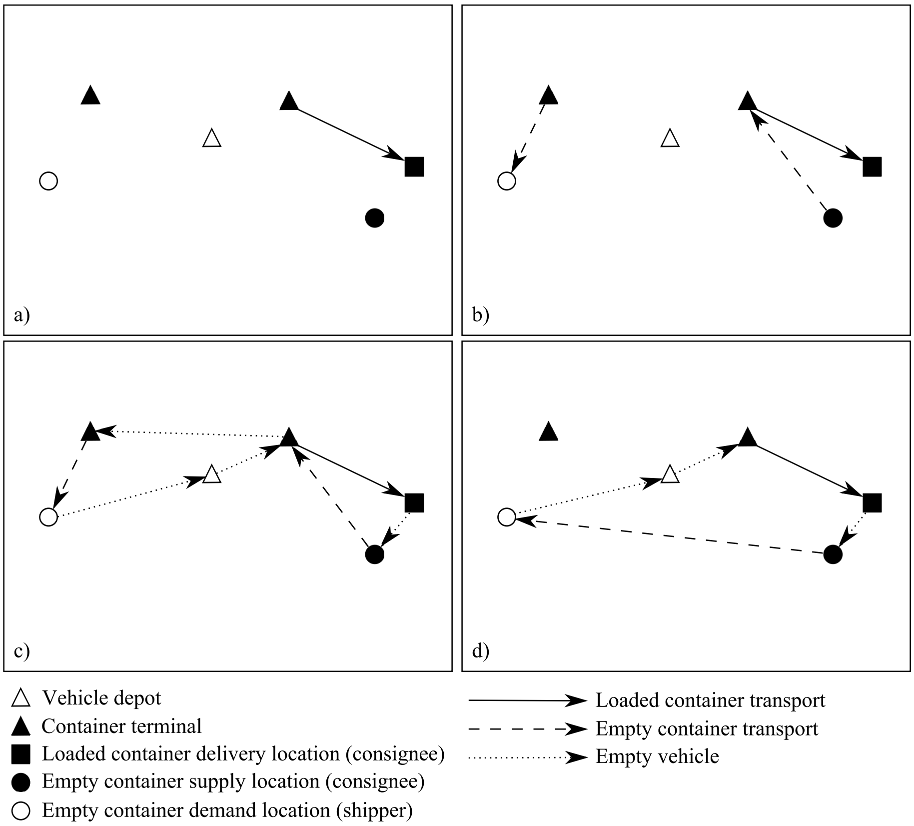

Figure 4.3: Advantage of integrated approach: example

In this thesis, a static, deterministic, single commodity allocation model which allows street turns is proposed. This allocation problem can be formulated as a Transportation Problem (TP). The set of origins N_{orig} is composed of the container terminals and locations of the empty containers supplied by consignees ($N_{orig} = N_T \cup N_S$). Each container terminal has a supply sup_g equal to the total number of empty containers demanded by shippers in the region. This ensures that all empty containers can be supplied by a single container terminal if this would be desirable. The supply sup_g of all other origins is equal to one. Similarly, the set of destinations N_{dest} is composed of the container terminals and the empty containers demanded by shippers ($N_{dest} = N_T \cup N_D$). Each container terminal has a demand dem_h equal to the total number of empty containers supplied by consignees in the region. The demand dem_h of all other destinations is equal to one. In case the total number of empty containers supplied does not equal the number of empty containers demanded, a dummy origin or destination is created to balance demand and supply. The set of possible allocations is $A_{alloc} = \{(g,h)|g \in N_{orig}, h \in N_{dest}\}$. The cost of each allocation $(g,h) \in A_{alloc}$ is denoted by c_{gh} and defined as follows:

$$c_{gh} = \begin{cases} d_{gh} & \text{if } a_g + l_g + t_{gh} + l_h \leq b_h \wedge (g \notin N_T \vee h \notin N_T) \\ 0 & g \in N_T \wedge h \in N_T \\ M & \text{else} \end{cases}$$

For each feasible allocation, the cost is represented by the distance between the origin and destination. Terminal-to-terminal allocations have a cost of zero since they do not represent actual movements of containers. The cost for allocations that are not feasible because of time window violations is set to a large value M. Integer decision variables y_{gh} indicate the number of empty containers allocated from origin $g \in N_{orig}$ to destination $h \in N_{dest}$. The formulation of the problem (P4.1) is as follows:

$$\text{(P4.1)} \min \sum_{(g,h) \in A_{alloc}} c_{gh} y_{gh} \tag{4.1}$$

Subject to

$$\sum_{h:(g,h) \in A_{alloc}} y_{gh} = sup_g \qquad \forall g \in N_{orig} \tag{4.2}$$

$$\sum_{g:(g,h) \in A_{alloc}} y_{gh} = dem_h \qquad \forall h \in N_{dest} \tag{4.3}$$

$$y_{gh} \geq 0 \text{ and integer} \qquad \forall (g,h) \in A_{alloc} \tag{4.4}$$

The objective is to minimize the distance traveled by empty containers (4.1). Constraints (4.2) and (4.3) ensure that supply and demand at each location are met. Finally, constraint (4.4) defines the integer decision variables.

The transportation problem is solved optimally by the well-known Ford-Fulkerson algorithm (Ford and Fulkerson, 1956). The optimal allocations (consignee-to-shipper, consignee-to-terminal and terminal-to-shipper) represent the empty container transports tasks that need to be performed. These transports now have a fixed start and end location.

Solving the empty container allocation problem for the example in Figure 4.3 leads to the optimal (least-distance) solution shown in part (b) of this figure. The empty container supplied is transported to the container terminal on the right while the empty container demanded is supplied from the container terminal on the left. Another option is to perform a street turn by transporting the empty container supplied directly to the empty container demand location, but then the distance traveled by the empty container would be larger.

4.4.1.2 Routing problem

Once the empty container allocation problem is solved, all transportation tasks to be performed are fully defined. Loaded containers should be transported from pickup nodes to the closest terminal and from the closest terminal to delivery nodes. Empty containers should be transported according to the optimal allocations found by the allocation problem. Thus, the routing problem can be formulated as a Full Truckload Pickup and Delivery Problem with Time Windows (FT-PDPTW).

Since vehicles are assumed to have a single container capacity, the origin and destination of a transport task should be visited immediately after each other by the same vehicle. Therefore, a transport task may be represented by a single node and the problem can be formulated as an *a*symmetric *m*ultiple vehicle Traveling Salesman Problem with Time Windows (*am*-TSPTW) (Wang and Regan, 2002; Jula et al., 2005).

The problem is defined on a graph $G_{seq}(N_{seq}, A_{seq})$. The node set N_{seq} (indices i, j) consists of a node for the vehicle depot (index 0) and a node for each (loaded and empty container) transport task to be performed. Each node $i \in N_{seq}$ has:

- a start location (index g),
- an end location (index h),
- a distance $d_i = d_{gh}$
- a duration $s_i = l_g + t_{gh} + l_h$
- a time window $[a_i, b_i]$ during which a vehicle should arrive at the node in order to be able to perform the task in time.

The node for the vehicle depot does not represent a task to be performed. The start and end location are assumed to be the same and hence distance and duration of this node are equal to zero. The time window is $[0, P]$. The time windows of the other nodes are calculated as shown in Table 4.2. These time windows are then tightened where possible. For example, the start of the time window of a terminal-to-demand allocation can be increased from zero to the time needed to reach the terminal from the vehicle depot.

Parameters d_{ij} and t_{ij} represent respectively the distance and travel time from the end location of task i to the start location of task j. The arc set $A_{seq} = \{(i, j)|i, j \in$

Table 4.2: Calculation of time windows $[a_i, b_i]$

Task type	Time window of		Time window of task
	Start loc.	End loc.	
Loaded container pickup	$[a_g, b_g]$	$[0, P]$	$[a_g, \min(b_g, P - l_g - t_{gh} - l_h)]$
Loaded container delivery	$[0, P]$	$[a_h, b_h]$	$[\max(0, a_h - l_g - t_{gh} - l_h),$ $b_h - l_g - t_{gh} - l_h]$
Supply-demand allocation	$[a_g, P]$	$[0, b_h]$	$[a_g, b_h - l_g - t_{gh} - l_h]$
Supply-terminal allocation	$[a_g, P]$	$[0, P]$	$[a_g, P - l_g - t_{gh} - l_h]$
Terminal-demand allocation	$[0, P]$	$[0, b_h]$	$[0, b_h - l_g - t_{gh} - l_h]$

$N_{seq}, i \neq j, a_i + s_i + t_{ij} \leq b_j\}$ contains links between nodes which are feasible with respect to time windows. Binary decision variables x_{ij} are used to determine whether any vehicle $v \in V$ travels directly from the end location of task i to the start location of task j. Continuous variables t_i represent the point in time at which a vehicle starts task i. The routing problem (P4.2) is formulated as follows:

$$\text{(P4.2) lexmin } \Big(\sum_{i:(0,i)\in A_{seq}} x_{0i}, \sum_{(i,j)\in A_{seq}} d_{ij}x_{ij} + \sum_{i\in N_{seq}} d_i\Big) \tag{4.5}$$

Subject to

$$\sum_{j:(i,j)\in A_{seq}} x_{ij} = 1 \qquad \forall i \in N_{seq}\backslash\{0\} \tag{4.6}$$

$$\sum_{j:(0,j)\in A_{seq}} x_{0j} \leq K \tag{4.7}$$

$$\sum_{j:(i,j)\in A_{seq}} x_{ij} = \sum_{j:(j,i)\in A_{seq}} x_{ji} \qquad \forall i \in N_{seq} \tag{4.8}$$

$$t_i + s_i + t_{ij} \leq t_j + M(1 - x_{ij}) \qquad \forall (i,j) \in A_{seq}, j \neq 0 \tag{4.9}$$

$$t_i + s_i + t_{i0} \leq P + M(1 - x_{i0}) \qquad \forall i \in N_{seq} \tag{4.10}$$

$$a_i \leq t_i \leq b_i \qquad \forall i \in N_{seq} \tag{4.11}$$

$$t_i \geq 0 \qquad \forall i \in N_{seq} \tag{4.12}$$

$$x_{ij} \in \{0,1\} \qquad \forall (i,j) \in A_{seq} \tag{4.13}$$

The notation 'lexmin' in the objective function (4.5) denotes that a hierarchical or lexicographic objective function is used (Ehrgott, 2005). The primary objective is to minimize the number of vehicles used ($\sum_{i:(0,i)\in A_{seq}} x_{0i}$). The secondary objective is to minimize total distance traveled, which consists of the distance traveled from each task to the next ($\sum_{(i,j)\in A_{seq}} d_{ij}x_{ij}$) and the distance traveled to perform each task itself ($\sum_{i\in N_{seq}} d_i$). Constraints (4.6), (4.7) and (4.8) are flow constraints. Constraint (4.9) ensures that a vehicle cannot start a new task before finishing the previous task and traveling to the new one. Constraint (4.10) ensures that all vehicles return to the vehicle depot before the end of the planning period. Time windows are represented by constraint (4.11). Finally, constraints (4.12) and (4.13) make sure that both types of variables only take on the appropriate values.

Figure 4.3(b) shows that after solving the empty container allocation problem for the small example, three transport tasks need to be performed: one loaded container transport and two empty container transports. Using the vehicle routing problem described above leads to the optimal solution for the sequential approach which is shown in Figure 4.3(c). First, the vehicle performs the loaded container transport. Second, it performs the first empty container transport by traveling via the empty container supply location back to the container terminal at the right. Finally, it travels to the container terminal at the left to perform the second empty container transport before returning to the vehicle depot.

4.4.2 Integrated approach

When using an integrated approach, empty container allocations are not made beforehand but simultaneously with vehicle routing decisions. This means that the origin (destination) of an empty container demanded by a shipper (supplied by consignee) is not fixed in advance.

The integrated problem can be formulated by creating a node for the vehicle depot, for all loaded container transports and for all feasible empty container allocations. Extra constraints should impose that a single allocation node for each empty container demanded/supplied is chosen. Such a formulation of the problem can be found in Braekers et al. (2010). Solving this problem is however problematic since the number of possible allocations and thus the number of nodes in the network becomes very large for problems of realistic size. Smilowitz (2006) uses a similar approach by defining feasible allocations as possible executions of a flexible task. To overcome the problem of the exponential growth of the network, a heuristic column generation approach is proposed and the number of feasible allocations is restricted by imposing a maximum distance.

Alternatively, the integrated problem can be formulated as an *am*-TSPTW like the routing problem for the sequential approach. This is done by introducing an intermediate stop at a container terminal when traveling between certain types of nodes (Ileri et al., 2006; Zhang et al., 2009). The node set N_{int} (indices i, j) is composed of:

- the vehicle depot (N_{VD}, index 0),
- a node for each loaded container pickup task and for each loaded container delivery task (N_L),
- a node for each empty container demanded (N_D),
- a node for each empty container supplied (N_S).

A distance d_i, a duration s_i and a time window $[a_i, b_i]$ are assigned to each node. For the vehicle depot and the nodes representing the loaded container transports, these values are identical as those for the routing problem from the sequential approach. For the empty containers supplied and demanded, d_i and s_i are equal to zero and their time windows are equal to those of the original nodes in N_D and N_S. These time windows are tightened where possible.

The main difference between the integrated problem and the routing problem of the sequential problem is that in some cases directly traveling between two nodes is not feasible. Instead, an intermediate stop at a container terminal is required. This is the case when traveling:

- from an empty container supply node to the vehicle depot, a loaded container task or another supply node,
- from the vehicle depot, a loaded container task or an empty container demand node to another demand node.

In the first case, it is necessary to drop off the empty container which was picked up at the supply node before the vehicle is able finish its route at the vehicle depot, transport a loaded container or pickup another empty container. The terminal which is used to drop off the empty container is chosen on a lowest distance basis. Similarly, when leaving the vehicle depot, finishing a loaded container task or dropping of an empty container at a demand node, an empty container needs to be picked up at a container terminal before traveling to an empty container demand node.

The calculation of the distance $\hat{d}_{ij}$ of traveling between two nodes $i \in N_{int}$ and $j \in N_{int}$ is shown in Table 4.3 where parameter d_{ij} represents the Euclidean distance between (the end location of) node i and (the start location of) node j. Travel times $\hat{t}_{ij}$ between two nodes are calculated similarly as the distances, but augmented with the container pickup and drop off time when making an intermediate stop at a container terminal or traveling directly from an empty container supply to an empty container demand location. A consequence of introducing these intermediate stops is that the triangle inequality does not hold anymore. For some combinations of nodes, inserting a node i' between nodes i and j might lead to a decrease in distance and travel time ($\hat{d}_{ij} > \hat{d}_{ii'} + \hat{d}_{i'j}$).

Table 4.3: Calculation of distance coefficients $\hat{d}_{ij}$

	$j \in N_{VD} \cup N_L$	$j \in N_S$	$j \in N_D$
$i \in N_{VD} \cup N_L$	d_{ij}	d_{ij}	$\min_{r \in N_T} (d_{ir} + d_{rj})$
$i \in N_S$	$\min_{r \in N_T} (d_{ir} + d_{rj})$	$\min_{r \in N_T} (d_{ir} + d_{rj})$	d_{ij}
$i \in N_D$	d_{ij}	d_{ij}	$\min_{r \in N_T} (d_{ir} + d_{rj})$

The arc set $A_{int} = \{(i,j) | i,j \in N_{int}, i \neq j, a_i + s_i + \hat{t}_{ij} \leq b_j\}$ is only composed of feasible links between nodes. The meaning of the other variables (K, M, x_{ij}, t_i) and the formulation of the problem are the same as for the sequential approach, except that node set N_{int} and arc set A_{int} are used and variables d_{ij} and t_{ij} are replaced by respectively $\hat{d}_{ij}$ and $\hat{t}_{ij}$.

Although the formulation is the same, the integrated problem is harder to solve than the routing problem of the sequential approach. The reason is twofold. First, the number of nodes slightly increases. Second, the nodes representing the empty container demand and supply locations have much wider time windows than the nodes representing empty container transport requests in the sequential approach.

When the integrated approach is applied to the small example in Figure 4.3(a), the optimal vehicle route is determined without first deciding on the origin and destination of the empty container demanded respectively supplied. Figure 4.3(d) shows the optimal solution. Clearly the total distance traveled is less than for the solution of the sequential approach (shown in Figure 4.3(c)). The reason for this lower distance is that another empty container allocation is chosen. In this case, an empty container is transported directly from the empty container supply location to the empty container demand location. Although the distance traveled by empty containers is larger for the integrated solution (since the optimal container allocation is not chosen), total distance traveled by the vehicle is smaller than for the solution of the sequential approach.

4.5 Conclusions

In this chapter, empty container management in the context of drayage operations is studied. The focus is on the operational planning level. A detailed problem description of planning drayage operations is presented. The objective is to find an efficient planning of loaded and empty containers transports within the service area of one or more container terminals. Two solution approaches are presented: a sequential and an integrated approach. With a sequential approach, empty container allocations are made in a first step while vehicle routes are created in a second step. This may lead to sub-optimal solutions. With an integrated approach, both types of decisions are taken simultaneously. It is shown that the routing problem of both solution approaches can be formulated as an *a*symmetric *m*ultiple vehicle Traveling Salesman Problem with Time Windows (*am*-TSPTW). Since the formulation is the same, a single solution method may be developed to solve the drayage problem according to both solution approaches. To solve these problems within a reasonable time frame, a meta-heuristic approach is proposed in Chapter 5.

Chapter 5

Optimization of drayage operations: deterministic annealing meta-heuristic

5.1 Introduction

In the previous chapter, an operational planning problem in drayage operations is presented. Two solution approaches, a sequential and integrated, are proposed. For both approaches, the routing problem can be formulated as an *am*-TSPTW. Solving problem instances of realistic size exactly seems not feasible. In this chapter[1], a Deterministic Annealing meta-heuristic (DA) is proposed to solve the problem (Figure 5.1). Meta-heuristics provide a more profound search of the objective space than traditional heuristics and are less likely to get stuck in a local optimum. For detailed overviews of meta-heuristics for solving vehicle routing problems, the reader is referred to Cordeau et al. (2007a,b, 2008) and Gendreau et al. (2008).

Deterministic annealing, also referred to as threshold accepting, is a variant on the well-known simulated annealing meta-heuristic. It was first introduced by Dueck and Scheuer (1990) and can be categorized as a meta-heuristic based on local search (Cordeau et al., 2007b). In each iteration, a neighboring solution $\boldsymbol{x'}$ of current solution $\boldsymbol{x}$ is generated. If the objective value of the new solution is better than that of the current solution, $\boldsymbol{x'}$ is automatically accepted and becomes the new current solution.

[1]This and the previous chapter are based on Braekers et al. (2012b).

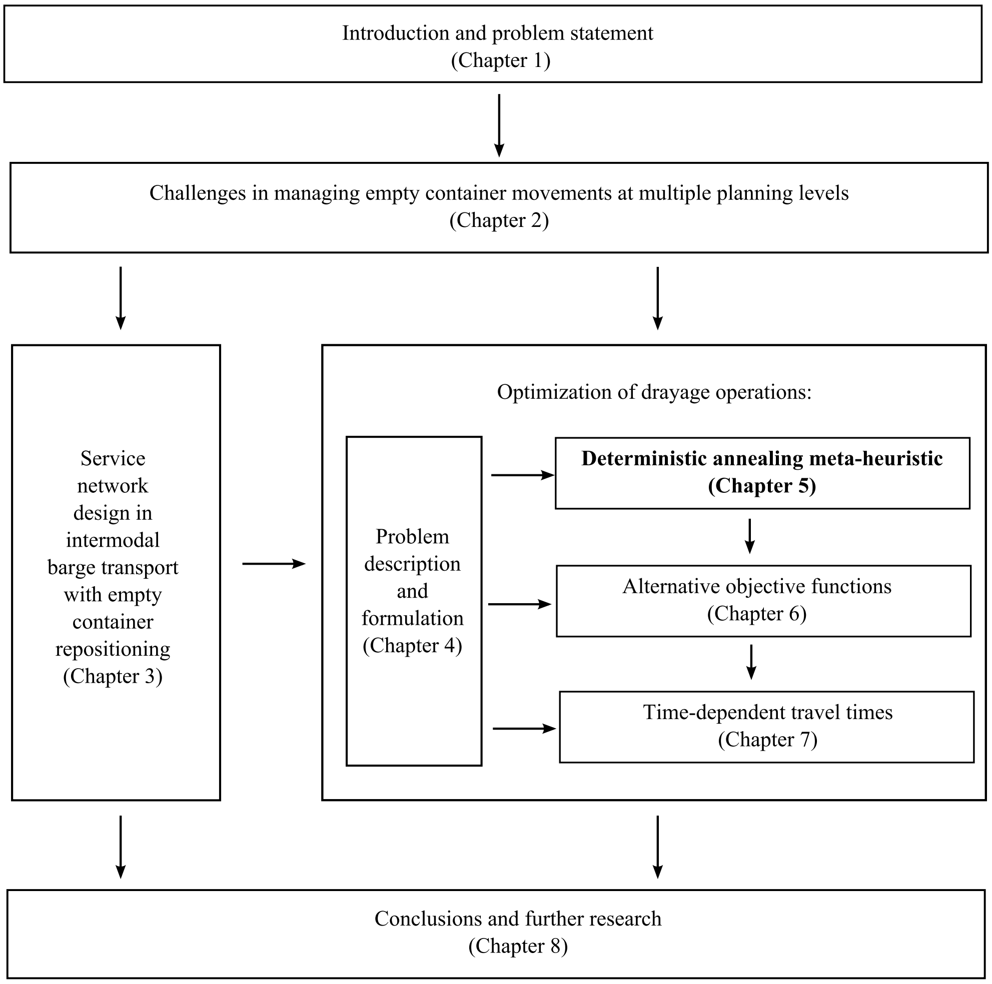

Figure 5.1: Outline of the thesis

Otherwise, solution $\boldsymbol{x}'$ is accepted as long as the worsening in the objective value $\Delta = f(\boldsymbol{x}') - f(\boldsymbol{x})$ is smaller than a deterministic threshold value T. This threshold value T is gradually lowered during the search until only solutions improving the objective value are accepted (Caris and Janssens, 2010). Recently, deterministic annealing has been successfully implemented for a number of vehicle routing problems (Bräysy et al., 2003, 2008a; Tarantilis et al., 2004; Nikolakopoulos and Sarimveis, 2007; Caris and Janssens, 2010).

The chapter is organized as follows. In Section 5.2, the deterministic annealing meta-heuristic is presented in detail. For both solution approaches a single and a two-phase variant are proposed. Next, a way to improve the meta-heuristic by introducing elements of tabu search is described (Section 5.3). An experimental design to test the algorithms is set up in Section 5.4. The calculation of lower bounds and parameter testing are discussed in Sections 5.5 and 5.6. In Section 5.7, results of the algorithms are presented. Finally, conclusions are drawn in Section 5.8.

5.2 Deterministic annealing algorithm

In this section, a deterministic annealing meta-heuristic is proposed for solving the routing problems discussed in Sections 4.4.1.2 and 4.4.2. To simplify notation, we will refer to a general problem for which the network consists of a vehicle depot and n nodes to be visited exactly once. Each of these nodes has a distance d_i, duration s_i and a time window $[a_i, b_i]$ associated with it. The problem is defined on a graph $G = (N, A)$ with parameters d_{ij} and t_{ij} indicating the distance and travel time between two nodes $i \in N$ and $j \in N$. A solution to this problem is represented by a decision vector $\boldsymbol{x} = (x_{01}, ..., x_{nn-1}, t_0, ..., t_n)$ and its corresponding objective vector $f(\boldsymbol{x})$.

In Section 5.2.1, the insertion heuristic used to find a feasible starting solution for the algorithm is described. The local search operators and the deterministic annealing scheme are respectively introduced in Sections 5.2.2 and 5.2.3. Finally, the implementation of the algorithm on the problem under study is discussed in Section 5.2.4.

5.2.1 Insertion heuristic

An initial solution for the problem is obtained by a parallel insertion heuristic. In a first step, a simple lower bound on the number of vehicles is calculated by equation (5.1). A lower bound on the total time needed to perform all tasks is found by taking the sum over all nodes of the duration of the task at the node and the minimal time needed to travel to another node. This total time is then divided by the maximal time a vehicle can be used (time window width of the vehicle depot).

$$lb_v = \left\lceil \sum_{i \in N} (s_i + \min_{j:(i,j) \in A} t_{ij}) \right\rceil / (b_0 - a_0) \tag{5.1}$$

The parallel insertion heuristic works as follows. A solution is created with lb_v empty routes. Next, a node is selected randomly and inserted in the best possible position (least increase in distance). This operation is repeated until all nodes are inserted. If a node is selected but no feasible insertion in one of the existing routes can be found, an additional route is created. The procedure is iterated a thousand times to obtain a good starting solution.

5.2.2 Local search operators

During each iteration of the deterministic annealing algorithm, several local search operators are used to find neighboring solutions of the current solution. A first improvement strategy is used for all operators.

Four operators try to reduce the distance traveled. One of these operators is an *intra-route* operator which changes the sequence of three succeeding nodes in a route. These nodes can be arranged in six different ways and each ordering is considered. Rearranging more than three nodes is not considered since experimental results have indicated that this offers only limited improvements while it results in a considerable increase in computation time[2]. An example of the operator can be found in Figure 5.2. In each iteration, the intra-route operator is used on all combinations of three succeeding nodes of a single randomly selected route.

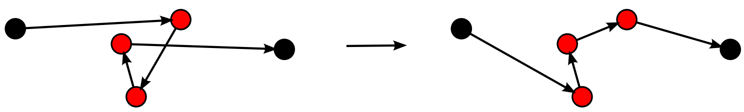

Figure 5.2: Example of the *intra-route* operator

The three other operators affecting distance are inter-route operators. A *relocate* operator is used to remove a node from its current route and insert it in another route (Figure 5.3).

The *2-Opt** operator (Potvin and Rousseau, 1995) removes an arc from two routes and recombines the resulting parts, that is: the first part of route one with the second part of route two and vice versa (Figure 5.4).

An *exchange* operator is used to swap a number of nodes between two routes. Several variations of this operator are considered, based on the number of nodes that are swapped: *exchange(1,1)*, *exchange(2,1)*, *exchange(2,2)*, *exchange(3,2)* and *exchange(3,3)*. An example of the *exchange(1,1)* operator is shown in Figure 5.5. In each iteration of the algorithm, one of these exchange operators is randomly selected

[2]For the test instances discussed in Section 5.4, rearranging four nodes instead of three reduces the relative gap with the lower bound on total distance only from 4.81% to 4.79% while average computation time increases from 5.02 to 6.25 seconds (for algorithm 2-DA_{TS}).

to be used. For the *exchange(1,1)* operator the insertion position of a node can also be one place before or after the removal position of the other node. When two or three nodes from a route are swapped to another route, the reverse insertion of these nodes is considered as well. For each inter-route operator, one route is selected randomly and all combinations of nodes or arcs of this route with those of all other routes are considered in a random order.

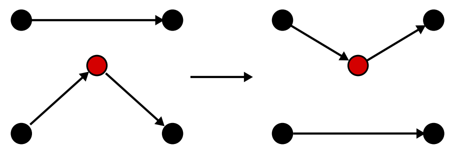

Figure 5.3: Example of the *relocate* operator

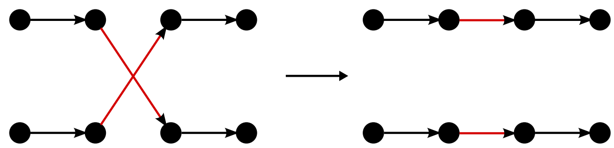

Figure 5.4: Example of the *2-Opt** operator

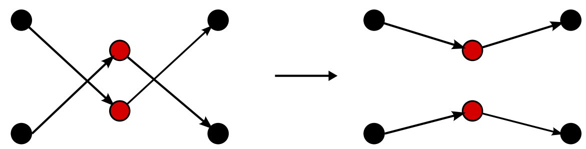

Figure 5.5: Example of the *exchange(1,1)* operator

Finally, two operators try to reduce the number of vehicles by reinserting all nodes of respectively one or several routes into the other routes. The first operator tries to insert all nodes of a randomly selected route into the other routes. The second operator tries to insert all nodes of the p shortest routes (in terms of the number of nodes) into all other routes and $p-1$ empty routes. The parameter p is defined as a percentage of the number of routes in the solution. The order in which the nodes are reinserted depends on a simple measure of difficulty similar to the one proposed by Bräysy et al. (2008a). This measure favors nodes which have a large duration (s_i) and a small time window ($b_i - a_i$) to be inserted first.

To ensure an efficient implementation of the local search operators, the earliest et_i and latest lt_i arrival time at each node are maintained during the search. Consider for example the evaluation of a *2-Opt**-move between links $(i, i+1)$ and $(j, j+1)$ of two different routes. First it is verified whether the new links $(i, j+1)$ and $(j, i+1)$ are part of the set of feasible links. Next, it is checked whether the move is feasible and whether the effect on the objective value is acceptable. Since the latter can be performed the fastest, this is done first. In this case, there is no effect on the number of vehicles when assuming ($i \neq 0$ or $j \neq 0$) and ($i+1 \neq 0$ or $j+1 \neq 0$). The effect on total distance is $\Delta d = d_{ij+1} + d_{ji+1} - d_{ii+1} - d_{jj+1}$. Only when the move is acceptable ($\Delta d < T$), a feasibility check should be performed. The move is feasible when the following inequalities are valid:

$$et_i + s_i + t_{ij+1} \leq lt_{j+1} \quad (5.2)$$

$$et_j + s_j + t_{ji+1} \leq lt_{i+1} \quad (5.3)$$

Finally, when the move is accepted, the earliest and latest arrival times of each node are updated.

5.2.3 Deterministic annealing scheme

The proposed deterministic annealing scheme is based on the one in Bräysy et al. (2008a) and Caris and Janssens (2010), as presented in Algorithm 1. The current best solution $\boldsymbol{x_b}$ is set to the best solution found by the insertion heuristic and the threshold value T is set to its maximum value T_{max}. The deterministic annealing algorithm is iterated n_{it} times. At each iteration, all local search operators are used in a random order. The acceptance rule is as follows. New solutions with a lower number of vehicles as the current solution are always accepted. New solutions with the same number of vehicles and total distance lower than the distance of the current solution plus the threshold value T are accepted as well. If a solution is better than the best solution found so far, this solution is set as best solution. When no new best solution has been found, the threshold value T is reduced by the threshold reduction parameter ΔT. Whenever T becomes negative, it is reset to $r \times T_{max}$, with r a random number between zero and one. In case T becomes negative and no improvement has been found for n_{imp} iterations, the search is restarted from the best solution.

5.2.4 Implementation

In this section, the implementation of the deterministic annealing algorithm is discussed. For both the sequential and integrated approach a single and a two-phase variant of deterministic annealing algorithm are presented. An overview of the structure of these variants can be found in Figure 5.1.

Algorithm 1 Implementation of the deterministic annealing algorithm

$T = T_{max}$, $i_{last} = 0$ and $\boldsymbol{x} = \boldsymbol{x_b}$ = best solution of the insertion heuristic
for $i = 1 \rightarrow n_{it}$ **do**
  for $j = 1 \rightarrow m$ **do**
    Apply local search operator j on $\boldsymbol{x}$ and accept or reject new solution $\boldsymbol{x'}$
    if $\boldsymbol{x'}$ is accepted **then**
      $\boldsymbol{x} \leftarrow \boldsymbol{x'}$
      if $f(\boldsymbol{x}) < f(\boldsymbol{x_b})$ **then**
        $\boldsymbol{x_b} \leftarrow \boldsymbol{x}$
        $i_{last} \leftarrow 0$
      end if
    end if
  end for
  if $i_{last} > 0$ **then**
    $i_{last} \leftarrow i_{last} + 1$
    $T \leftarrow T - \Delta T$
    if $T < 0$ **then**
      $T \leftarrow r \times T_{max}$
      if $i_{last} > n_{imp}$ **then**
        $\boldsymbol{x} \leftarrow \boldsymbol{x_b}$
        $i_{last} \leftarrow 0$
      end if
    end if
  end if
end for

5.2.4.1 Single phase algorithms

The implementation of the single phase algorithms is straightforward. For the sequential problem, first the optimal empty container allocations are determined by solving the transportation problem (TP). Second, an initial solution is found by the insertion heuristic. Finally, this solution is improved by the deterministic annealing algorithm (DA) for a predefined number of iterations. All local search operators are used during the algorithm which means that the number of vehicles and total distance are minimized simultaneously.

For the integrated problem, the implementation is similar: the insertion heuristic is used to find an initial solution and next the number of vehicles and total distance

Table 5.1: Structure of algorithms

	Sequential	Integrated
Single phase	- TP: optimal allocations - Insertion heuristic - DA: minimize vehicles + distance	- Insertion heuristic - DA: minimize vehicles + distance
Two-phase	- TP: optimal allocations - Insertion heuristic - DA: minimize vehicles - DA: minimize distance	- TP: optimal allocations - Insertion heuristic - { DA: minimize vehicles (50%); Relax optimal allocations; DA: minimize vehicles (50%) } - DA: minimize distance

are minimized by the deterministic annealing algorithm.

5.2.4.2 Two-phase algorithms

As pointed out by Homberger and Gehring (2005) and Bent and Van Hentenryck (2006), the simultaneous reduction of the number of vehicles and total distance traveled in vehicle routing problems by a meta-heuristic controlling a neighborhood search, may lead to an important shortcoming. The objective function often drives the search towards solutions with a small distance. This complicates reaching solutions with a low number of vehicles but higher distance, i.e. the search is mainly guided by the secondary objective. To overcome this shortcoming, a two-phase solution method may be used for which the number of vehicles is minimized during the first phase and total distance is minimized during the second phase. According to Nagata and Bräysy (2009) most of the recent and best heuristics use such a two-phase method. Examples can be found in Bent and Van Hentenryck (2004, 2006), Bräysy et al. (2004) and Homberger and Gehring (2005). Bent and Van Hentenryck (2004, 2006) use simulated annealing during the first phase and Large Neighborhood Search (LNS) during the second phase for respectively the vehicle routing problem with time windows and the pickup and delivery problem with time windows. Bräysy et al. (2004) propose a new operator, similar to ejection chains, to reduce the number of routes during the first phase of their local search algorithm for the vehicle routing problem with time windows. Another two-phase solution method for the vehicle routing problem with time windows is presented by Homberger and Gehring (2005). The first phase uses a (μ, λ)-evolution strategy. A population of μ solutions is created and in each iteration λ descendants are generated and evaluated. A tabu search algorithm is used during the second phase. Since these two-phase methods provide very good results, a two-phase solution method for our problem is proposed as well. During both phases the deterministic annealing meta-heuristic is used.

First phase: reduce the number of vehicles Instead of using objective function (4.5), a specific hierarchical objective function presented by Bent and Van Hentenryck (2006) is used during the first phase of the algorithm. This objective function (5.4) guides the search towards solutions with a small number of vehicles, while partially ignoring the secondary objective to reduce total distance. Parameter z_v represents the number of nodes visited by vehicle $v \in V$.

$$\text{lexmin } (\sum_{i \in N} x_{0i}, \ -\sum_{v \in V} z_v^2, \ \sum_{(i,j) \in A} d_{ij} x_{ij} + \sum_{i \in N} d_i) \tag{5.4}$$

The objective function (5.4) consists of three hierarchically structured objectives. The primary objective is to minimize the number of vehicles used while the secondary objective is to maximize the sum of the squares of the number of nodes in each route. Finally, minimizing total distance is the third objective. The purpose of the second objective is to favor solutions with an unbalanced distribution of nodes over the vehicles over solutions with an even distribution of nodes, i.e. a solution with a few long and a few short routes is preferred over a solution for which all routes have a length close to the average. The idea behind this objective is to remove nodes from shorter routes and insert them into longer routes, thereby gradually reducing the number of vehicles (Bent and Van Hentenryck, 2006).

During each iteration of the deterministic annealing algorithm, all six types of local search operators are applied in a random order. The two route reducing operators have an effect on the primary objective, while the *relocate*, *2-Opt**, *exchange(2,1)* and *exchange(3,2)* operators affect the secondary objective. The *intra-route*, *exchange(1,1)*, *exchange(2,2)* and *exchange(3,3)* operators only have an effect on the third objective and are mainly used to diversify the search. During this phase, the acceptance rule of a neighboring solution differs from the general rule described in Section 5.2.3. A new solution is accepted when it is better than the current solution according to objective function (5.4) or when it has the same number of vehicles and the worsening of the second objective value is smaller than the threshold value T.

The implementation of the first phase of the sequential algorithm is straightforward: the initial solution found by the insertion heuristic is improved by the deterministic annealing algorithm for a fixed number of iterations. The implementation for the integrated algorithm is more complex. The insertion heuristic and first phase of the algorithm are not directly applied on the integrated problem. Instead, an initial solution is found in the same way as for the sequential problem (by first determining the optimal empty container allocations by the transportation problem) and during half the number of iterations of the first phase, the number of vehicles is reduced while keeping the empty container allocations fixed. Next, the best solution found so far is transformed to a solution for the integrated problem by relaxing the optimal allocations. During the second half the number of iterations of the first phase, the number of vehicles is reduced further.

Second phase: reduce total distance During the second phase, the best solution found during the first phase is further improved with respect to total distance. The original objective function (4.5) is used. The two route reducing operators are not used since reducing the number of vehicles is not considered anymore.

5.3 Combination with tabu search

In this section, the deterministic annealing algorithm (DA) described in the previous section is improved by introducing elements of tabu search. Tabu search (TS) is a well-known meta-heuristic introduced by Glover (1986) and formalized in Glover (1989, 1990). Generally, a tabu search method works as follows. In each iteration, it finds a set of feasible local search moves in the neighborhood of the current solution and selects the best among these moves. Since the selected local search move does not necessarily improve the objective function, cycling between solutions might occur. The basic idea of tabu search is to prevent cycling by keeping information on recently visited solutions in memory and forbidding local search moves that would result in a solution visited recently. Detailed surveys about the use of tabu search for solving vehicle routing problems can be found in Bräysy and Gendreau (2002), Toth and Vigo (2002) and Cordeau and Laporte (2005).

In the algorithm presented in the previous section, local search moves that worsen the objective value might be accepted as well and hence a risk of cycling between solutions exists. This risk is already reduced in several ways. First, local search operators are applied in a random order, each operator starts its search at a random node/arc in a random route and a first improvement strategy is followed. Second, if no global best solution has been found in an iteration, the threshold value T is decreased, thereby changing the set of acceptable moves in the next iteration. Still, a risk of cycling remains, especially when the set of feasible and acceptable local search moves is limited. Therefore, it is proposed to use a simple tabu search method in combination with the deterministic annealing algorithm.

Although recently there has been a growing interest in hybrid algorithms which combine several meta-heuristic methods (Blum et al., 2011), to the author's knowledge only two papers deal with the combination of deterministic annealing and tabu search. Chao (2002) presents a tabu search method for the truck and trailer routing problem. The author incorporates the concept of deterministic annealing in a tabu search algorithm by forbidding moves that would deteriorate the objective value more than an adaptive threshold value. Bräysy et al. (2008b) develop a deterministic annealing algorithm for the fleet size and mix vehicle routing problem with time windows. The authors propose to include a simple tabu search method to prevent cycling. Arcs that are introduced in a solution and improve the objective function are forced to be kept in the solution for a given number of iterations.

In this thesis, another method which combines deterministic annealing with some elements of tabu search is proposed. The idea is that when an arc is removed from a solution, it is forbidden to re-enter the solution for a given number of iterations. This will prevent the search from returning to a previously visited solution. No aspiration criterion is implemented which means that an arc with tabu status can never enter the solution. This offers the advantage that no feasibility checks and evaluation of local search moves have to be performed when one of the involved links has the tabu status. The combination of deterministic annealing with this tabu search method is considered for both the single and two phase algorithm variants discussed in Section 5.2.4. For the single phase algorithms, the tabu search method is implemented for all distance-reducing operators (*intra-route*, *relocate*, *2-Opt**, *exchange*). For the two-phase algorithms, the tabu search method is only implemented during the second solution phase. During the first solution phase, where the number of vehicles is minimized, the method is not implemented. The secondary objective during this first phase favors an uneven distribution of the number of nodes over the routes. Such a distribution of nodes is obtained by gradually inserting nodes of routes which become shorter into routes which become longer. This procedure may require some links to be removed and inserted repeatedly and hence cycling is not forbidden. As a result, four variants of the deterministic annealing algorithm for both the sequential and integrated solution approach are considered:

- a single phase deterministic annealing algorithm: 1-DA
- a two-phase deterministic annealing algorithm: 2-DA
- a single phase deterministic annealing algorithm combined with tabu search elements: 1-DA_{TS}
- a two phase deterministic annealing algorithm combined with tabu search elements: 2-DA_{TS}

5.4 Experimental design

The robustness of the proposed algorithms is tested by setting up a 2^4 factorial design (Law, 2007). Four problem characteristics are identified. For each characteristic a high (+) and low (-) value is determined. The *time window width* for loaded containers (F1) is a random number between 60 and 120 minutes (-) or between 120 and 240 minutes (+). The *number of container terminals* (F2) is one (-) or three (+). For each instance the *number of nodes* (F3) is 100 (-) or 200 (+). These nodes exist of an even amount of loaded container delivery locations, loaded container pickup locations, empty container supply locations and empty container demand locations. Finally, the *(X, Y)-coordinates* of all nodes (F4) are randomly chosen between 0 and 25 kilometers (-) or between 0 and 50 kilometers (+) on both axes. This results in 16 problem classes as shown in Table 5.2. For each problem class three random problem instances are generated, resulting in 48 problem instances. Besides, for parameter testing purposes an additional test instance is generated for each problem class.

It is assumed that a single vehicle depot is located in the center of the square region and the location of the container terminals is the same for each instance. The planning period equals eight hours. Service time for picking up or dropping off a container is ten minutes.

5.5 Lower bounds

In order to evaluate the performance of the proposed meta-heuristic, lower bounds on the number of vehicles and total distance are calculated. A time window partitioning

Table 5.2: Overview of problem classes

Class	F1	F2	F3	F4	Class	F1	F2	F3	F4
1	-	-	-	-	9	-	-	-	+
2	+	-	-	-	10	+	-	-	+
3	-	+	-	-	11	-	+	-	+
4	+	+	-	-	12	+	+	-	+
5	-	-	+	-	13	-	-	+	+
6	+	-	+	-	14	+	-	+	+
7	-	+	+	-	15	-	+	+	+
8	+	+	+	-	16	+	+	+	+

or time window discretization method is used for this purpose. This method has been proven effective in the past. A first time partitioning method for the *am*-TSPTW was introduced by Wang and Regan (2002). The authors propose a method to both to solve their problem and to calculate lower bounds by iteratively solving an over- and underconstrained version of the model. Zhang et al. (2010) improve this method by immediately selecting a good partitioning width and thereby avoiding the need to solve both models several times. They apply the method to their *am*-TSPTW which is very similar to our problem as discussed in Section 4.3. Preliminary results on our instances have shown that solving the problem discussed in the previous chapter for realistic sizes by a time window partitioning method does not offer good results. However, the method can be used to find strong lower bounds.

A time window partitioning formulation of our problem with node set ω (indices v, w) and arc set Ω is created as follows. The time window of each node $i \in N\backslash\{0\}$ is discretized into smaller parts. For each part, a subnode $v \in \omega$ is created with time window $[a_v, b_v]$. The vehicle depot is still represented by a single node ($v = 0$). The fact that v is a subnode of original node i is denoted by $\delta(v) = i$. The distance and duration of the task to be performed at subnode $v \in \omega$ are equal to the values of its original node i: $d_v = d_{\delta(v)}$ and $s_v = s_{\delta(v)}$. Distance and travel times between two subnodes $v, w \in \omega$ are the same as the values between the original nodes $i, j \in N$ as well: $d_{vw} = d_{\delta(v)\delta(w)}$ and $t_{vw} = t_{\delta(v)\delta(w)}$.

No links are defined between two subnodes of the same node, i.e. $\Omega = \{(v, w)|v, w \in \omega, \delta(v) \neq \delta(w), a_v + s_v + t_{vw} \leq b_w\}$. Binary flow variables x_{ij} for feasible links

$(i,j) \in A$ between nodes are replaced by binary flow variables $x_{vw} \in \Omega$ for feasible links between subnodes. Continuous variables t_v indicate the moment in time that a subnode is visited by a vehicle. The formulation of the problem (P5.1) is as follows:

$$\text{(P5.1) lexmin } \Big(\sum_{v:(0,v)\in\Omega} x_{0v}, \sum_{(v,w)\in\Omega} d_{vw}x_{vw} + \sum_{i\in N} d_i \Big) \tag{5.5}$$

Subject to

$$\sum_{\substack{(v,w)\in\Omega \\ \delta(v)=i}} x_{vw} = 1 \qquad \forall i \in N \backslash \{0\} \tag{5.6}$$

$$\sum_{w:(0,w)\in\Omega} x_{0w} \leq K \tag{5.7}$$

$$\sum_{w:(w,v)\in\Omega} x_{wv} = \sum_{w:(v,w)\in\Omega} x_{vw} \qquad \forall v \in \omega \tag{5.8}$$

$$t_v + s_v + t_{vw} \leq t_w + M(1 - x_{vw}) \qquad \forall (v,w) \in \Omega, \; w \neq 0 \tag{5.9}$$

$$t_v + s_v + t_{v0} \leq P + M(1 - x_{v0}) \qquad \forall v \in \omega \tag{5.10}$$

$$a_v \leq t_v \leq b_v \qquad \forall v \in \omega \tag{5.11}$$

$$t_v \geq 0 \qquad \forall v \in \omega \tag{5.12}$$

$$x_{vw} \in \{0,1\} \qquad \forall (v,w) \in \Omega \tag{5.13}$$

The objective function (5.5) still minimizes first the number of vehicles used and then the total distance traveled. Constraint (5.6) ensures that exactly one subnode of each node is visited while constraint (5.7) controls the maximum number of vehicles. A vehicle must enter and leave the same subnode (5.8) of an original node. Constraints (5.9), (5.10) and (5.11) ensure that time windows are respected and no cycles occur. Finally, constraints (5.12) and (5.13) determine the domain of the decision variables.

The above formulation is still valid for the original problem. To obtain a lower bound, constraints (5.9), (5.10), (5.11) and (5.12) are removed from problem (P5.1). This problem is referred to as problem (P5.2). By removing these constraints, all links $(v,w) \in \Omega$ are assumed to be feasible, regardless of the time that node v is visited. This may result in cycles and infeasibilities regarding time windows. Solutions to problem (P5.2) are not necessarily feasible to the original problem, but the reverse is true and therefore problem (P5.2) represents a lower bound on the original problem. The strength of this lower bound will depend on the width of the time windows of the subnodes. The smaller the partitioning width, the better the lower bound will be.

Both Wang and Regan (2002) and Zhang et al. (2010) use this type of binary integer programming (BIP) problem to find a lower bound on their problem. Here, two improvements are proposed. First, the set of links in the network is drastically reduced as follows. From each subnode, at most one link is allowed to a subnode of another original node. This is the feasible link to the subnode with the earliest time window. For example, consider two original nodes i and j with each three subnodes, respectively v_1, v_2, v_3 and w_1, w_2, w_3. Assume that link (v_1, w_1) is feasible i.e. $a_{v_1} + s_i + t_{ij} \leq b_{w_1}$. The links (v_1, w_2) and (v_1, w_3) will be feasible as well, since $b_{w_1} < b_{w_2} < b_{w_3}$. However, links (v_1, w_2) and (v_1, w_3) are not added to the network because a feasible solution which uses one of these links can easily be transformed to a feasible solution which uses link (v_1, w_1). Second, instead of solving the BIP problem, the LP relaxation is solved. The advantage is that problems with much larger networks (i.e. smaller partitioning width) can be solved within a comparable amount of computation time. This results in a better lower bound.

Since two objectives are considered in this chapter, a lower bound on both objectives is calculated using the time window partitioning method. To obtain a lower bound on the number of vehicles (LB_v), problem (P5.3) is solved.

$$\text{(P5.3)} \min \sum_{(v,w)\in\Omega} (t_{vw} + wait_{vw})x_{vw} + \sum_{i\in N} s_i \tag{5.14}$$

Subject to

$$\sum_{\substack{(v,w)\in\Omega \\ \delta(v)=i}} x_{vw} = 1 \qquad \forall i \in N\backslash\{0\} \tag{5.15}$$

$$\sum_{w:(0,w)\in\Omega} x_{0w} \leq K \tag{5.16}$$

$$\sum_{w:(w,v)\in\Omega} x_{wv} = \sum_{w:(v,w)\in\Omega} x_{vw} \qquad \forall v \in \omega \tag{5.17}$$

$$0 \leq x_{vw} \leq 1 \qquad \forall (v,w) \in \Omega \tag{5.18}$$

The objective function (5.14) minimizes the sum of travel times, service times and unavoidable (or necessary) waiting times. The unavoidable waiting time $wait_{vw}$ for a link $(v, w) \in \Omega$ is calculated as follows: $wait_{vw} = \max(0, a_w - b_v - s_v - t_{vw})$. The objective value is itself a lower bound on the total time needed to perform all tasks (there might be additional waiting times) and is then divided by the length of the planning period P to find a lower bound on the number of vehicles (Koo et al., 2004). For example, when the minimal time needed to perform all tasks is at least 95 hours and the planning period is 10 hours, at least 10 vehicles are required.

Lower bounds on total distance are calculated for each number of vehicles. This allows to compare each solution with the lower bound on distance for the corresponding number of vehicles. A lower bound on total distance when k vehicles are used ($LB_{d(k)}$) is found by solving problem (P5.4). A general lower bound on total distance (LB_d), independent of the number of vehicles, can be found by removing constraint (5.20) from this problem.

$$\text{(P5.4)} \min \sum_{(v,w)\in\Omega} d_{vw}x_{vw} + \sum_{i\in N} d_i \tag{5.19}$$

Subject to

(5.6) to (5.8)

$$\sum_{v:(0,v)\in\Omega} x_{0v} = k \tag{5.20}$$

$$0 \leq x_{vw} \leq 1 \qquad \forall(v,w) \in \Omega \tag{5.21}$$

To evaluate the quality of the lower bounds obtained by the proposed time window partitioning method, results are compared with lower bounds calculated by two simple methods. The first method is to solve the LP relaxation of the original formulation of the problem. The second method is to slightly relax the Subtour Elimination Constraints (SEC) of the original formulation by replacing constraints (4.9) and (4.10) by constraints (5.22) and (5.23).

$$a_i + s_i + t_{ij} \leq t_j + M(1 - x_{ij}) \qquad \forall(i,j) \in A, j \neq 0 \tag{5.22}$$

$$t_i + s_i + t_{ij} \leq b_j + M(1 - x_{ij}) \qquad \forall(i,j) \in A \tag{5.23}$$

In Table 5.3, the three methods for calculating general lower bounds on total distance (LB_d) are compared for the integrated problem for eight different problem instances. For each method the corresponding lower bound and its computation time are shown. The partitioning width for the LP relaxation of the time window partitioning method ranges from three to fifteen minutes, depending on the problem class, and is chosen to ensure that the problem can be solved within five minutes. The partitioning width for the BIP model is chosen in such a way that the computation time is about the same as for the LP relaxation. All lower bounds are computed in AIMMS using the CPLEX 12.0 solver. The two simple methods result in a rather weak lower bound. The time window partitioning method offers stronger lower bounds. Although computation times are much larger than for the relaxations of the original formulation, they are still acceptable. When comparing the BIP and LP relaxation of the time window partitioning method, it is clear that the LP relaxation offers on average the best results. Therefore, the LP relaxation of the time window partitioning method will be used to calculate lower bounds.

Table 5.3: Analysis of lower bounds

Class	LP relax.		relax SEC		TW partitioning			
					BIP		LP relax.	
	LB_d	T	LB_d	T	LB_d	T	LB_d	T
1.1	918	1	940	2	993	243	990	230
4.1	595	1	601	2	646	180	664	171
6.1	1524	1	1541	20	1571	294	1585	219
7.1	1153	1	1192	41	1273	229	1303	254
10.1	1806	1	1824	3	1893	123	1898	129
11.1	1435	1	1494	2	1565	157	1563	113
13.1	2908	1	2961	28	3169	493	3187	254
16.1	2329	1	2373	25	2486	175	2576	189

Finally, it should be noted that separate lower bounds are calculated for the sequential and integrated problem and that the lower bounds on the sequential problem are tighter than those on the integrated problem. The reason is that the average time window width is smaller for the sequential problem because the one-sided time windows of empty container supply and demand nodes are combined into a two-sided time window for allocations representing a street turn (see Section 4.4.1.2). Therefore a smaller partitioning width for the sequential approach is chosen without increasing computation time. For the sequential problem, partitioning width ranges from two to ten minutes, depending on the problem class.

5.6 Parameter testing

Several parameters are used in the deterministic annealing scheme which is discussed in Section 5.2.3. These parameters are:

- n_{it}: number of iterations,
- T_{max}: maximum threshold value,
- ΔT: threshold reduction parameter,
- n_{imp}: number of iterations without new best solution after which the search is restarted.

To optimize results, good parameter values need to be determined. Since the deterministic annealing scheme is implemented in several ways as discussed in 5.2.4, several values are defined for parameters T_{max}, ΔT and n_{imp}. Parameters are tested on a set of 16 test instances, one per problem class defined in Section 5.4.

First, the set of parameter values to be used in the single phase algorithms is determined. The following initial values are considered: $n_{it} = 100000$, $T_{max} = 6$, $\Delta T = 0.003$ and n_{imp} equal to 500 times the number of vehicles in the initial solution. A sensitivity analysis is performed on these values. The sensitivity analysis on the maximum threshold value T_{max} is shown in Figure 5.6. On the horizontal axis, the different values of T_{max} are shown while the vertical axis represents the average gap between the total distance of a solution and its lower bound ($LB_{d(k)}$). Results for both the sequential and integrated approach are presented. Gaps for the sequential approach are smaller than for the integrated approach since different and tighter lower bounds are used as discussed in the previous section. It is assumed that the value of T_{max} is related to the distances in the network under consideration. Therefore, a distinction is made between problems defined on a small region (25km^2) and problems defined on a large region (50km^2). The best solutions are found with T_{max} equal to four kilometers for problems defined on a small region and with T_{max} equal to eight kilometers for problems defined on a large region.

Instead of explicitly distinguishing between small and large regions, the value for ΔT is defined as a fraction of T_{max} i.e. $\Delta T = T_{max}/q$ with $q = 2000$ for the initial values. A sensitivity analysis on the value of q is presented in Figure 5.7. The figure shows that the value of q has only a small impact on solution quality. For both solution approaches, parameter ΔT is fixed at $T_{max}/2500$ since this offers on average the best results. The number of iterations without finding a new best solution after which the search is restarted n_{imp} has little effect on the solution quality as well. This parameter is kept at 500 times the number of vehicles in the initial solution.

The number of iterations n_{it} to be performed is analyzed in Figures 5.8 and 5.9. Figure 5.8 shows the average number of reductions in the number of vehicles found per step of 5000 iterations for both solution approaches. It is clear that reductions in the number of vehicles are almost all found during the first 40000 iterations. Similarly, Figure 5.9 shows the average reduction in total distance traveled per 5000 iterations. Performing 50000 iterations is assumed to be sufficient, since thereafter improvements are rather small.

Second, parameter values for the two-phase algorithms are determined. For each phase, the number of iterations is fixed at 50000 as for the single phase algorithms. For the second phase, where total distance is minimized, the parameter values of

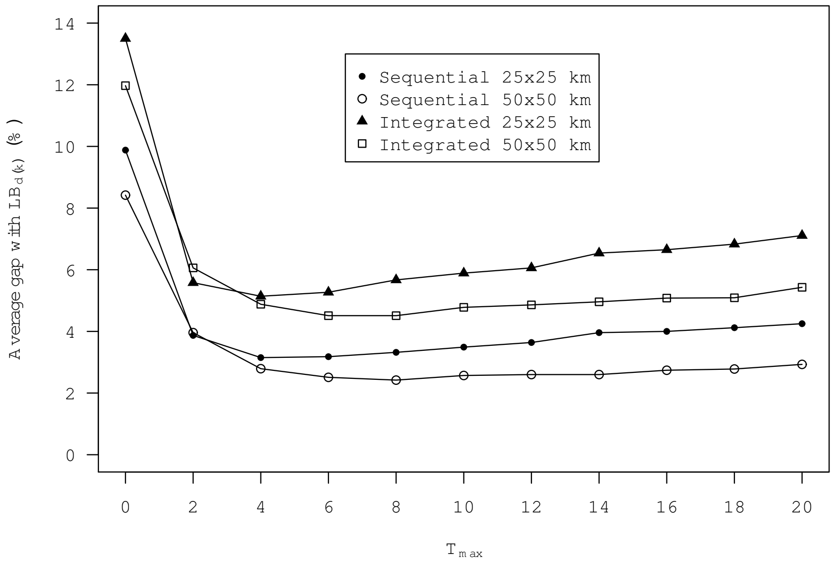

Figure 5.6: Sensitivity analysis on parameter T_{max} (single phase)

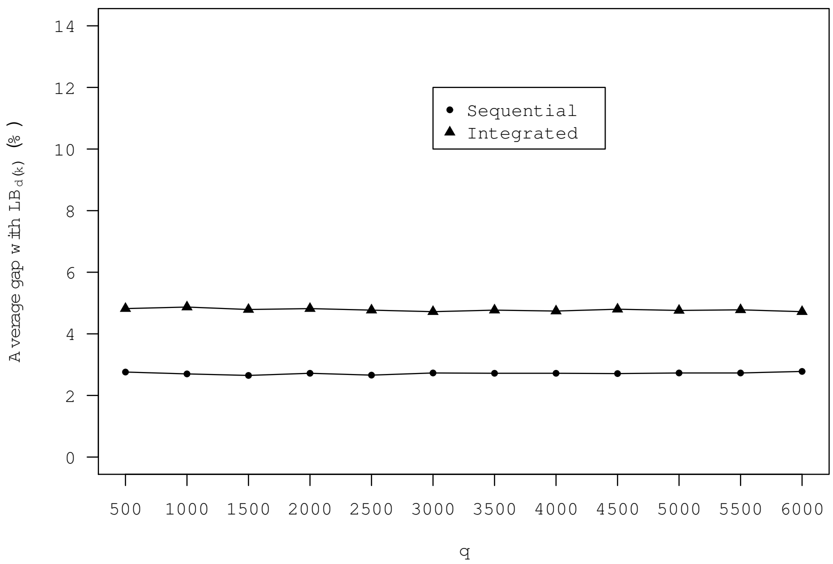

Figure 5.7: Sensitivity analysis on parameter $\Delta T = T_{max}/q$ (single phase)

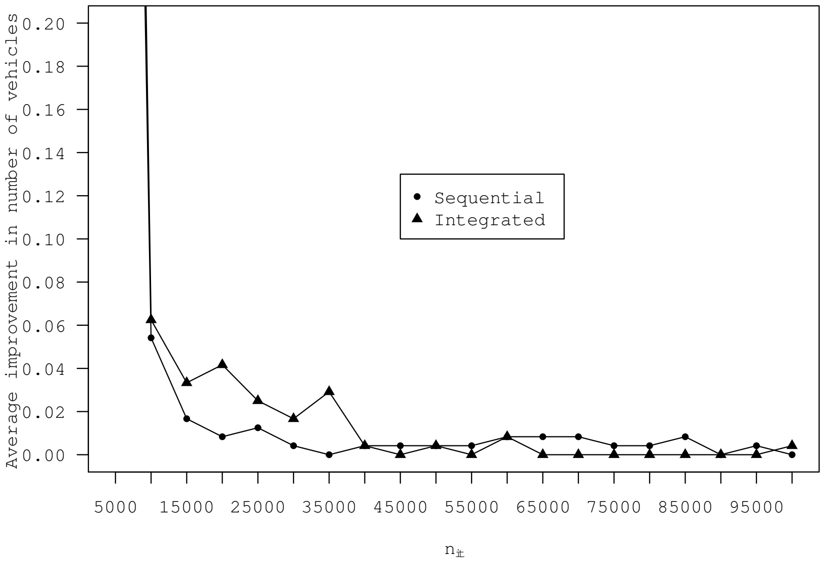

Figure 5.8: Effect of parameter n_{it} on number of vehicles

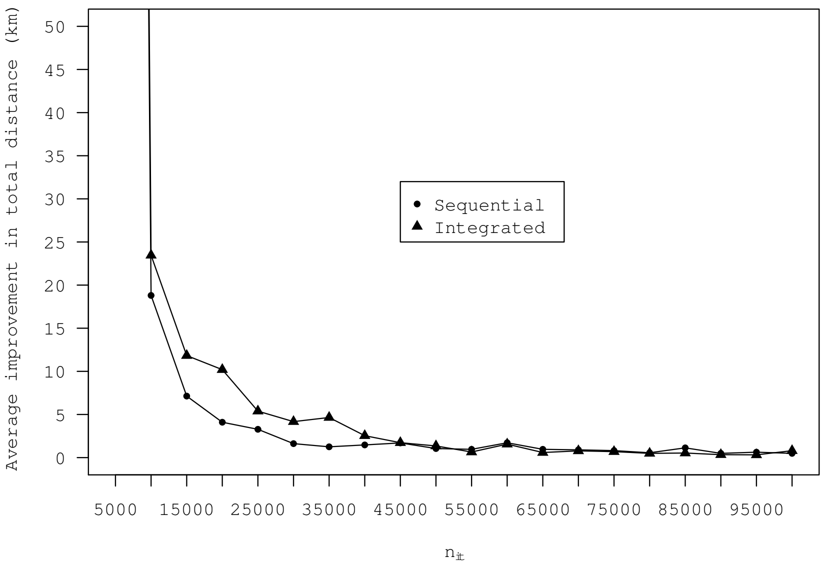

Figure 5.9: Effect of parameter n_{it} on total distance

the single phase algorithms are used. In the first phase, the number of vehicles is minimized by using objective function (5.4). The threshold value T is related to the secondary objective, minimizing the sum of squares of the number of nodes in each route, as explained in Section 5.2.4. Figure 5.10 shows the average gap between the number of vehicles used and its lower bound (LB_v) for several values of T_{max} for both the sequential and integrated approach. Based on the results in Figure 5.10, the value of parameter T_{max} is fixed at 8 for the sequential approach and at 12 for the integrated approach.

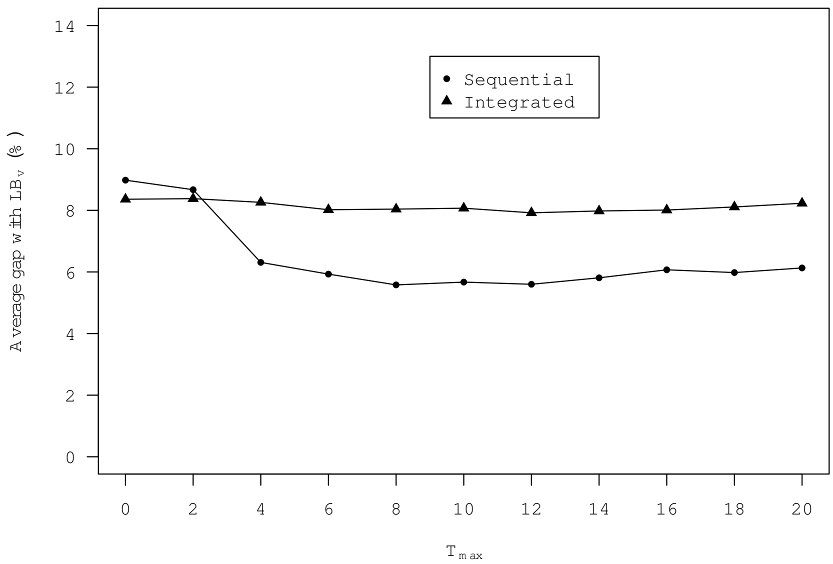

Figure 5.10: Sensitivity analysis on parameter T_{max} (first phase of two-phase algorithms)

The parameter value for ΔT during the first phase of the two-phase algorithms is analyzed in Figure 5.11. As for the single phase algorithm, the value of ΔT has only a limited effect on solution quality. Best results are obtained for a parameter value of $\Delta T = T_{max}/2000$. The number of iterations without finding a new best solution after which the search is restarted n_{imp} is again fixed 500 times the number of vehicles in the initial solution.

Finally, for the 1-DA_{TS} and 2-DA_{TS} algorithms, the number of iterations for which an arc cannot re-enter the current solution after it has been removed, is set at twenty. This value offers on average the best results, although differences are small (see Figure 5.12).

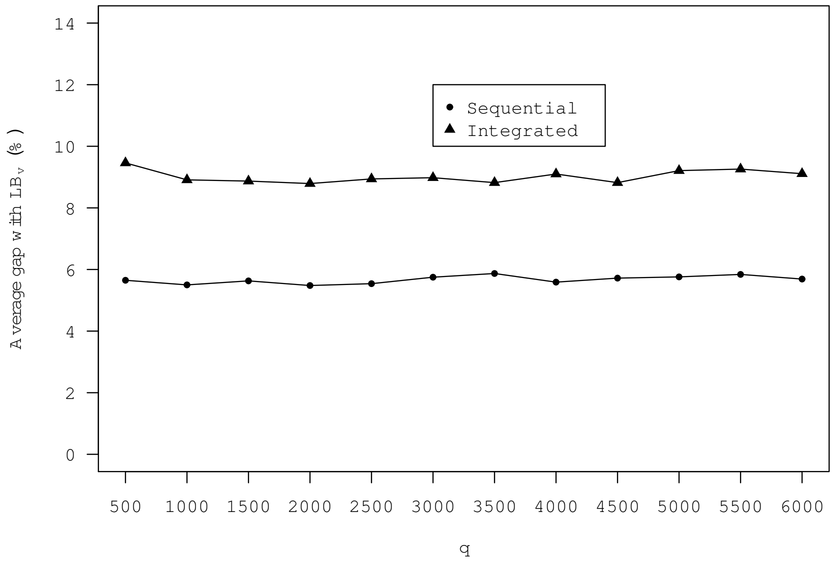

Figure 5.11: Sensitivity analysis on parameter $\Delta T = T_{max}/q$ (first phase of two-phase algorithms)

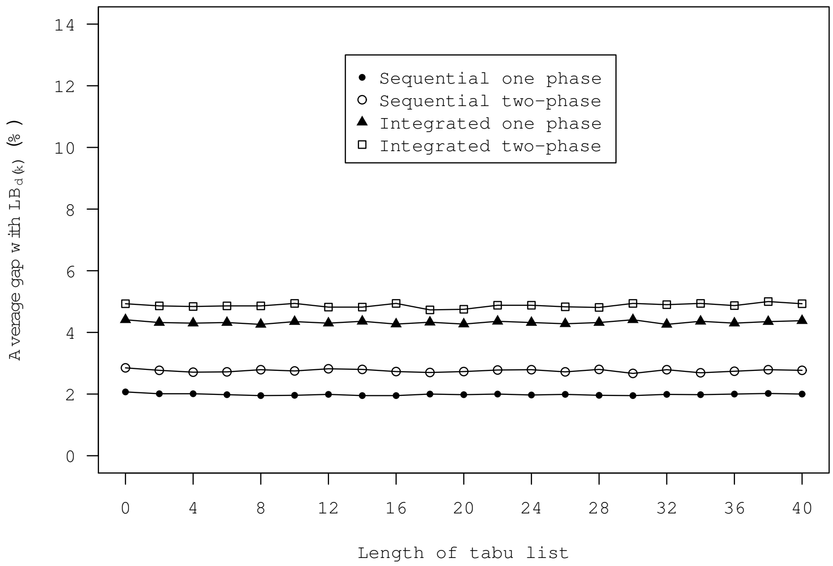

Figure 5.12: Sensitivity analysis on length of tabu list

5.7 Experimental results

This section discusses the experimental results of the deterministic annealing algorithm on the problem instances discussed in Section 5.4. An overview of these results and a comparison of the different variants of the algorithm is given in Section 5.7.1. Next, the sequential and integrated approach are compared with each other (Section 5.7.2). In Section 5.7.3, the robustness of the deterministic annealing algorithm with respect to changes in problem characteristics is discussed. The contribution to solution quality of the different local search operators and of the deterministic annealing scheme is analyzed in Section 5.7.4. Finally, the effect of performing street turns is discussed (Section 5.7.5).

5.7.1 Overview of results

The transportation problem and the deterministic annealing algorithm are implemented in C on a 2.1GHz Intel Core 2 laptop with 4GB RAM. All four variants of the algorithm are tested on the 48 problem instances for both the sequential and integrated solution approach. For each instance, average results over fifty runs of the algorithm are obtained. Detailed results for the sequential and integrated solution approach are presented respectively in Appendices B and C. A summary of these results is presented in Table 5.4 for the sequential approach and in Table 5.5 for the integrated approach. The first two rows in these tables show the average number of vehicles used and the average absolute gap with the corresponding lower bound. The average distance traveled and the average relative gap with the corresponding lower bound are presented in rows three and four. Different lower bounds are calculated for the sequential and integrated approach as discussed in Section 5.5. In the last row, average computation time in seconds is shown.

Tables 5.4 and 5.5 demonstrate that all algorithms are able to find good quality solutions in a small amount of computation time. When comparing the results of the single and two-phase algorithms, it is clear that the two-phase method performs much better in terms of number of vehicles. Average distances are higher for the two-phase algorithms than for the single phase algorithms which can be explained by the fact that the two objectives (minimize vehicles and distance) are often conflicting. Since minimizing the number of vehicles is prioritized over minimizing total distance, best solutions are obtained by the two-phase algorithms. This corresponds with the findings of Homberger and Gehring (2005) and Bent and Van Hentenryck (2006) that two-phase methods work well on problems with a hierarchical objective function.

Table 5.4: Summary of results: sequential approach

Value	1-DA	2-DA	1-DA$_{TS}$	2-DA$_{TS}$
Average number of vehicles	10.45	10.00	10.46	10.00
Average gap (absolute)	0.99	0.54	1.00	0.54
Average distance (km)	1802	1822	1800	1821
Average gap (%)	2.07	2.85	1.97	2.75
Average computation time (s)	2.51	3.91	2.94	4.39

Table 5.5: Summary of results: integrated approach

Value	1-DA	2-DA	1-DA$_{TS}$	2-DA$_{TS}$
Average number of vehicles	10.30	9.99	10.30	9.99
Average gap (absolute)	1.05	0.74	1.05	0.74
Average distance (km)	1800	1809	1797	1807
Average gap (%)	4.41	4.93	4.31	4.86
Average computation time (s)	3.01	4.43	3.49	4.91

When the deterministic annealing algorithms (1-DA, 2-DA) are compared with their variants in which tabu search elements are implemented (1-DA$_{TS}$, 2-DA$_{TS}$), results indicate that introducing elements of tabu search has a small, positive effect on solution quality. On the other hand, the algorithm becomes more complex and average computation time increases slightly. Whether an algorithm with or without the simple tabu search method should be used, is open for discussion and may be selected by the decision maker. In the remainder of this thesis, the 2-DA$_{TS}$-variant of the deterministic annealing algorithm will be considered unless stated otherwise.

5.7.2 Comparison of sequential and integrated approach

A comparison of the sequential and integrated approach should be based on real values instead of the gaps with the lower bounds since different bounds are calculated for both problems. Results in Tables 5.4 and 5.5 show that on average the integrated approach offers better results than the sequential approach for all algorithm variants and both in terms of the number of vehicles and total distance. Comparing results for each problem instance individually shows that the integrated approach almost always performs better (21%) or equally good (70%) in terms of the number of vehicles used. When both approaches result in the same number of vehicles, the integrated approach is able to find a better solution in terms of distance in 87% of the cases.

To further substantiate the fact that an integrated approach provides better results than a sequential one, a statistical test is performed on the results. For all 48 problem instances and for all four algorithm variants, the results of the integrated approach are compared with those of the sequential approach. This means that for each solution approach in total 192 results are obtained. Each of these results represents the average of the best solutions obtained during fifty runs of the algorithm. Clearly, for a given problem instance and algorithm variant, a dependence between the solutions of the sequential and integrated approach exists. As a consequence, a statistical test for two dependent samples should be used. Since it is not guaranteed that the populations of both solution sets follow the normal distribution and that they have the same variance, the t test for two dependent samples should not be used. Instead, the Wilcoxon matched-pairs signed-ranks test is used. This is a nonparametric test which may be applied on dependent samples when one or more of the assumptions of the t test for two dependent samples are violated. (Sheskin, 1997) The test will be used separately on the number of vehicles and on total distance traveled.

The Wilcoxon matched-pairs signed-ranks test works as follows. For each of the 192 solution pairs a difference score is calculated by subtracting the solution of the integrated approach from that of the sequential approach. Next, the test evaluates whether or not the median of these differences scores (indicated θ_D) equals zero. Since the aim is to demonstrate that the integrated approach outperforms the sequential one, a one-tailed test with the following null and alternative hypotheses is applied:

$$H_0 : \theta_D = 0 \tag{5.24}$$

$$H_1 : \theta_D > 0 \tag{5.25}$$

When the null hypothesis is rejected, the integrated approach offers significantly better solutions (solutions with lower objective values).

The Wilcoxon T statistic is calculated based on the difference scores. First, the absolute values of these difference scores are ranked. The highest absolute difference receives the highest rank. Difference scores of zero are eliminated from the analysis. Next, the sign of each difference score is placed in front of its rank. Finally, all ranks with positive signs are summed together ($\sum R+$) and all ranks with negative signs are summed together ($\sum R-$). The Wilcoxon T statistic is equal to the lowest absolute value of $\sum R+$ and $\sum R-$. The number of non-zero difference scores is indicated by

n. For small values of n ($n < 50$), critical values for the Wilcoxon T statistic are available in tabular form. When n is larger, like in this thesis, the distribution of the Wilcoxon T statistic may be approximated by the normal distribution. Equation 5.26 shows the calculation of the normal approximation z of the Wilcoxon T statistic. (Sheskin, 1997)

$$z = \frac{T - \frac{n(n+1)}{4}}{\sqrt{\frac{n(n+1)(2n+1)}{24}}} \tag{5.26}$$

At a significance level of 0.01, the alternative hypothesis H_1 is supported when:

- $\sum R+ > |\sum R-|$
- the absolute value of z is equal to or greater than the corresponding critical value of the normal distribution which is 2.33

Table 5.6 gives an overview of the test results. For both objectives, the number of vehicles (V) and total distance (D), the sum of the positive ranks, the sum of the negative ranks, the Wilcoxon T statistic and the corresponding absolute value of z are shown. Since both $|z|$ values are larger than 2.33, the integrated approach offers significantly better results than the the sequential approach, both in terms of the number of vehicles and total distance (at a 1% significance level).

Table 5.6: Results of Wilcoxon matched-pair signed-rank test

	V	D
$\sum R+$	1408	14941
$\sum R-$	-303	-3587
Wilcoxon T	303	3587
n	58	192
$\|z\|$	4.28	7.39

5.7.3 Robustness of the algorithm with respect to problem characteristics

To analyze the robustness of the deterministic annealing algorithm with respect to problem characteristics, a distinction between both solution approaches is made. Table 5.7 presents effects on solution quality when problem characteristics are altered.

Solution quality is indicated by average gaps between solutions and their lower bounds on both objectives. For each problem characteristic defined in Section 5.4, average gaps over all instances with a high value (+) minus average gaps over all instances with a low value (-) are presented. This difference gives an indication of the effect on solution quality of increasing a problem characteristic from its low to its high value. It should be stressed that only an indication of the effect is given since different problem instances are randomly generated for each combination of factor values. Table 5.7 shows that the largest effect on solution quality stems from increasing the number of nodes. Problem instances with a larger number of nodes have a larger number of feasible links which increases problem complexity. Finding good quality solutions becomes slightly more difficult. For the same reason, a similar but smaller effect is noticed when the number of terminals is increased. The effects of time window width and area of problem region are rather small. Based on these results, it is concluded that the deterministic annealing algorithm offers results of similar quality for all types of problems i.e. the algorithm is robust to changes in problem characteristics.

Table 5.7: Comparison of problem classes

Factor	Sequential		Integrated	
	V	D	V	D
F1: time window width	-0.03	0.40	-0.21	0.04
F2: number of terminals	0.08	0.64	0.23	1.04
F3: number of nodes	0.72	1.36	0.63	2.44
F4: coordinates	0.30	-0.20	0.47	-0.44

5.7.4 Contribution of local search operators

The contribution to solution quality of the different local search operators and of the deterministic annealing scheme may be analyzed as well. The second phase of the two-phase deterministic annealing algorithm with tabu search (2-DA_{TS}) is used for this analysis. The algorithm is used five more times (fifty runs each) on each instance. The first time, the deterministic annealing scheme is left out, meaning that only solutions resulting in an improvement of the objective function are accepted. The other four times, each time a single local search operator is removed from the search. Table 5.8 gives an overview of the results. As expected, removing the deterministic annealing scheme has by far the largest negative impact on results. With respect to the local search operators, the *exchange* and *2-Opt** operators seem to have the largest impact on results, although interaction effects between local search operators are ignored in this analysis.

Table 5.8: Contribution of local search operators and deterministic annealing scheme

	Average distance (km)	Average gap with $LB_{d(k)}$ (%)
Original algorithm	1807	4.86
No deterministic annealing	1891	9.88
No *intra-route* operator	1812	5.12
No *relocate* operator	1813	5.20
No *2-Opt** operator	1823	5.78
No *exchange* operator	1826	5.91

5.7.5 Effect of street turns

Both in literature and practice the direct transportation of empty containers between consignees and shippers is often proposed as a method to reduce empty container movements around intermodal container terminals. These types of transports, called street turns, are allowed in this thesis as well. Although street turns are considered as highly desirable by all parties involved, some practical limitations for implementing them exists (see Section 2.2.2 for a detailed description).

In this section, the advantage of allowing and implementing street turns is analyzed. The 2-DA_{TS} algorithm is applied on the integrated problem for this purpose. This algorithm is already used in the previous sections for the problem situation where street turns are allowed. Two additional problem situations are considered in this section.

As discussed in Section 2.2.2, street turns may require some extra work related to damage inspection and paperwork regarding insurance and liability issues. The first additional problem situation takes into account the additional time which might be needed to perform these activities. The original problem setting where street turns are allowed is considered but the travel time between two nodes $i \in N_S$ and $j \in N_D$ is augmented with a constant value. This constant values is varied from five minutes to one hour, in steps of five minutes.

Second, the problem is solved with the restriction that street turns are not allowed. This means that it is no longer possible to travel directly between two nodes $i \in N_S$ and $j \in N_D$. Instead, a detour to a container terminal is required to drop off the empty container picked up at node $i \in N_S$. At this container terminal another empty container is picked up and delivered to node $j \in N_D$. The distance d_{ij} between the nodes is calculated as follows:

$$d_{ij} = \min_{r \in N_T} (d_{ir} + d_{rj}) \qquad \forall i \in N_S, \forall j \in N_D \tag{5.27}$$

The travel time t_{ij} is calculated in a similar way but augmented with the pickup and drop off times for both empty containers involved.

Table 5.9: Effect of street turns

Problem situation	Additional time (min)	V	D
	0	9.99	1807
	5	10.26	1826
	10	10.58	1838
	15	10.90	1850
	20	11.12	1866
Street turns	25	11.35	1885
allowed	30	11.63	1901
	35	11.80	1916
	40	11.90	1938
	45	11.95	1966
	50	11.97	2000
	55	11.98	2033
	60	12.00	2064
No street turns	-	11.93	2320

For each problem situation the average number of vehicles (V) and the average total distance (D) is shown in Table 5.9. Not allowing street turns considerably increases the number of vehicles used (+19%) and total distance traveled (+28%). When taking additional time to perform street turns into account, both objective values increase as well. However, as long as the additional time to perform a street turn is not more than 40 minutes, solutions are better than when no street turns are implemented. When the additional time is larger than 40 minutes, the number of vehicles is higher than when no street turns are allowed, although total distance is still much lower. This is an interesting conclusion since it indicates that even when performing a street turn would take a considerable amount of additional time, it is still a good approach to reduce the number of vehicles and total distance traveled.

5.8 Conclusions and further research

A deterministic annealing meta-heuristic is proposed to solve a full truckload routing problem in drayage operations which is described in the previous chapter. The primary objective is to minimize the number of vehicles used while the secondary objective is to minimize total distance traveled. For both the sequential and integrated solution approach, four variants of the algorithm are described. Extensive numerical experiments on a set of randomly generated problem instances are performed. By comparing solutions with lower bounds, it is demonstrated that all variants are able to find high quality solutions in a small amount of computation time. The robustness of the algorithms with respect to changes in problem characteristics is indicated as well. Results show that a two-phase algorithm which combines deterministic annealing with some elements of tabu search offers the best results. In the first phase of the algorithm, the number of vehicles is minimized while partially ignoring the secondary objective. In the second phase, total distance is minimized. A comparison of the sequential and integrated solution approach indicates that an integrated approach for planning daily drayage operations is significantly better than a sequential approach. Finally, the advantage of implementing street turns is analyzed. It is concluded that allowing street turns considerably reduces the number of vehicles required and total distance traveled in drayage operations. Even when performing a street turn would take a limited amount of additional time, performing street turns is still favorable to situations in which street turns are not allowed.

In Chapter 6, two alternative objective functions for the (integrated) drayage problem are considered. First, the problem is interpreted as a bi-objective problem by not assigning priority to one of the objectives. Second, the objective to minimize total route duration instead of total distance traveled is introduced. It is analyzed how the deterministic annealing algorithm may be adapted to accommodate these alternative objective functions.

Further research could focus on a number of extensions of the problem. Currently it is assumed that sufficient empty containers are available at each container terminal. This assumption might be relaxed by imposing a limit on container availability at each terminal. This reduces the set of feasible solutions for the empty container allocation subproblem and strongly complicates the integrated drayage problem as is discussed by Zhang et al. (2011b). Another extension may be to consider a problem with multiple container and vehicle types. For some combinations of container and vehicle type it may for example be feasible to transport two containers simultaneously by a single vehicle. Besides, containers of different owners may be assumed, restricting the use of a container to a particular set of consignees and shippers. Future research could focus on how the solution algorithm may be adapted to take this variety in containers and vehicles into account. Finally, in order to use the proposed modeling approach in real-time dispatching, a dynamic version of the algorithm should be developed. In a dynamic problem setting, some problem information changes or becomes available during the planning period rather than being known beforehand. Examples include new requests arriving or existing requests being canceled during the day, changes in customer time windows and vehicle breakdowns. Although the current modeling approach provides good results within an acceptable time frame for real-time usage, a slightly different algorithm would be required. In a dynamic environment it may not be desirable to plan vehicle routes completely from scratch each time new information becomes available. Instead, the existing planning could be adapted to take the new problem information into account. A new request may for example be inserted in an existing route, after which the solution may be reoptimized. Furthermore, in a highly dynamic environment it may be reasonable to focus on optimizing vehicle routes for the near future, while less attention is being paid to the far future, since it is likely that the problem situation will be considerably different by the time this moment is reached. (Berbeglia et al., 2010; Pillac et al., 2011)

Chapter 6

Optimization of drayage operations: alternative objective functions

6.1 Introduction

In the previous chapters, drayage operations are optimized according to a hierarchical objective function. A deterministic annealing algorithm is proposed to solve both the sequential and integrated drayage problem. This chapter analyzes how the algorithm may be applied in situations where alternative objective functions are preferred (Figure 6.1). Since the previous chapter showed that an integrated approach outperforms a sequential one, only an integrated approach is considered in this chapter.

In the first part of the chapter[1] (Section 6.2), the hierarchical objective function from the previous chapter is replaced by a bi-objective function which gives no priority to one of the two objectives (minimizing the number of vehicles and minimizing total distance traveled). By interpreting the problem as a bi-objective problem, the trade-off between both objectives can be analyzed. A bi-objective version of the deterministic annealing algorithm is proposed to solve the problem. In the second part of the chapter (Section 6.3), the objective to minimize total route duration instead of total distance is considered. Using total route duration as an objective makes the evaluation of the effect of a local search move on the objective value more complex

[1]This part of the chapter is based on Braekers et al. (2011a) and Braekers et al. (2012a).

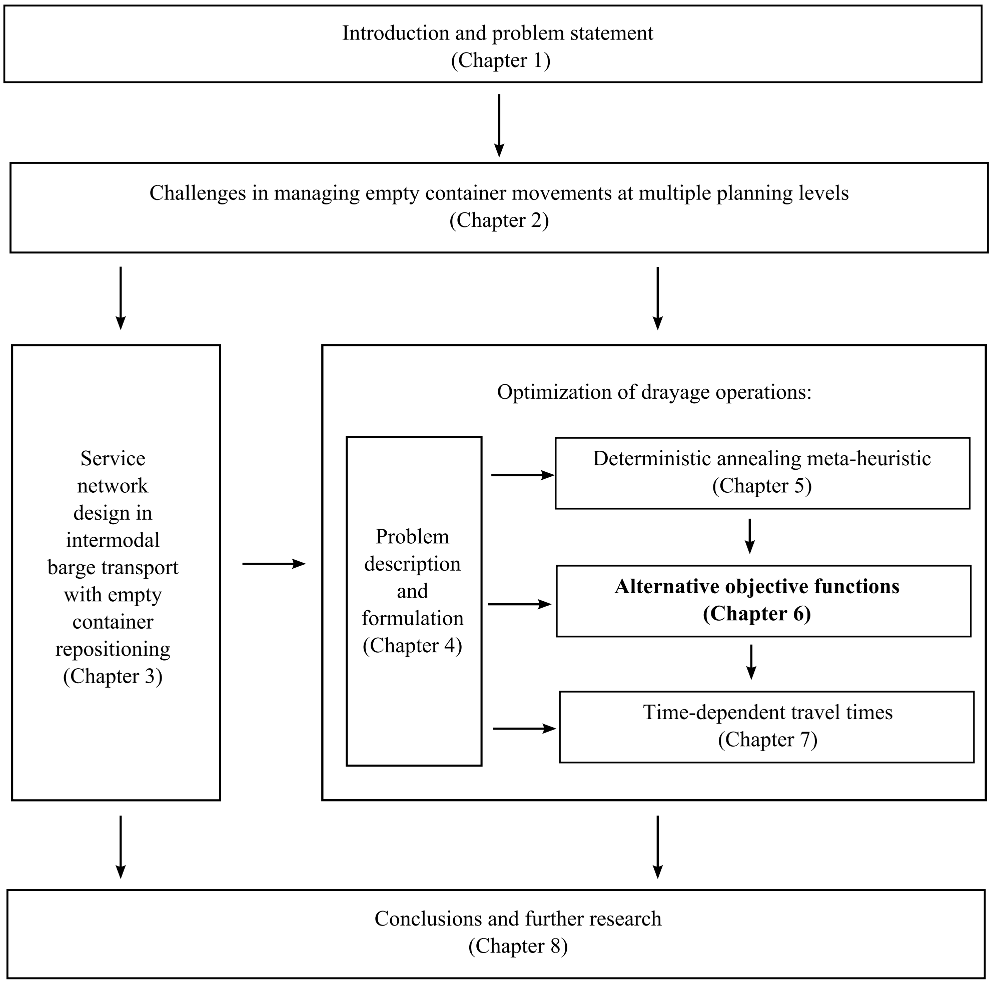

Figure 6.1: Outline of the thesis

than in the previous chapter. A method to deal with this increased complexity is discussed. Results indicate that the proposed deterministic annealing algorithm outperforms a recent time window partitioning method proposed by Zhang et al. (2010). Finally, Section 6.4 contains conclusions and opportunities for further research.

6.2 Bi-objective approach

Typically a hierarchical objective function is used in vehicle routing problems. The primary objective is to minimize the number of vehicles while the secondary objective is to minimize total distance, total travel time or total route duration (Bräysy and Gendreau, 2005a; Jozefowiez et al., 2008; Gendreau and Tarantilis, 2010). In the previous chapter, a hierarchical objective function is used for the integrated drayage problem as well. A natural extension is to take a bi-objective approach by not assigning priority to one of the objectives. While minimizing the number of vehicles affects vehicle investment and labor costs, minimizing distance affects time and fuel resources (Ombuki et al., 2006). Clearly, both objectives might be conflicting in some cases (Caseau and Laburthe, 1999; Jozefowiez et al., 2008). Solutions with the minimal number of routes k_{opt} may have a total distance which is higher than the total distance of solutions with $(k_{opt} + 1)$ or $(k_{opt} + 2)$ vehicles. Using a hierarchical objective function will bias the search towards minimizing the number of vehicles, while a bi-objective approach will result in a set of good solutions which use different numbers of vehicles. In this way, the possible trade-off between both objectives will be revealed. This trade-off information can be very useful to the decision maker. For example, given a number of vehicles that are available, expected routing costs to perform all transportation tasks can be estimated. On the other hand, when the transportation tasks to be performed are known, the minimum number of trucks that need to be allocated to these tasks in order to keep the operational routing cost below a certain level can be deducted. Even tactical decisions about changing the fleet size may be supported by the provided trade-off information. (Tan et al., 2006a) In the latter case, daily distance-related costs should be compared over a longer planning horizon (e.g. three months) for different fleet sizes. To the author's knowledge, no other bi- or multi-objective approach is proposed for a drayage problem in intermodal freight transportation.

The problem formulation of the bi-objective integrated drayage problem is exactly the same as that of the integrated problem in the previous chapter (see Section 4.4.2), except that objective function (4.5) is replaced by objective function (6.1).

$$\min f = (f_1, f_2) \tag{6.1}$$

with:

$$f_1 = \sum_{i:(0,i)\in A} x_{0i} \tag{6.2}$$

$$f_2 = \sum_{(i,j)\in A} d_{ij}x_{ij} + \sum_{i\in N} d_i \tag{6.3}$$

In Section 6.2.1, literature on bi- and multi-objective vehicle routing is reviewed. Pareto optimality and the dominance concept are discussed in Section 6.2.2. Section 6.2.3 discusses how the two-phase integrated algorithm (2-DA$_{\text{TS}}$) presented in the previous chapter is adapted to take into account the bi-objective optimization function. Finally, in Section 6.2.4 results are discussed.

6.2.1 Related literature

A recent overview of research on multi-objective vehicle routing problems can be found in Jozefowiez et al. (2008). According to the authors, three approaches exist to deal with a multi-objective problem. In an a priori approach, the decision maker provides preferences for the different objectives, while in an interactive approach the decision maker's choices are made during the solution process. Finally, in an a posteriori approach the decision maker chooses among a set of non-dominated solutions that has been generated. The approach followed here clearly fits in the last category.

Several methods may be used to solve multi-objective problems. Overviews of these methods can be found among others in Ehrgott and Gandibleux (2002, 2004) and Jozefowiez et al. (2008). Two main categories of solution methods for multi-objective problems can be distinguished: scalar methods, using mathematical transformations, and Pareto methods, directly using the notion of Pareto dominance. The most popular scalar method is to use a weighted objective function. The advantage of this method is that the problem is transformed to a single objective problem and thus existing (meta-)heuristics described in literature may be used. (Ehrgott and Gandibleux, 2002; Jaszkiewicz, 2004; Jozefowiez et al., 2008) A disadvantage is that agreeing on a set of weights is not straightforward (Corberan et al., 2002). Other scalar methods include goal programming and the ϵ-constraint method. In the goal programming method, goals are set for each of the objectives and the distance between solutions and these goals is minimized. A recent goal programming method for a bi-objective Vehicle Routing Problem with Time Windows (VRPTW) is presented by Ghoseiri and Ghannadpour (2010). In the ϵ-constraint method, a single objective is optimized while the other objectives are considered as constraints. (Jozefowiez et al., 2008)

In contrast to scalar methods, Pareto methods use the notion of Pareto dominance directly. They are often used within an evolutionary approach. An overview of evolutionary multi-objective optimization methods can be found in Zitzler et al. (2004), while references to papers using such methods are presented among others in Jozefowiez et al. (2008). Evolutionary algorithms for VRPTW and truck and trailer vehicle routing problems with the same objective function as in this chapter can be found in Ombuki et al. (2006) and Tan et al. (2006a,b).

The solution algorithm presented in this chapter for the bi-objective integrated drayage problem can be categorized as a scalar method and resembles the ϵ-constraint method. For each number of vehicles, a solution with minimal total distance is sought, while keeping the number of vehicles constant. A similar method is used by Corberan et al. (2002) and Pacheco and Marti (2006) for the rural school bus routing problem where the number of buses and the maximum time a student spends on a bus are minimized.

6.2.2 Pareto optimality and dominance concept

Since a bi-objective approach is used and the objectives might be conflicting, a single optimal solution to the problem will often not exist. Instead, the goal is to find the set of Pareto optimal or efficient solutions.

According to Ehrgott and Gandibleux (2004), a multi-objective optimization problem can be defined as

$$\min_{\boldsymbol{x}\in X}(f_1(\boldsymbol{x}), ..., f_p(\boldsymbol{x})) \tag{6.4}$$

where $X \subset \mathbb{R}^n$ is the set of feasible solutions and $f : \mathbb{R}^n \to \mathbb{R}^p$ is a vector valued objective function with p different objectives. A solution $\boldsymbol{x} \in X$ is said to weakly dominate solution $\boldsymbol{x'}$ ($\boldsymbol{x} \preceq \boldsymbol{x'}$) if $\forall 1, ..., p : f(\boldsymbol{x}) \leq f(\boldsymbol{x'})$. A solution $\boldsymbol{x}$ dominates solution $\boldsymbol{x'}$ ($\boldsymbol{x} \prec \boldsymbol{x'}$) if and only if $\boldsymbol{x} \preceq \boldsymbol{x'}$ and $\exists j \in \{1, ..., p\} : f_j(\boldsymbol{x}) < f_j(\boldsymbol{x'})$. A solution $\boldsymbol{x} \in X$ is called efficient or Pareto optimal if no other solution $\boldsymbol{x'} \in X$ exists which dominates $\boldsymbol{x}$. In other words, no solution is at least as good as $\boldsymbol{x}$ for all criteria, and strictly better for at least one. If $\boldsymbol{x}$ is efficient then the corresponding objective vector $f(\boldsymbol{x}) = (f_1(\boldsymbol{x}), ..., f_p(\boldsymbol{x}))$ is called non-dominated. Solving a multi-objective optimization problem means finding the set of efficient solutions X_E. Its image in objective space Y_N is referred to as the non-dominated frontier or efficient frontier. For a more detailed description of Pareto optimality and its underlying principles, the reader is referred to Ehrgott and Gandibleux (2002, 2004) and Ehrgott (2005).

Since exactly solving our problem within reasonable computation time seems not feasible for large problem instances, in the following section a meta-heuristic approach is proposed to find a set of solutions S that approximates the set of efficient solutions X_E. This set S is composed of mutually non-dominated points, i.e. $\nexists \boldsymbol{x^1}, \boldsymbol{x^2} \in S | \boldsymbol{x^1} \prec \boldsymbol{x^2}$. In the remainder of this chapter, the set of objective vectors corresponding to solution set S is referred to as the set of non-dominated solutions.

6.2.3 Bi-objective deterministic annealing algorithm

The bi-objective problem has the advantage that one of the objective values (the number of vehicles) can only take on a limited number of discrete values: integers between the lower bound and the total number of nodes. Preliminary results even showed that total distance could only be decreased by adding a limited number of extra vehicles to the lower bound. Solutions that use even more vehicles are likely to be dominated by solutions which use less vehicles. Hence, an efficient method to find a set of non-dominated solutions is to look for a solution with minimum total distance for each of these limited values for the number of vehicles.

A simple approach would be to repeatedly solve the problem using the algorithm for a hierarchical objective function presented in Chapter 5. This algorithm gives priority to minimizing the number of vehicles. After the problem is solved for the first time, a solution with the minimum number of vehicles k_{min} would be obtained. Next, the problem can be solved repeatedly while imposing a lower limit of $(k_{min} + 1), (k_{min} + 2)$, etc. on the number of vehicles. This means that from the moment a solution with the number of vehicles equal to this limit is found, no further attempts to reduce the number of vehicles are made. Only total distance is minimized during the following iterations. In the remainder of this chapter, this approach is referred to as the iterative method (IM). The disadvantage of this iterative method is that each time the problem is solved, information from previous iterations is neglected.

A more sophisticated approach is presented in this section. The approach explicitly takes the bi-objective problem context into account and is compared with the iterative method in Section 6.2.4. The approach is denoted as a bi-objective deterministic annealing algorithm (BI-DA). The idea is that when looking for a minimal-distance solution with k vehicles, information on previously found solutions (with less than k vehicles) may be used. The proposed two-phase solution algorithm works as follows. In the first phase, a solution with the minimal number of vehicles k_{min} is searched for. Hence, this solution phase is very similar to the first solution phase for the integrated problem with a hierarchical objective function described in Section 5.2.4.2. Optimal empty container allocations are found by solving a transportation problem and a simple parallel insertion heuristic is used to find an initial solution for the problem. The number of vehicles used by this solution is denoted by k_{init}. The algorithm then tries to reduce the number of vehicles of the initial solution one by one during a predefined number of iterations of the deterministic annealing meta-heuristic. After half of the predefined number of iterations, the optimal empty container allocations are relaxed to return to an integrated problem setting and the solution is improved further. Meanwhile, for each number of vehicles for which a solution is found, the solution with minimum distance is stored in solution set S. This set will serve as input for the second solution phase. At the end of the first solution phase, a solution with the minimum number of vehicles k_{min} is obtained and S contains $k_{init} - k_{min} + 1$

solutions.

In the second phase, a set of non-dominated solutions for the bi-objective problem is obtained. This is done by iteratively minimizing total distance and increasing the number of vehicles by one. The deterministic annealing meta-heuristic combined with elements of tabu search is used (see Section 5.3). An overview of the second solution phase can be found in Algorithm 2. The current number of vehicles k_{cur} is set equal to the lowest number of vehicles for which a solution was found in phase one. The current solution $\boldsymbol{x}$ is initialized as the corresponding solution in solution set S. The solution phase consists of a loop which is continued until a predefined stopping criterion is met. Each iteration in the loop consists of two steps. First, the total distance of the current solution $\boldsymbol{x}$ is minimized while keeping the number of vehicles fixed at k_{cur}. A predefined number of iterations of the deterministic annealing meta-heuristic is used for this purpose. The *intra-route*, *relocate*, *2-Opt** and *exchange* operators are applied. A new solution is accepted if it has a total distance lower than the total distance of the current solution plus the threshold value. No route reduction operators are applied. After a predefined number of iterations, the final solution $\boldsymbol{x_b}$ with k_{cur} vehicles is obtained. This solution is stored in solution set S (and replaces the solution with k_{cur} vehicles currently in S). Second, it is checked whether the stopping criterion is met. If this is not the case, the current number of vehicles k_{cur} is increased by one. A new current solution with k_{cur} vehicles is then selected. This solution can be obtained in two ways:

- Solution $\boldsymbol{x^1}$ in S with k_{cur} vehicles, if there exists one
- Solution $\boldsymbol{x^2}$ obtained by applying a route splitting operator on solution $\boldsymbol{x_b}$

The best of these solutions is selected to become the new current solution and another iteration in the loop is started. The advantage of selecting the new current solution in this way is that information on a previously found solution is used. This previous solution is either a solution found during the first phase of the algorithm or a solution with one vehicle less which was found during the second phase of the algorithm. As a result, a good initial solution is obtained for the deterministic annealing meta-heuristic in the next iteration. Another advantage over the iterative method is that the proposed algorithm spends only once computation time on reducing the number of vehicles.

The route splitting operator that is used to transform a solution with k vehicles to a solution with $(k + 1)$ vehicles works as follows. It finds the best (least distance) way to split one of the current routes into two new routes. The operator is tested

Algorithm 2 Overview of second solution phase

$k_{cur} = k_{min}$
$\boldsymbol{x} = \boldsymbol{x_b} = \{\boldsymbol{x} \in S : f_1(\boldsymbol{x}) = k_{cur}\}$
$stop = 0$
while $stop = 0$ **do**
  Minimize distance of $\boldsymbol{x} \rightarrow \boldsymbol{x_b}$
  Save $\boldsymbol{x_b}$ in S
  if stopping criterion is met **then**
    $stop \leftarrow 1$
  else
    $k_{cur} \leftarrow k_{cur} + 1$
    Find $\boldsymbol{x}$ with $f_1(\boldsymbol{x}) = k_{cur}$:
      $\boldsymbol{x}$ is best of $\{\boldsymbol{x^1}, \boldsymbol{x^2}\}$ with
        $\boldsymbol{x^1} = \{\boldsymbol{x} \in S : f_1(\boldsymbol{x}) = k_{cur}\}$
        $\boldsymbol{x^2}$ found by applying split operator on $\boldsymbol{x_b}$
  end if
end while
Remove dominated solutions from S

on all routes and a best improvement strategy is followed. The stopping criterion of the second solution phase is defined as a number of times (three in this thesis) the number of vehicles was increased without obtaining a solution with a lower total distance. When the stopping criterion is met, dominated solutions are removed from solution set S. The set S then represents the final solution set to the problem.

Finally, a further improvement of the BI-DA algorithm is proposed. This improvement is related to the maximum threshold value T_{max} during the second solution phase. Up to now, T_{max} is kept constant throughout the search while the number of vehicles is increased after each iteration in the loop. The proposed improvement is to gradually reduce T_{max} while the number of vehicles is increased. The reason is as follows. When the number of vehicles increases, the nodes are divided over more routes and hence more spare time will be available in each route. As a result, the number of feasible local search moves will increase. To avoid the acceptance of local search moves that considerably worsen the objective value while numerous other and better moves exist, the maximum threshold value may be reduced. In this thesis, it is proposed to reduce T_{max} by ten percent each time the number of vehicles is increased. This version of the bi-objective deterministic annealing algorithm is denoted BI-DA*.

6.2.4 Experimental results

Three solution algorithms are proposed for the bi-objective drayage problem: an iterative method (IM), a bi-objective deterministic annealing algorithm (BI-DA) and a bi-objective deterministic annealing algorithm where the maximum threshold value is gradually reduced (BI-DA*). The 48 randomly generated problem instances presented in Section 5.4 are used to test the robustness and to compare the performance of the algorithms. The same parameter settings as discussed in Section 5.6 are implemented and the lower bounds which are calculated in the previous chapter (LB_v, LB_d, $LB_{d(k)}$) are valid for the bi-objective problem as well.

For all three algorithms, 50 runs are performed on all 48 problem instances. An example of a solution set obtained by a single run of the BI-DA* algorithm for instance 1.1 is shown in Figure 6.2. The number of vehicles and total distance are shown respectively on the x- and y-axis. A set of five non-dominated solutions is found. They are indicated by a circle. Besides these solutions, lower bounds for the problem instance are depicted. The vertical bar represents the lower bound on the number of vehicles (LB_v) while the horizontal bar represents the general lower bound on total distance, independent of the number of vehicles used (LB_d). Finally, the squares indicate the specific lower bounds on total distance for the corresponding number of vehicles ($LB_{d(k)}$).

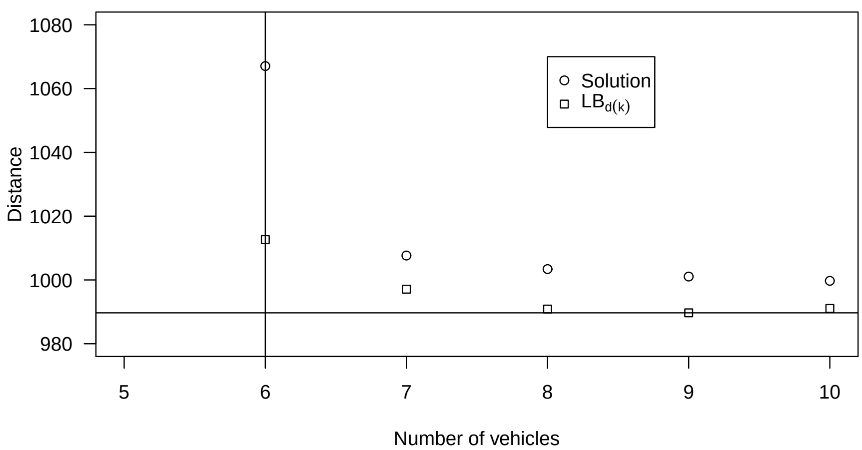

Figure 6.2: Solution set for instance 1.1

Figure 6.2 shows that a solution with the number of vehicles equal to the lower bound has been found. As for most instances, increasing the number of vehicles by one leads to a considerable reduction in total distance traveled. On average this reduction is 1.96%. When increasing the number of vehicle further, the reduction in total distance is generally much lower. From one to two extra vehicles and from two to three extra vehicles, average reductions in total distance of 0.63% and 0.29% are found. Another observation that can be made from Figure 6.2 is that the gap between the total distance traveled and the specific lower bound becomes smaller when the number of vehicles increases. A similar observation is made for all other instances. Often this is even the case when the number of vehicles is increased further and the solutions that are found are dominated by others.

Evaluating the quality of solutions of a bi- or multi-objective problem is not straightforward. The same accounts for comparing different solution techniques on these problems. In literature, various quality indicators are proposed and often a combination of these is used. (Zitzler et al., 2003, 2008; Knowles et al., 2006) According to Knowles et al. (2006), only quality indicators that are Pareto compliant should be used. An indicator is Pareto compliant when it does not contradict the weak Pareto dominance criterion. This means that the indicator value for solution set A should be at least as good as the indicator value of solution set B whenever A if preferable to B with respect to weak Pareto dominance (every solution in B is weakly dominated by at least one solution in A). (Knowles et al., 2006)

In this thesis, three Pareto compliant quality indicators are used: the hypervolume indicator (I_H), the unary multiplicative epsilon indicator (I_ϵ) and the coverage indicator (I_C). The hypervolume indicator $I_H(A)$, introduced by Zitzler and Thiele (1999), measures the portion of the objective space weakly dominated by a solution set A. In order to calculate the hypervolume, a reference point that bounds the objective space is needed. This reference point should be (weakly) dominated by all solutions considered. In this thesis, this reference point consists of the combination of the worst objective values over all solutions of all algorithms, increased by 1%. Normalized objective values are used to calculate the hypervolume and higher values are preferable. The unary epsilon indicator $I_\epsilon(A)$ gives the minimum number ϵ by which each point in a reference set R should be multiplied such that the resulting transformed approximation set is weakly dominated by solution set A (Zitzler et al., 2003). Ideally, the reference set R should be equal to the efficient frontier. In case this is unknown, as here, R can be approximated by using the union of all solutions considered and removing dominated solutions. Lower values are preferable for this indicator. For a more detailed discussion of these two quality indicators, the reader is referred to Zitzler and Thiele (1999), Zitzler et al. (2003), Knowles et al. (2006) and Parragh et al. (2009). Finally, the coverage indicator $I_C(A, B)$ represents the fraction of solutions in set B that are weakly dominated by at least one solution of set A. Higher values are preferable for solution set A. (Zitzler and Thiele, 1999; Garcia-Najera and Bullinaria, 2011)

Table 6.1 gives an overview of the average values over all runs and all instances for the hypervolume and epsilon indicators for each solution algorithm. This table further provides some useful information on the average gaps between the non-dominated solutions and their lower bounds:

- The average absolute gap in number of vehicles between LB_v and the solution with the smallest number of vehicles
- The average relative gap in distance traveled between LB_d and the solution with minimum distance
- The average relative gap in distance traveled between each solution and its corresponding specific lower bound on distance $\text{LB}_{d(k)}$

Finally, Table 6.1 shows the average computation time in seconds. An overview of the average values for the coverage indicator is given in Table 6.2. To calculate these values, for each instance the average is taken over the indicator value of all 2500 combinations of the 50 solution sets provided by the two algorithms that are compared.

Table 6.1: Comparison of algorithms

Algorithm	I_H	I_ϵ	Average gaps			Computation
			LB_v	LB_d	$\text{LB}_{d(k)}$	time (s)
IM	0.4744	1.0273	0.74	2.83	3.38	18.02
BI-DA	0.4893	1.0258	0.74	2.72	3.24	13.53
BI-DA*	0.5022	1.0257	0.74	2.56	3.14	14.50

Tables 6.1 and 6.2 show that the proposed bi-objective deterministic annealing algorithm (BI-DA) provides on average better results than the iterative method (IM) on each of the three quality indicators: the hypervolume indicator I_H is larger ($0.4893 > 0.4744$), the unary epsilon indicator $I_\epsilon(A)$ is smaller ($1.0258 < 1.0273$) and

Table 6.2: Coverage indicator $I_C(A, B)$

		B		
		IM	BI-DA	BI-DA*
	IM	-	0.37	0.29
A	BI-DA	0.58	-	0.38
	BI-DA*	0.65	0.57	-

the fraction of solutions of IM that are dominated by solutions of BI-DA is larger than the other way around (0.58 > 0.37). By gradually lowering the maximum threshold value even better results on all three quality indicators are obtained by the BI-DA* algorithm. Although the average gaps in Table 6.1 cannot be considered as quality indicators for comparing the different solution algorithms, they show that on average each of the algorithms is able to find solutions close to the lower bounds. In line with the results on the quality indicators, these values suggest that the BI-DA* algorithm provides the best results. Detailed results of the BI-DA* algorithm on all 48 problem instances are shown in Appendix D.

6.3 Minimization of total route duration

In Chapters 4 and 5 and in the first section of this chapter, the two objectives to be minimized are the number of vehicles used and total distance traveled. Reasons for choosing these objectives are discussed in Section 4.3. In this section, the objective to minimize total distance traveled is replaced by the objective to minimize total route duration.

The duration of a vehicle route is defined as the time period between a vehicle leaving from and returning to the vehicle depot. This time period includes travel times between locations, service times for picking up and dropping of containers and waiting times at customer locations or container terminals when arriving before the opening of a time window. Minimizing total route duration might be preferred over minimizing total distance traveled in some cases, for example when drivers are paid on an hourly basis. The reason for introducing the objective to minimize total route duration in this section is that this allows to compare our deterministic annealing algorithm with a recent time window partitioning method on a similar problem. The hierarchical objective function which minimizes first the number of vehicles used and second total route duration can be expressed as follows:

$$\text{lexmin } \Big(\sum_{i:(0,i)\in A} x_{0i}, \sum_{i:(i,0)\in A} x_{i0}(t_i + s_i + t_{i0}) - \sum_{i:(0,i)\in A} x_{0i}(t_i - t_{0i}) \Big) \tag{6.5}$$

Section 6.3.1 discusses how the proposed deterministic annealing algorithm may be adapted to take the objective to minimize total route duration into account. Results on the random instances introduced in Section 5.4 are presented in Section 6.3.2. The comparison with a recent time window partitioning method on a similar problem is described in Section 6.3.3.

6.3.1 Modified algorithm

The deterministic annealing algorithm has to be modified slightly to cope with the objective to minimize total route duration. Up to now it was assumed that vehicles leave the vehicle depot at the beginning of the planning period ($t_0 = 0$), although in reality vehicles may leave the vehicle depot at any time. For a given route, changing the departure time of a vehicle will not affect total distance, total travel time and total service time of the route. However, when minimizing total route duration, the departure time of a vehicle at the depot will have an impact on the objective value. By postponing the departure of a vehicle, unnecessary waiting times at customers might be avoided.

For a given route, determining the departure time of the vehicle at the depot that minimizes the duration of the route is straightforward. The optimal departure time t_0^* is equal to the latest possible departure time. Leaving the depot earlier may invoke unnecessary waiting times along the route while leaving later will result in infeasibilities regarding time windows. (Savelsbergh, 1992; Van Der Bruggen et al., 1993; de Jong et al., 1996; Campbell and Savelsberg, 2004)

While determining the optimal departure time for a given route is rather simple, determining the effect of a local search move on total route duration is more complex. Total distance and total travel time are only affected by the length and duration of the nodes and arcs that are introduced or removed, while the effect on total route duration is less clear. For example exchanging two nodes between two routes will not only affect the travel times from and to these nodes, but will also change the time that other nodes in these routes are visited. This might change the optimal departure times of vehicles and/or result in additional or reduced waiting times. Hence, it is not straightforward to determine the effect on total route duration. (Savelsbergh, 1992)

Minimizing route duration is considered as an objective in several contributions to the vehicle routing literature (see Bräysy and Gendreau (2005a,b) for references). Others consider a maximum route duration constraint, especially when studying Dial-A-Ride Problems (Cordeau and Laporte, 2003; Cordeau et al., 2004; Parragh et al., 2010). Several methods to efficiently calculate the effect of a local search move on route duration are proposed. One method is the concept of forward and backward time slack at a node introduced by Savelsbergh (1992). This method is used among others by Cordeau and Laporte (2003), Cordeau et al. (2004) and Parragh et al. (2010). Fleischmann et al. (2004) propose to use the concept of time window of a route, which is based on earlier work of Van Landeghem (1988) and Savelsberg (1990). Finally, Campbell and Savelsberg (2004) propose an efficient method to determine whether the insertion of a node in a route violates the maximum route duration constraint. The method makes use of variables for the earliest and latest arrival time at a node to calculate the duration of a route.

Since variables for the earliest and latest arrival time (et_i, lt_i) are already maintained by our algorithm to check the feasibility of a local search move, the method of Campbell and Savelsberg (2004) is chosen. This method works as follows. Besides the variables et_i and lt_i, a variable ct_i needs to be maintained. This variable ct_i indicates the core time after node i and is equal to the sum of all travel, service and unavoidable waiting times in the route after the node. Unavoidable waiting time on a link $(i, j) \in A$ is calculated as $\max(0, a_j - b_i - s_i - t_{ij})$. Variable ct_0 indicates the total core time of the route i.e. the sum of all travel, service and unavoidable waiting times. Consider a route $(0, 1, ...i, i+1, ...n, n+1)$ which visits n nodes and where indices 0 and $n+1$ indicate the vehicle depot. Campbell and Savelsberg (2004) show that when a node j is inserted between nodes i and $i+1$, the earliest arrival time $\hat{et}_{n+1}$ of the vehicle at the depot may be computed as:

$$\hat{et}_{n+1} = \max(et_{n+1}, \hat{et}_j + s_j + t_{ji+1} + ct_{i+1}) \tag{6.6}$$

where et_{n+1} indicates the previous earliest arrival time at the depot and $\hat{et}_j$ is the new earliest arrival time at node j. Similarly, the latest departure time $\hat{lt}_0$ of the vehicle at the depot may be computed as follows:

$$\hat{lt}_0 = \min(lt_0, \hat{lt}_j - t_{ij} - s_i - (ct_0 - ct_i)) \tag{6.7}$$

where lt_0 indicates the previous latest departure time at the depot and $\hat{lt}_j$ is the new latest arrival time at node j.

Suppose a vehicle leaves the depot at time $\hat{lt}_0$. When there are no unnecessary waiting times, the total duration of the route will be determined by the new core time

($\hat{ct}_0$) which is the sum of all travel, service and unavoidable waiting times. When there are unnecessary waiting times, total duration will be higher. Since there are waiting times, it is obvious that when the vehicle leaves the depot at $\hat{lt}_0$, it can still return to the depot at $\hat{et}_{n+1}$. Hence, total duration is equal to $\max(\hat{ct}_0, \hat{et}_{n+1} - \hat{lt}_0)$.

The method of Campbell and Savelsberg (2004) is only valid when a node is inserted in a route and not when a node is removed. More precise, it is valid when $\forall i : \hat{et}_i \geq et_i \wedge \hat{lt}_i \leq lt_i$. In this paragraph a slight adaptation of the method is introduced to make the method valid for all types of local search moves. Two extra slack variables at each node are maintained during the search. The first variable sl_{1i} is similar to the backward time slack of Savelsbergh (1992) and indicates how much the arrival time at node i can be shifted backwards in time (i.e. be earlier) without introducing extra waiting time after the node:

$$sl_{1i} = \min_{j=i+1,\ldots n}(et_j - a_j) \tag{6.8}$$

The second variable sl_{2i} indicates by how much the latest departure time at the vehicle depot lt_0 will increase at most when the latest arrival time lt_i at node i increases. In other words this means that when lt_i increases by more than sl_{2i}, lt_0 will only increase by sl_{2i}. This variable is computed as follows:

$$sl_{2i} = \min_{j=1,\ldots,i-1,i}(b_j - lt_j) \tag{6.9}$$

Both slack variables are used in the calculation of the earliest arrival and latest departure time of a vehicle at the depot. Assuming link $(j, i+1)$ is the latest new link in the route and $\hat{et}_j$ is the earliest time node j can be reached, it can be shown that the new earliest arrival time at the vehicle depot is:

$$\hat{et}_{n+1} = \max(et_{n+1} - sl_{1j}, \hat{et}_j + s_j + t_{ji+1} + ct_{i+1}) \tag{6.10}$$

Assuming link (i, j) is the first new link in the route and $\hat{lt}_j$ is the latest arrival time at node j, the new latest departure time at the vehicle depot is:

$$\hat{lt}_0 = \min(lt_0 + sl_{2j}, \hat{lt}_j - t_{ij} - s_i - (ct_0 - ct_i)) \tag{6.11}$$

Finally, total route duration is still equal to $\max(\hat{ct}_0, \hat{et}_{n+1} - \hat{lt}_0)$.

6.3.2 Results on own instances

In this section, results on the problem instances introduced in Section 5.4 are discussed for a hierarchical objective function which first minimizes the number of vehicles and second total route duration (6.5).

Lower bounds are calculated by the time window partitioning method discussed in Section 5.5. Objective function (6.5) is not used since relaxing the integrality constraints results in a very weak lower bound. Instead, a general lower bound on total core time and hence on total route duration is found by solving problem (P5.3). When this lower bound is divided by the length of the planning period, a lower bound on the number of vehicles is obtained as well. A lower bound on total duration when k vehicles are used, is found by adding constraint (6.12) to problem (P5.3).

$$\sum_{v:(0,v)\in\Omega} x_{0v} = k \tag{6.12}$$

Table 6.3 gives an overview of the results for the two-phase integrated deterministic annealing algorithm (2-DA$_{\mathrm{TS}}$). Detailed results are available in Appendix E. Again, the algorithm provides good results in a small amount of computation time. Results for the number of vehicles are similar to those presented in Table 5.5 for the objective to minimize the number of vehicles and total distance. This is obvious since the first solution phase is the same.

Table 6.3: Summary of results

Value	Result
Average number of vehicles	9.98
Average gap (absolute)	0.73
Average duration (min)	4247
Average gap (%)	1.89
Average computation time (s)	5.85

When analyzing the solutions provided by the algorithm in more detail, it appears that unnecessary waiting times are often negligible. Unnecessary waiting times are those waiting times that are not included in the unavoidable or necessary waiting times. Only 30% of all solutions contain one or more route with unnecessary waiting time. Average total core time is 4246 minutes, indicating that on average less than 0.02% of the duration of a route represents unnecessary waiting time.

Although differences between total route duration and total core time are often very small in the solutions obtained by the algorithm, using an objective function that minimizes total core time in order to obtain solutions with low total route duration is not a good approach. Experimental results have shown that using this objective function yields an average total route duration of 4294 minutes, even when optimal departure times of vehicles are calculated in a post-optimization phase.

Finally, the similarity between the solutions obtained in this section and those obtained in Section 5.7 with the secondary objective to minimize total distance traveled, is analyzed. Although it may be assumed that a certain level of correlation exists between distance traveled and route duration, the analysis reveals that both objectives should not be used interchangeably. An overview of this analysis is shown in Table 6.4. From this table, it is clear that applying one of both objectives does not necessarily lead to good solutions on the other objective. Furthermore, when two solutions obtained by different secondary objectives are compared, on average only 43% of the links appear on both solutions. When two solutions obtained by the same secondary objective are compared, this percentage increases up to 60% which indicates that differences between solutions are considerably larger when they are obtained by different secondary objectives.

Table 6.4: Comparison of distance and duration

Results	Secondary objective	
	Total distance	Total duration
Average total distance (km)	1807	1835
Average gap (%)	4.86	6.83
Average total duration (min)	4391	4247
Average gap (%)	5.62	1.89

6.3.3 Comparison with time window partitioning method

Up to now, the quality of the proposed deterministic annealing algorithm is shown by comparing results with a lower bound. To further assess the quality of our algorithm, it is compared with another solution method in this section.

Zhang et al. (2010) describe a problem which is very similar to the one described in Section 4.3. The authors take an integrated solution approach and formulate their problem in a similar way as discussed in 4.4.2. The single objective is to minimize total route duration. A time window partitioning method is proposed to solve the problem and results on twenty random problem instances are reported. In this section, our single phase integrated deterministic annealing algorithm (1-DA_{TS}) is compared with the time window partitioning heuristic on the problem instances of Zhang et al.

(2010). The single phase algorithm is used because minimizing the number of vehicles is not an objective of Zhang et al. (2010).

Since there are slight differences between the problem in this thesis and that of Zhang et al. (2010), a number of changes to the single phase integrated algorithm need to be made. First, the modifications described in Section 6.3.1 are introduced to change the objective function to minimizing total route duration. Second, Zhang et al. (2010) assume that empty container depots are located at the vehicle depots rather than at container terminals. Besides, when a vehicle delivers a loaded container to a consignee, it has to wait at this location until the container is unloaded and can be picked up. Instead, in this thesis it is assumed that the vehicle may leave for another task and an empty container which becomes available at the consignee's location may be picked up by any vehicle. These differences do not ask for an adaption of the single phase integrated algorithm since for each problem instance all network information is provided by Zhang et al. (2010) i.e. the nodes with their time windows and all feasible links with their travel times. Finally, in this thesis only a single vehicle depot is assumed, while Zhang et al. (2010) assume multiple vehicle depots which all have a limited number of vehicles. The authors make the simplifying assumption that a vehicle does not have to return to its original depot at the end of a tour and the vehicles depots do not have time window constraints. Therefore, only a small modification to our algorithm is needed. First, the deterministic annealing algorithm is used to solve the problem with a single artificial vehicle depot. The travel time between this artificial vehicle depot and another node is equal to the travel time from the closest vehicle depot to this node. Similarly, the travel time between a node and the artificial vehicle depot is set equal to the travel time from this node to the closest depot. Second, the solution to this problem is transformed to a feasible solution of the problem with multiple vehicle depots by imposing the constraint that a limited number of vehicles may leave a certain depot. This is done by solving a small transportation problem which minimizes the sum of the travel times form the vehicle depots to the first node of each route while ensuring that the number of routes starting at each vehicle depot is not higher than number of vehicles available. Clearly, the solution procedure could be improved by taking this constraint into account during the search of the deterministic annealing algorithm. For example, additional operators that change the starting vehicle depot of a route or swap the starting vehicle depots of two routes might be introduced. This is not considered in this thesis.

Zhang et al. (2010) generate twenty random problem instances. For each instance, locations are randomly generated in a Euclidean plane with length and width equal to a travel time of 180 minutes. Three container terminals and five vehicle depots with an empty container depot and ten vehicles available each are assumed. Container pickup/drop off times are five minutes while, container loading and unloading time is uniformly distributed between five and sixty minutes. Each instance consists of eighty-five nodes. Forty nodes represent inbound loaded container transports for which a loaded container should be picked up at the terminal, transported to the consignee, dropped off, unloaded, picked up and transported either to a depot or to an empty container demand location. Five nodes represent outbound loaded container transports for which an empty container should be delivered to the shipper, dropped off, loaded, picked up, transported to the terminal and dropped off. Finally, forty nodes represent empty containers which are available at a container terminal. These empty containers should be transported from the terminal to a depot or to an empty container demand location. Time window width is randomly generated between one and respectively 60, 120, 180 and 240 minutes (five problem instances for each maximum width).

These instances are less complex than those presented in Section 5.4 for several reasons. First, the transportation of loaded containers from terminals to consignees and the empty container transport following on this, are considered as a single task which should be performed by the same vehicle. The same reasoning is followed when considering loaded container transports from shipper to terminals: the empty container needed by the shipper should be delivered by the same vehicle. Therefore, vehicles spend a lot of time waiting for a container to be (un)packed and transportation tasks have a large duration. Hence, a vehicle can only perform a limited number of transportation tasks during the planning period. Second, the number of transportation tasks to be performed is smaller. Third, average time window widths are smaller, ranging from about 30 minutes to 120 minutes.

Zhang et al. (2010) use a time window partitioning method to both compute lower bounds and solve the problem. Lower bounds are found by solving an underconstrained version of the problem as discussed in Section 5.5. Solutions for the problem are found by solving an overconstrained version of the problem. The under- and overconstrained problems are exactly the same, except that the set of links in the network is different. Instead of allowing all links (v, w) that might be feasible $(a_v + s_v + t_{vw} \leq b_w)$, only links (v, w) that are always feasible, independent of the arrival time at node v are included in the overconstrained problem: $\Omega = \{v, w \in \omega, \delta(v) \neq \delta(w), b_v + s_v + t_{vw} \leq b_w\}$. In Section 5.5, two improvements are proposed for calculating lower bounds by this time window partitioning method. The first improvement, reducing the set of links in the network, is applied to the overconstrained problem as well. The second improvement, relaxing the integrality constraints, cannot be applied since this would result in infeasible solutions. The improved overconstrained problem is solved for the twenty instances of Zhang et al. (2010). Since, these instances are rather simple, the improved overconstrained problem can be solved efficiently with a partitioning width of a single minute. Because this version of the problem is equivalent to a time-indexed formulation, the obtained solutions are optimal. Next, the single phase deterministic annealing algorithm is used to solve the instances as well.

An overview of the results can be found in Table 6.5. The first two columns show the optimal solutions found by the improved overconstrained problem and its computation time. The following columns present the solutions obtained by Zhang et al. (2010) and average solutions obtained over five runs of the single phase deterministic annealing algorithm. For each solution, the relative gap with the optimal solutions and the computation times are shown as well. Results show that the single phase deterministic annealing algorithm outperforms the time window partitioning method of Zhang et al. (2010). On average, better solutions are found in 18 out of 20 instances. Computation times are reduced drastically as well. Finally, it is noticed that the average number of vehicles used drops from 44.1 to 42.5.

The quality of the deterministic annealing algorithm is confirmed by the fact that its solutions are very close to the optimal solutions. The average gap is only 0.33%. For all instances, solutions within 1% of the optimal solution are found. Two reasons may be suggested why small gaps remain. First, the allocation of vehicles to routes is done after the solution algorithm has finished, as explained above. Second, improvements in the number of vehicles are always accepted in our algorithm (without considering a possible increase in total route duration). As a result, the solutions found by our algorithm tend to use slightly less vehicles than the optimal solution (42.5 versus 42.9 on average).

Although the improved overconstrained problem can be solved efficiently for the instances of Zhang et al. (2010), even with a partitioning width of a single minute, using this approach to solve the instances discussed in Section 5.4 does not provide good results. Experimental results have shown that in order to solve the integer restricted overconstrained problem within reasonable time, the partitioning width should be considerably larger than a single minute. As a result, a lot of links that might appear in a feasible solution of the original problem are excluded in the overconstrained problem. Hence, resulting solutions are of poor quality. It can therefore be concluded that the improved time window partitioning method is only able to generate good solutions for problem instances of limited complexity, while the proposed deterministic annealing algorithm also performs well on more complex problem instances.

Table 6.5: Comparison with time window partitioning method

Max. TW width	No.	Optimal		Zhang et al. (2010)			1-DA_{TS}		
		Dur	Time	Dur	Gap	Time	Dur	Gap	Time
60	1	14983	0.65	15042	0.39	69	15128	0.97	3.20
	2	15769	0.47	15803	0.22	104	15774	0.03	3.20
	3	14823	0.48	14829	0.04	141	14848	0.17	3.40
	4	15794	0.38	15857	0.40	96	15795	0.01	3.20
	5	12757	0.53	12863	0.83	105	12795	0.30	3.00
120	6	17706	0.83	17946	1.36	107	17733	0.15	3.20
	7	14620	1.17	14688	0.47	116	14666	0.31	3.00
	8	15991	0.90	16082	0.57	80	16006	0.09	3.20
	9	12726	1.36	12892	1.30	72	12726	0.00	3.00
	10	17639	0.78	17829	1.08	70	17664	0.14	3.40
180	11	14293	2.70	14495	1.41	195	14386	0.65	3.00
	12	15516	2.39	15870	2.28	124	15545	0.19	3.00
	13	14433	11.15	14905	3.27	150	14458	0.17	3.20
	14	15929	6.04	15960	0.19	199	15930	0.01	3.00
	15	13816	3.31	13887	0.51	123	13881	0.47	3.00
240	16	15068	17.74	15334	1.77	75	15127	0.39	3.00
	17	13291	10.47	13476	1.39	105	13396	0.79	3.20
	18	14187	4.54	14485	2.10	130	14287	0.70	3.20
	19	15988	3.62	16110	0.76	98	16079	0.57	3.00
	20	11893	8.63	12032	1.17	212	11960	0.56	3.00
Average			3.91		1.09	119		0.33	3.12

6.4 Conclusions and further research

In this chapter, alternative objective functions for the integrated drayage problem are introduced. First, a bi-objective approach is taken by not assigning priority to the minimization of the number of vehicles or the minimization of total distance. To our knowledge, this type of problem has not been considered from a bi- or multi-objective perspective before. A bi-objective approach has the advantage that a set of good solutions is handed to the decision maker, rather than a single solution. It allows to analyze the trade-off between both objectives as well. Experimental results have shown that this trade-off is rather small for the problem instances considered in this thesis. By using more vehicles, only limited savings in total distance may be achieved. To solve the problem, a bi-objective version of the deterministic annealing algorithm is proposed. A comparison based on a set of three quality indicators reveals that this algorithm offers solution sets of higher quality than when iteratively solving the problem using the algorithm for a hierarchical objective function presented in Chapter 5. Second, the objective to minimize route duration is considered instead of the objective to minimize total distance. The necessary modifications to the deterministic annealing algorithm are described. The algorithm is then compared with a recent time window partitioning method on a similar integrated drayage problem. Our algorithm outperforms this method.

Future research may focus on a multi-objective approach for the integrated drayage problem by considering three or more objectives. Minimizing the number of vehicles, total distance and total route duration have already been introduced in this thesis. An additional objective might be to balance the workload among vehicles. Such an objective is often introduced in vehicle routing problems in order to bring an element of fairness into play (Jozefowiez et al., 2008). The workload of a vehicle may be expressed in terms of the number of nodes visited, total distance traveled or total duration of the route.

Chapter 7

Optimization of drayage operations: time-dependent travel times

7.1 Introduction

The vast majority of research on vehicle routing problems focuses on situations where travel times between locations are constant and known in advance. This approach was adopted in the previous chapters as well. In reality, travel times in a region are not solely a function of the distance traveled. Rather they will vary from time to time. Several causes for these variations may be identified. A major cause is the temporal variation in traffic density. Average traffic volumes are affected by hourly, daily, weekly and seasonal influences. Traffic density will be higher during peak hours than during non-peak hours, while holidays and specific events may result in daily or weekly variations. Other causes of travel time variation include stochastic or unforeseeable events like accidents, vehicle breakdowns and weather conditions. (Malandraki and Daskin, 1992; Balseiro et al., 2011) Neglecting the time-dependency of travel times may seriously affect the applicability of vehicle routing models in practice, especially when time windows at customers are involved and vehicle movements are planned in heavily congested areas (Hill and Benton, 1992).

In this chapter[1], the effect of hourly variations in travel times on the operational

[1]This chapter is based on Braekers et al. (2012d).

planning of drayage operations is studied (Figure 7.1). Travel times are assumed to be a deterministic function of distance and time of day. This means that although travel times are not constant during the planning period, travel times at each point in time are known in advance. As a result, a deterministic planning approach may be used like in the previous chapters. Travel time variations due to random events like weather conditions and accidents are not considered. To take these variations into account, a stochastic approach should be considered.

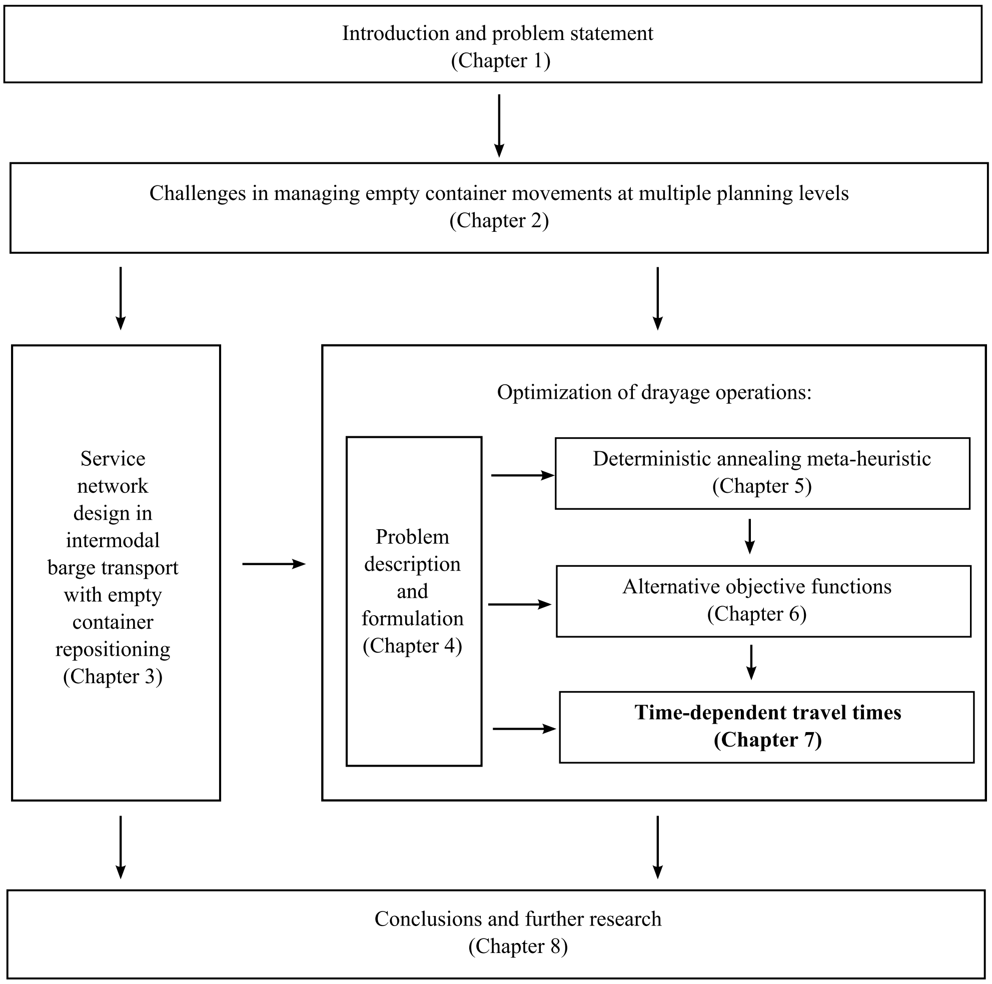

Figure 7.1: Outline of the thesis

The chapter is organized as follows. In Section 7.2 concepts related to the modeling of time-dependent travel times in vehicle routing problems are discussed. The formulation of the time-dependent drayage problem is presented in Section 7.3. An integrated planning approach and a hierarchical objective function which first minimizes the number of vehicles and next total route duration are considered. Next, a time-dependent version of the two-phase deterministic annealing algorithm is introduced (Section 7.4). Section 7.5 describes the speed profile of the vehicles that is used in this chapter. Results are presented in Section 7.6 while two approaches to speed-up the algorithm are analyzed in Section 7.7. Finally, Section 7.8 contains conclusions and opportunities for further research.

7.2 Time-dependent vehicle routing

The first steps to account for time-dependency of travel times in vehicle routing problems are presented by Hill and Benton (1992) and Malandraki and Daskin (1992). Hill and Benton (1992) propose a model to calculate time-dependent travel times based on time-dependent travel speeds. For each time period, a travel speed is assigned to each node. This travel speed represents the average travel speed in the area of the node at that time. The average travel speed on a link (i, j) is then defined as the averages of the speed levels of nodes i and j. Malandraki and Daskin (1992) propose to use stepwise functions for modeling travel time variations. The planning period is divided in a number of intervals and the travel time on a link differs from interval to interval. As a result, the travel time on a link makes a jump at discrete moments in time.

A major drawback of these early approaches is that they violate the non-passing or FIFO ('First-In-First-Out') property. This property encompasses the common sense idea that when a vehicle leaves node i for node j at a given time, any identical vehicle that leaves node i at a later time, cannot arrive earlier at node j. (Ahn and Shin, 1991; Malandraki and Dial, 1996) A simple example can demonstrate how the method of Malandraki and Daskin (1992) may violate the non-passing property. Assume that the travel time on a link (i, j) is 10 minutes when leaving before 14h and 6 minutes when leaving at or later than 14h. A vehicle leaving node i at 13h59 will arrive node at node j at 14h09 while a vehicle leaving node i at time 14h00 will arrive at time 14h06. Clearly this violates the non-passing property.

Fleischmann et al. (2004) describe a method to exclude the possibility of passing. The authors propose to remove the discrete jumps in stepwise travel time functions by smoothing the function. This smoothing relies on two parameters that have to be set appropriately. The resulting smoothed travel time function satisfies the non-passing property as long as the slope of the function is everywhere larger than minus one (Fleischmann et al., 2004; Kuo et al., 2009). Furthermore, Fleischmann et al. (2004) describe a method to efficiently check the feasibility of inserting nodes in a route and of 2-Opt local search moves. Another method to ensure the non-passing property is presented by Ichoua et al. (2003). The authors propose to use a stepwise function for travel speed instead of a stepwise function for travel time. This means that the speed on a link changes at discrete points in time. It is easy to see that this method satisfies the non-passing property since at any time all vehicles traveling along an arc will have the same speed no matter where they are. The corresponding travel time function for a link can be calculated by a simple procedure. Assume that the planning period is divided in a number of time intervals $P_k =]\underline{t}_k, \bar{t}_k]$ with different speed levels. The distance of link (i, j) is indicated by d_{ij} and the speed level on link (i, j) during time interval k is indicated by v_{ijk}. Let t denote the current time and t_j the arrival time at node j. The travel time $\tau_{ij}(t_i)$ of a vehicle on link (i, j) when leaving node i at time $t_i \in P_k$ can then be determined by Algorithm 3. An example of a stepwise travel speed function and its corresponding travel time function for a link of length 1 are shown in Figures 7.2 and 7.3.

Algorithm 3 Travel time calculation (adapted from Ichoua et al. (2003))

$t \leftarrow t_i$
$d \leftarrow d_{ij}$
$t_j \leftarrow t + (d/v_{ijk})$
while $t_j > \bar{t}_k$ **do**
  $d \leftarrow d - v_k(\bar{t}_k - t)$
  $t \leftarrow \bar{t}_k$
  $t_j \leftarrow t + (d/v_k)$
  $k \leftarrow k + 1$
end while
return $(t_j - t_i)$

Even when the non-passing property is satisfied, time-dependent travel times might not be fully realistic. Often the simplifying assumption is made that the route taken between two locations is always the same, namely the one with shortest distance. Instead, when not all links have the same speed profile, the route which minimizes travel time might depend on the time of the day. Not taking this into account might

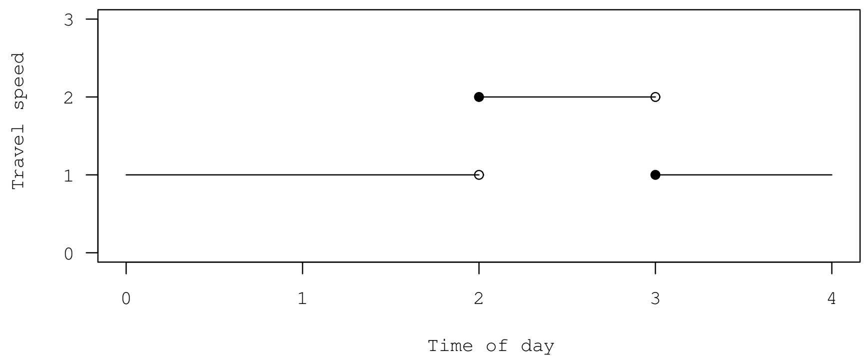

Figure 7.2: Stepwise speed function (adapted from Ichoua et al. (2003))

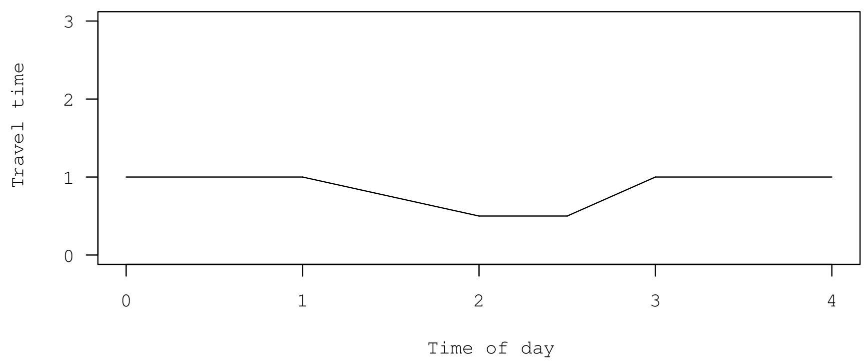

Figure 7.3: Travel time function (adapted from Ichoua et al. (2003))

lead to a violation of the triangle inequality. A solution to this problem would be to calculate time-dependent shortest paths for all possible start times between all pairs of locations in the network. (Fleischmann et al., 2004; Wohlgemuth and Clausen, 2009) Efficient methods to calculate such time-dependent shortest paths are described by Sung et al. (2000) and Dean (2004).

Recently, time-dependency of travel times in vehicle routing problems has received increased attention. All recent papers consider travel times that satisfy the non-passing property. Most of them use a method which is similar to the one of Ichoua et al. (2003) to ensure this (Jabali et al., 2009; Kuo et al., 2009; Balseiro et al., 2011; Dabia et al., 2011; Figliozzi, 2012). Calculation of time-dependent shortest paths is generally not considered.

To the author's knowledge, only Namboothiri and Erera (2004) deal with time-dependent travel times in a full truckload pickup and delivery problem. The authors study a drayage problem involving the transport of loaded containers between customers and a single terminal at the port. Delays at the terminal due to congestion are the only source of time-dependency of travel times. A simple exact and heuristic column generation approach are proposed to solve the problem.

Kuo et al. (2009) present a tabu search algorithm for the Time-Dependent Vehicle Routing Problem (TD-VRP). A tabu search algorithm for a TD-VRP where unexpected delays at customer locations are considered is proposed by Jabali et al. (2009). Jung and Haghani (2001) propose a genetic algorithm for a dynamic time-dependent vehicle routing problem with multiple vehicle types and mixed linehauls and backhauls (goods have to be delivered to and from the depot). Soft time windows are considered. Additional experimental results and the calculation of a lower bound on the problem are discussed in Haghani and Jung (2005). Sifa et al. (2011) propose a tabu search heuristic for a similar problem. They consider time-dependent travel times which are based on time-dependent fuzzy vehicle speeds. Other research on time-dependency in vehicle routing has focused on the Time-Dependent Vehicle Routing Problem with Time Windows (TD-VRPTW). Hashimoto et al. (2008) present an iterated local search algorithm for the TD-VRPTW where time windows are soft. Ant colony system algorithms for the TD-VRPTW with hard time windows are proposed by Donati et al. (2008) and Balseiro et al. (2011). Figliozzi (2012) proposes a solution algorithm based on a route construction and route improvement heuristic to solve the TD-VRPTW with both hard and soft time windows. Exact solution approaches for the TD-VRPTW are considered by Soler et al. (2009) and Dabia et al. (2011). Soler et al. (2009) describe a method to transform the TD-VRPTW into an asymmetric capacitated vehicle routing problem which can be solved exactly for small problem instances. Dabia et al. (2011) present a column generation approach embedded in a branch and cut framework. Finally, Kok et al. (2011) study a TD-VRPTW where driving regulations are imposed. The authors introduce a ILP formulation to optimize the vehicle departure time at the depot. An insertion heuristic which takes the driving regulations into account is proposed as well.

Vehicle routing problems with stochastic time-dependent travel times are studied by Van Woensel et al. (2007, 2008), Lecluyse et al. (2009) and Janssens et al. (2009).

Van Woensel et al. (2007, 2008) apply queueing theory to capture the dynamic and stochastic nature of travel times. Respectively an ant colony optimization and tabu search algorithm are used to solve the TD-VRP. Lecluyse et al. (2009) build on the work of Van Woensel et al. (2007, 2008). The authors introduce the aspect of variability in the objective function of the problem. As a result, vehicle routes tend to have slightly longer travel times but are more reliable. Finally, Janssens et al. (2009) show how time Petri nets may be used to evaluate the sensitivity of solutions regarding travel time uncertainties.

7.3 Problem formulation

The time-dependent integrated drayage problem is formulated similarly as its time-independent counterpart in Section 4.4.2, although some modifications are required to reflect the time-dependency of travel times. The problem is formulated on a graph $G_{td} = (N_{td}, A_{td})$. The node set N_{td} is the same as that of the time-independent problem and consists of:

- the vehicle depot (N_{VD}, index 0),
- a node for each loaded container transport request (N_L)
- a node for each empty container demanded (N_D),
- a node for each empty container supplied (N_S).

For each node $i \in N_{td}$, a time window $[a_i, b_i]$ during which a vehicle should arrive at the node is defined. The meaning of these time windows is the same as for the time-independent problem.

Let $A_{ij}(t)$ denote the arrival time function which indicates the earliest arrival time at node j when arriving at node i at time t. Table 7.1 shows how these arrival times are calculated (assuming that $t \in [a_i, b_i]$). When the first node represents a loaded container transport request ($i \in N_L$), indices g and h denote the location of respectively the origin and destination of this request. Similarly, indices g' and h' denote the location of the origin and destination of a loaded container request $j \in N_L$. The container pickup or drop off time at a location is indicated by l_i. Travel time between two locations i and j when leaving location i at time t is calculated by the method of Ichoua et al. (2003) and is denoted by $\tau_{ij}(t)$. Finally, N_T represents

Table 7.1: Calculation of arrival time function $A_{ij}(t)$

Node i	Node j	Arrival time at j when arriving at node i at time t
$i \in N_{VD}$	$j \in N_{VD}$	t
$i \in N_{VD}$	$j \in N_L$	$\max(a_j, t + \tau_{ig'}(t))$
$i \in N_{VD}$	$j \in N_S$	$\max(a_j, t + \tau_{ij}(t))$
$i \in N_{VD}$	$j \in N_D$	$\max(a_j, t + \min_{r \in N_T} (\tau_{ir}(t) + l_r + \tau_{rj}(t + \tau_{ir}(t) + l_r) + l_j))$
$i \in N_L$	$j \in N_{VD}$	$q + \tau_{hj}(q)$
$i \in N_L$	$j \in N_L$	$\max(a_j, q + \tau_{hg'}(q))$
$i \in N_L$	$j \in N_S$	$\max(a_j, q + \tau_{hi}(q))$
$i \in N_L$	$j \in N_D$	$\max(a_j, q + \min_{r \in N_T} (\tau_{hr}(q) + l_r + \tau_{rj}(q + \tau_{hr}(q) + l_r) + l_j))$
$i \in N_S$	$j \in N_{VD}$	$l_i + \min_{r \in N_T} (\tau_{ir}(t + l_i) + l_r + \tau_{rj}(t + l_i + \tau_{ir}(t + l_i) + l_r))$
$i \in N_S$	$j \in N_L$	$\max(a_j, l_i + \min_{r \in N_T} (\tau_{ir}(t + l_i) + l_r + \tau_{rg'}(t + l_i + \tau_{ir}(t + l_i) + l_r)))$
$i \in N_S$	$j \in N_S$	$\max(a_j, l_i + \min_{r \in N_T} (\tau_{ir}(t + l_i) + l_r + \tau_{rj}(t + l_i + \tau_{ir}(t + l_i) + l_r))$
$i \in N_S$	$j \in N_D$	$\max(a_j, l_i + \tau_{ij}(t + l_i) + l_j)$
$i \in N_D$	$j \in N_{VD}$	$t + \tau_{ig'}(t)$
$i \in N_D$	$j \in N_L$	$\max(a_j, t + \tau_{ig'}(t))$
$i \in N_D$	$j \in N_S$	$\max(a_j, t + \tau_{ij}(t))$
$i \in N_D$	$j \in N_D$	$\max(a_j, t + \min_{r \in N_T} (\tau_{ir}(t) + l_r + \tau_{rj}(t + \tau_{ir}(t) + l_r) + l_j))$

the set of container terminals in the region. To improve the readability of the table, $t + l_g + \tau_{gh} + l_h$ is replaced by q.

As is shown in Table 7.1, the arrival time function $A_{ij}(t)$ takes into account:

- the execution of the transport task at node i (if $i \in N_L$),
- the travel time between nodes i and j including possible detours to a container terminal and container pickup and drop off times,
- possible waiting times at node j.

When an intermediate stop at a container terminal is required, the choice of the terminal now depends on the duration of the detour, rather than on the distance as in Section 4.4.2. As a result, the container terminal that is selected is not necessarily the same at every moment during the planning period.

Since travel times between two locations are calculated by the method of Ichoua et al. (2003) which ensures that the non-passing property is satisfied, the arrival time function $A_{ij}(t)$ is a (strictly) monotonic increasing function. As a consequence the inverse of this function $A_{ij}^{-1}(t)$ exists and is a monotonic function as well. This inverse function $A_{ij}^{-1}(t)$ indicates the latest arrival time at node i in order to arrive at the latest at time t at node j. The values of $A_{ij}^{-1}(t)$ are calculated in a similar way as those of the arrival time function. The major advantage of the existence of the inverse function $A_{ij}^{-1}(t)$ is that it is possible to calculate backwards in a route and hence the route feasibility checks may be performed in a similar way as discussed in Section 5.2.2 (Ahn and Shin, 1991; Fleischmann et al., 2004; Donati et al., 2008).

The arc set A_{td} in the network consists of all feasible links between nodes: $A_{td} = \{i, j \in N_{td}, i \neq j, A_{ij}(a_i) \leq b_j\}$. The problem is formulated as an *am*-TSPTW. Binary variables x_{ij} indicate whether a vehicle travels directly between two nodes i and j or not, while variables t_i indicate the time that a vehicle visits node i. The problem (P7.1) may be formulated as follows:

$$\text{(P7.1) lexmin } \Big(\sum_{i:(0,i)\in A_{td}} x_{0i}, \quad \sum_{(i,0)\in A_{td}} x_{i0} A_{i0}(t_i) - \sum_{(0,i)\in A_{td}} x_{0i} A_{0i}^{-1}(t_i) \Big) \qquad (7.1)$$

Subject to

$$\sum_{j:(i,j)\in A_{td}} x_{ij} = 1 \qquad \forall i \in N_{td}\backslash\{0\} \qquad (7.2)$$

$$\sum_{j:(0,j)\in A_{td}} x_{0j} \leq K \qquad (7.3)$$

$$\sum_{j:(i,j)\in A_{td}} x_{ij} = \sum_{j:(j,i)\in A_{td}} x_{ji} \qquad \forall i \in N_{td} \qquad (7.4)$$

$$A_{ij}(t_i) \leq t_j + M(1 - x_{ij}) \qquad \forall (i,j) \in A_{td}, \; j \neq 0 \qquad (7.5)$$

$$A_{i0}(t_i) \leq P + M(1 - x_{i0}) \qquad \forall i \in N_{td} \qquad (7.6)$$

$$a_i \leq t_i \leq b_i \qquad \forall i \in N_{td} \qquad (7.7)$$

$$t_i \geq 0 \qquad \forall i \in N_{td} \qquad (7.8)$$

$$x_{ij} \in \{0,1\} \qquad \forall (i,j) \in A_{td} \qquad (7.9)$$

A hierarchical objective function is used (7.1). The primary objective is to minimize the number of vehicles used while the secondary objective is to minimize total route duration. Constraints (7.2), (7.3) and (7.4) are flow constraints. Constraint (7.5) ensures that a vehicle cannot arrive at a node before leaving the previous node and traveling to the new one. Constraint (7.6) ensures that all vehicles return to the vehicle depot before the end of the planning period. Time windows are represented by constraint (7.7). Finally, constraints (7.8) and (7.9) make sure that both types of variables only take on the appropriate values.

7.4 Time-dependent algorithm

A time-dependent version of the two-phase integrated deterministic annealing algorithm presented in Chapter 5 is introduced in this section. The objective is to minimize first the number of vehicles and second total route duration. The algorithm is implemented in a similar way as discussed in Sections 5.2.3 and 5.2.4. A transportation problem is solved to find good empty container allocations and an initial solution is found by a parallel insertion heuristic. In the first phase of the algorithm, the number of vehicles is reduced. After half the number of iterations of this first phase, the empty container allocations are relaxed and the current best solution is transformed to a solution for the integrated problem. In the second phase, total route duration is reduced. In the following paragraphs, more details on the implementation of the time-dependent algorithm are provided. During this discussion, let $\hat{\tau}_{ij}(t) = A_{ij}(t) - t$ denote the time needed to arrive at node j when arriving at node i at time t. Furthermore, $\hat{\tau}_{ij}^{min}$ represents the least possible duration of a link $(i, j) \in A_{td}$:

$$\hat{\tau}_{ij}^{min} = \min_{t \in [a_i, b_i]} \{\hat{\tau}_{ij}(t) | A_{ij}(t) \leq b_j\} \tag{7.10}$$

7.4.1 Transportation problem

In the time-independent case, the transportation problem minimizes total distance of the empty container allocations. In the time-dependent case, it is more appropriate to minimize total travel time. The reason is as follows. Assume three nodes: an empty container supply node $i \in N_S$ and two empty container demand nodes $j, j' \in N_D$ with $d_{ij} < d_{ij'}$. When minimizing total distance, the empty container which is available at node i will rather be assigned to node j than to node j'. However, due to time-dependent travel times, it is perfectly possible that $\hat{\tau}_{ij}^{min} > \hat{\tau}_{ij'}^{min}$. This means that the time needed to traverse link (i, j') might be smaller than the time needed to traverse link (i, j). Such a situation might occur when the time window of empty container demand node j forces the empty container to be transported during a congested period, while this is not the case when allocating the empty container to node j' $(b_j < b_{j'})$.

Of course, using the objective to minimize travel time is in itself complicated by the fact that the travel time between two locations is not a unique value but depends on the time of the day. Three approaches are considered to overcome this problem. The travel time between two locations is set equal to: the least possible travel time $(\hat{\tau}_{ij}^{min})$, the average travel time or the largest possible travel time. Experimental results have shown that using the least possible travel time offers the best results, although differences with the other approaches are rather small.

7.4.2 Optimal departure time at the vehicle depot

When travel times are time-independent, the optimal departure time of a vehicle at the depot is the latest possible start time $(t_0^* = lt_0)$. By leaving the depot at this time, unnecessary waiting times are avoided as much as possible. This is no longer true when travel times are time-dependent. Leaving the depot earlier than the latest possible time, might result in a route of shorter duration. Travel times depend on the time that the nodes are visited. Visiting nodes earlier might in some cases reduce travel times and even route duration. (Fleischmann et al., 2004; Donati et al., 2008) In this thesis, the optimal start time of a vehicle is calculated as follows. First an interval in which t_0^* lies is determined. The upper bound of this interval is the latest possible start time lt_0 which is maintained during the search similarly as the latest times at all other nodes. The lower bound is the latest possible start time of the vehicle at the depot while returning to the depot at the earliest possible time et_{n+1}. This value, indicated as et_0, can be found by a backward loop through the route while calculating the latest time at each node in order to arrive at the depot at et_{n+1}. Leaving the depot earlier than et_0 will only increase route duration since the vehicle cannot return to the depot earlier than et_{n+1}. Hence, $t_0^* \in [et_0, lt_0]$. All the departure times in this interval result in a route without waiting time. Which of these departure times results in the minimal route duration is found by an iterative method. For each departure time t_0 the corresponding route duration is calculated by a forward loop through the route. The optimal departure time is the one which results in the smallest duration.

7.4.3 Implementation of local search operators

The same local search operators as presented in Section 5.2.2 are used for the time-dependent problem. As discussed in Section 7.3, the feasibility of a local search move can still be inspected efficiently by using the earliest and latest arrival times at each node. Section 6.3.1 describes how the effect of a local search move on route duration can be calculated for the time-independent case. Unfortunately, this method no longer works when travel times are time-dependent. A shift in the arrival time at a node does not only affect arrival times at other nodes and waiting times in the route. It may affect the travel time between any pair of consecutive nodes in the route as well. As a result, it is not possible to predict the effect of a local search move on total route duration. (Fleischmann et al., 2004; Balseiro et al., 2011)

The duration-reducing operators (*intra-route*, *relocate*, *2-Opt** and *exchange*) are implemented as follows. Each time an operator finds a feasible local search move, this move is carried out. Next, the optimal start time of the affected routes is recalculated and the new total route duration is found. The new solution is accepted when the new total route duration is less than the old total route duration plus the deterministic annealing threshold value. When the new solution is not accepted, the local search move is reversed and the search of the operator is continued.

The two operators that reduce the number of routes are implemented in a different way. These operators are involved with inserting several nodes into a number of existing (and empty) routes. Often multiple feasible insertion positions for a node can be found. Evaluating each feasible location by calculating the effect on total route duration would take too much computation time. Therefore, the insertion position of a node is selected by looking at the effect on total minimal duration. The total minimal duration of a route is defined as the sum of the least possible travel times $\hat{\tau}_{ij}^{min}$ of all links in the route. The effect on total minimal duration of inserting node i' between nodes i and j is calculated as $\hat{\tau}_{ii'}^{min} + \hat{\tau}_{i'j}^{min} - \hat{\tau}_{ij}^{min}$. The insertion position which results in the least increase in total minimal duration is selected. Selecting insertion positions this way has the advantage that the optimal start time of the route and the corresponding total route duration do not have to be calculated after every insertion. Instead these values only have to be updated at the end of the search of the operator and only when the operator succeeds in inserting all nodes in the existing (and empty) routes, thereby reducing the number of vehicles in the solution.

7.5 Speed profile

In literature often different speed profiles are assigned to different (types of) links in the network. This requires a good understanding of the different types of links and the extent to which they are subject to congestion. This may be the case when working with travel speeds on an actual road network. On the other hand, (randomly) assigning speed profiles to links might not make much sense when working with problem instances which are randomly generated on a Euclidean plane like here. Furthermore, when assigning different speed profiles to different links, time-dependent shortest paths should be calculated to adhere to the triangle inequality as discussed in the previous section.

In this chapter, the assumption is made that the whole region in which drayage operations take place is equally affected by congestion during peak hours. This means that all links in the network have the same speed profile. A similar approach is considered by Jabali et al. (2009) and Figliozzi (2012). The advantage of this assumption is that there is no need to calculate time-dependent shortest paths between all locations since the shortest path will always be the one with minimal Euclidean distance. For each problem instance, the total planning period of eight hours is divided into five time intervals. Speed during the first, third and fifth interval is assumed to be 60 kilometers per hour. This speed is considered in the previous chapters as well. Two periods of congestion are considered during which speeds drops to 36 kilometers per hour (a reduction of 40%). Figure 7.4 gives an overview of the speed profile, while the corresponding travel times on a link of 20 kilometers are shown in Figure 7.5.

7.6 Experimental results

The random problem instances discussed in Section 5.4 cannot be used to test the time-dependent algorithm. Since at some moments during the planning period travel speed is lower than 60 km/hour, it is not ensured that all tasks defined by these instances can be performed within their time windows. A new set of 48 random problem instances is created according to the same 2^4 full factorial design (3 problem instances per class).

Lower bounds on the number of vehicles and on total route duration are found using a time window partitioning method as discussed in Section 6.3.2. The travel time between each combination of subnodes is set equal to the least possible travel time when leaving the first subnode during its time window. Since the actual travel time between two subnodes might be slightly larger than this least possible travel

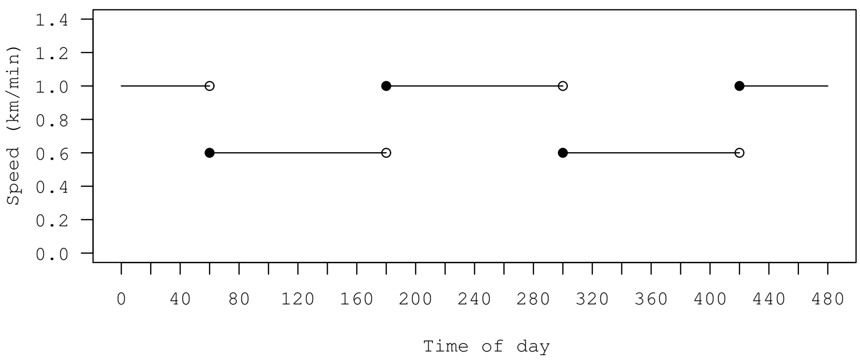

Figure 7.4: Speed profile

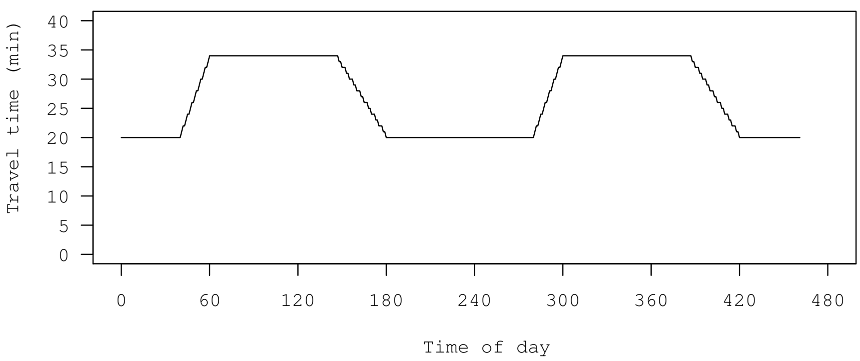

Figure 7.5: Travel times for a link of 20 kilometers

time, the resulting lower bounds are likely to be less tight than those of the time-independent case.

Fifty runs of the algorithm are performed on each of the 48 problem instances. Table 7.2 gives an overview of the average results for the time-dependent two-phase integrated deterministic annealing algorithm. Detailed results are available in Appendix F. Average results are close to the lower bounds which indicates that the deterministic annealing algorithm is able to deal with deterministic time-dependent travel times.

Gaps are larger than those that were obtained for the time-independent problem (see Section 6.3.2) because the problem is more complex and the lower bounds are less tight. Finally, it is noted that the average computation time of the time-dependent algorithm (14.83s) is substantially higher than that of the time-independent algorithm (5.69s). This results from the complexity in determining the effect of a local search move on total route duration. Repeatedly local search moves have to be reversed because the resulting total route duration is not acceptable for the current threshold value.

Table 7.2: Summary of results

Value	Result
Average number of vehicles	11.17
Average gap (absolute)	1.17
Average duration (min)	4751
Average gap (%)	3.40
Average computation time (s)	14.83

7.7 Speed-up approaches

To reduce the computation time of the time-dependent algorithm, two speed-up approaches are considered. These approaches are compared with the base algorithm (v0) described in Section 3. The first approach (v1) is to calculate the optimal departure time of a vehicle at the depot only in a post-optimization step, rather than recalculating the optimal departure time every time a local search move affects the route. Dabia et al. (2011) note that this is a common approach both in literature and in practice. A similar approach is among others proposed by Fleischmann et al. (2004) and Hashimoto et al. (2008). When studying solutions of the base algorithm in detail, it appeared that the optimal start time of route is often equal to the latest possible start time. This is because leaving the depot earlier may result in (additional) unnecessary waiting time. Although leaving the depot earlier might in some cases also result in reduced travel times along the route, this reduction in travel times only has an effect on total route duration when there are no waiting times along the route. By postponing the calculation of the optimal start time until the end of the search, computation time is saved. During the search, the latest possible start time is considered as optimal. To reduce the risk of ignoring potentially promising solutions, the fifty best solutions are maintained during the search instead of just the single best solution. At the end of the algorithm, optimal departure times are calculated for each of these fifty solutions and the solution which offers the least total route duration is reported.

The second speed-up approach is related to reducing the number of feasible local search moves which are carried out and subsequently need to be reversed because the increase in route duration is larger than the deterministic annealing threshold value. It is proposed to only carry out a selection of the feasible local search moves while rejecting other moves immediately. The following selection rule is implemented in version v2 of the algorithm. During the search, the threshold value T for accepting solutions with a higher total route duration as the current solution, will be between 0 and its maximum value T_{max}. When a local search move increases the total minimal duration of a solution with more than the current threshold value T plus the maximum threshold value T_{max}, the local search move is rejected immediately. The idea is that a move which results in a considerable increase in total minimal duration will probably not result in an acceptable effect on total route duration. Finally, a combination of both speed-up approaches is considered as well (v3).

An overview of the results of each version of the time-dependent algorithm is shown in Table 7.3. Using one of the speed-up approaches (v1 or v2) hardly affects solution quality while computation times are reduced by 20 to 25%. Even when a combination of both speed-up approaches is considered (v3), the negative effect on solution quality is limited, while computation times are reduced by 30%. Which of the speed-up approaches should be used, if any, depends on the preferences of the decision maker. Finally, it should be noted that although the speed-up approaches seem to work well here, this does not guarantee a similar performance in other problem contexts. For example when links in the network all have different and more complex speed profiles, selecting local search moves based on the effect on minimal duration might not be a good approach.

7.8 Conclusions and further research

Travel times are generally not constant but depend on the time of day. Several causes for this variation can be identified: congestion, accidents, weather conditions and other random events. This chapter studies how hourly variations in travel times due to congestion may be taken into account when planning drayage operations. A time-

Table 7.3: Speed-up approaches

Value	Result			
	v0	v1	v2	v3
Average number of vehicles	11.17	11.17	11.17	11.17
Average gap (absolute)	1.17	1.17	1.17	1.17
Average duration (min)	4751	4752	4752	4752
Average gap (%)	3.40	3.41	3.42	3.43
Average computation time (s)	14.83	11.74	11.11	10.35

dependent version of the two-phase deterministic annealing algorithm is presented. Good results are obtained which indicates that the solution algorithm is able to deal with deterministic time-dependent travel times. Finally, two approaches to reduce computation time are proposed.

In the future, supplementary computational tests could be performed. It would be interesting to analyze the performance of the algorithm when not all links in the network have the same speed profile. In order to ensure that realistic travel times are considered, time-dependent shortest paths between all locations should be calculated. Furthermore, more complex speed profiles with multiple speed levels may be considered. Another interesting research direction would be to study a dynamic version of the problem, similarly as discussed for the time-independent case at the end of Chapter 5. Next to the dynamic aspects discussed in Section 5.9, information on congestion and travel times may be updated during the planning horizon, although this would require that real-time traffic information is available to the decision maker.

Chapter 8

Final conclusions and further research

The purpose of this thesis was to analyze how empty container movements in the hinterland of a major seaport may be optimized. Special attention has been paid to the integration of empty container movements with loaded container transports which take place on the same network. In Chapter 2, a detailed overview of literature on the topic is presented. In the following chapters, two main aspects of the problem are analyzed. On the one hand, empty container repositioning decisions at a tactical decision level are studied in the context of service network design for an intermodal barge transportation network (Chapter 3). On the other hand, the operational planning of drayage operations in the service area of intermodal container terminals is investigated (Chapters 4 to 7). This final chapter summarizes the main conclusions and indicates opportunities for further research (Figure 8.1).

8.1 Final conclusions

Empty container repositioning is one of the longstanding and ongoing issues in containerized transport. Empty container movements are costly while not generating any revenue. Minimizing these movements is therefore of crucial importance to shipping lines and transportation companies. A social benefit in terms of reduced external effects of transport is identified as well.

In this thesis, the optimization of empty container movements in the hinterland of a major seaport is studied. With the majority of papers being published less than

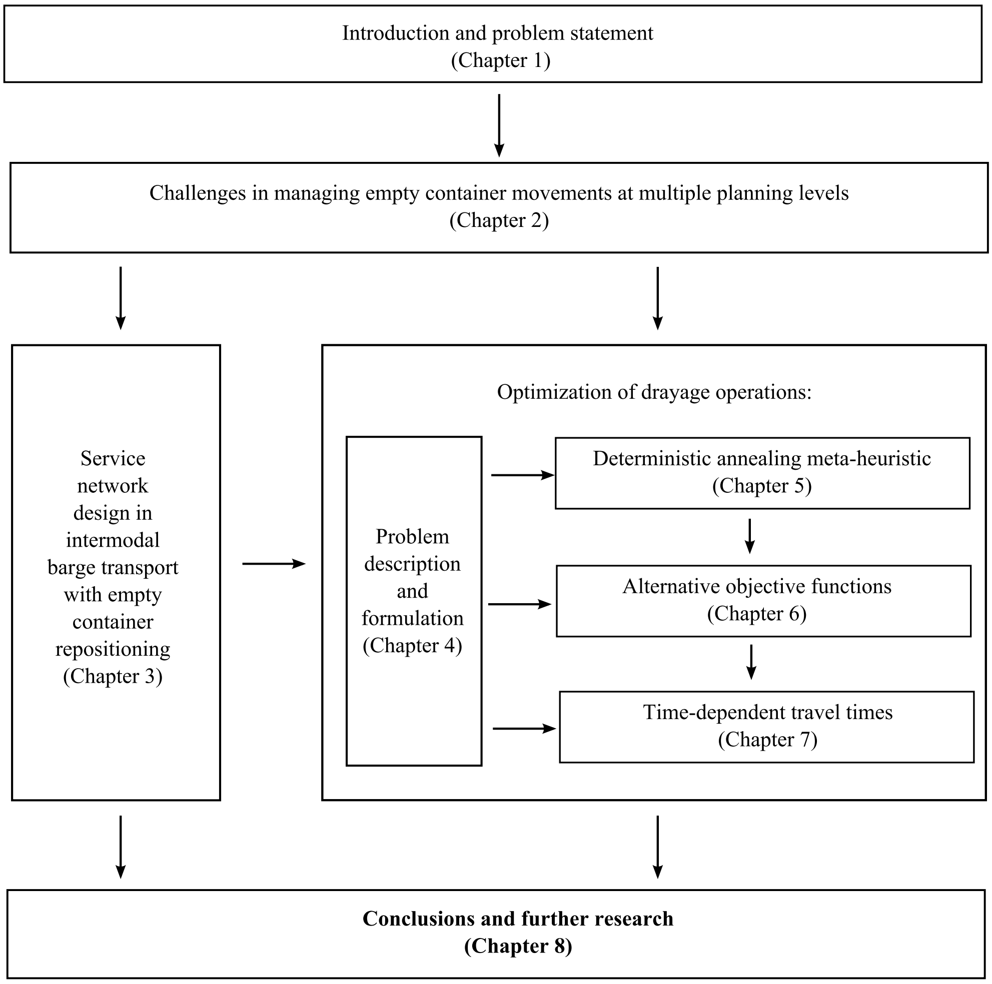

Figure 8.1: Outline of the thesis

twenty years ago, empty container repositioning is a relatively young research domain. An overview of existing research on the topic is presented in order to identify research gaps and interesting opportunities for further research. Most existing research has focused on maritime repositioning movements while empty container repositioning on a regional level in the hinterland of seaports has only received increased attention since ten years. The literature review indicates that especially research on strategic and tactical aspects of the repositioning problem is rather scarce. Besides, research on regional repositioning has mainly focused on a single transportation mode (road transport). Designing physical and service networks which consider empty container repositioning decisions in a multimodal context is therefore identified as an interesting research direction. For the operational planning level, it is concluded that recently promising efforts are made to integrate container allocation and vehicle routing decisions in drayage operations and that future research could focus on designing efficient heuristics and meta-heuristics for this problem. These two research opportunities are studied in this thesis.

At at tactical planning level, service network design in the context of intermodal barge transportation between a seaport and a number of hinterland ports is analyzed. Service network design is concerned with decisions regarding shipping routes on which transport services should be offered and the characteristics of these services. A mathematical model is proposed to assist barge operators and shipping lines with these decisions. The model determines optimal shipping routes for a given vessel capacity, service frequency and transport demand scenario. Vessel capacity and service frequency decisions may be evaluated by the model. When the model is applied from the perspective of a shipping line which offers door-to-door transportation services, empty container repositioning decisions should be made. These decisions can be taken either after barge services are planned or simultaneously with service network decisions. Results indicate that operating costs may be reduced if barge services and empty container repositioning movements are planned simultaneously.

The operational planning of drayage operations constitutes the second aspect of the empty container repositioning problem which is studied in this thesis. This planning problem is involved with determining efficient vehicle routes for performing all loaded and empty container transports in the service area of one or more intermodal container terminals. This thesis proposes solution algorithms which may be used in practice for the daily planning of these container transports. In the past, the problem has been divided into two subproblems to reduce problem complexity. These subproblems are solved sequentially. In a first step, the distribution or allocation of empty containers between consignees, shippers and container terminals is determined. In a second step, vehicle routes are created. Recently, several efforts to integrate both planning steps into a single model are proposed. This means that empty container allocations are made simultaneously with vehicle routing decisions. Although the advantage of an integrated approach over a sequential one seems clear, no comparison between both approaches has been made before. In this thesis planning models for both a sequential and an integrated planning approach are presented. The primary objective is to minimize the number of vehicles used. The secondary objective is to minimize total distance traveled. By extensive numerical experiments, the advantage of an integrated approach is demonstrated and quantified. A statistical test is employed to confirm that an integrated approach offers significantly better results than a sequential approach in terms of both objectives.

Both in literature and practice the direct transportation of empty containers between consignees and shippers is often proposed as a method to reduce empty container movements in the service area of intermodal container terminals. These type of transports are called street turns. The integrated planning model is used to assess the effect of implementing street turns in drayage operations on the number of vehicles and total distance traveled. Results indicate that street turns are highly beneficial, even when accounted for supplementary time needed to take care of paperwork, damage checks or other issues.

To solve the sequential and integrated planning models, a deterministic annealing algorithm is proposed. Several variants of this algorithm are discussed and compared with each other. Results show that on average a two-phase algorithm which combines deterministic annealing with some elements of tabu search offers the best solutions. The quality of this algorithm is analyzed in several ways. First, its results are compared with lower bounds obtained by a time window partitioning method. This comparison demonstrates that the algorithm provides near-optimal solutions within an acceptable time frame. Second, results show that the algorithm outperforms an existing solution method on a similar problem. Third, the effect of changes in problem characteristics on solution quality is analyzed. The algorithm is robust with respect to these changes.

The versatility of the deterministic annealing algorithm is demonstrated as well. It is discussed how the algorithm may be adapted when alternative objective functions are preferred. First, a bi-objective version of the integrated drayage problem is considered by not assigning priority to the minimization of the number of vehicles or the minimization of total distance. This way, the trade-off between both objectives is analyzed. Numerical experiments have shown that this trade-off is rather limited for the problem instances considered in this thesis. Second, it is discussed how the algorithm may be adapted in order to minimize total route duration instead of total distance.

Finally, time-dependent travel times in drayage operations are considered. Travel times are generally not constant but depend on the time of the day. Several causes for this variation can be identified: congestion, accidents, weather conditions and other random events. It is studied how hourly variations in travel times due to congestion may be taken into account when planning drayage operations. A time-dependent version of the two-phase deterministic annealing algorithm is presented. Good results are obtained which indicates that the solution algorithm is able to deal with deterministic time-dependent travel times.

8.2 Further research

Empty container repositioning constitutes a broad domain of research, ranging from long-term strategic issues to day-to-day operational decisions. Although research attention for the problem has increased in the last years, several opportunities for further research may be identified.

The effect of cooperation between shipping lines or transportation companies on empty container repositioning has only been studied by a few authors. In case future research could indicate that substantial benefits may be achieved from cooperation, companies might be less reluctant to participate in container sharing initiatives. A similar argumentation may be made for technological developments (Internet-based platforms, foldable containers, ...). These technologies seem interesting options to facilitate and/or reduce the costs of empty container management. By demonstrating potential savings which they could bring about, the probability and speed of adopting these technologies in practice may be increased.

Further research opportunities concerning the aspects of empty container repositioning studied in this thesis, may be identified as well. Currently, the tactical planning model for service network design in barge transportation concentrates on a single corridor while often several waterways are connected to a seaport. In such a situation, the simultaneous optimization of repositioning decisions for the complete network may be required. Only a single decision maker, either a barge operators or a shipping line, is assumed by the model, although it may be expected that in reality port authorities and terminal operators may play a role in the decision making process as well. In some case, when certain ports are able to attract sufficient volumes on their own, even a direct service between a hinterland port and the seaport may be established. In addition, transport demand is assumed to be deterministic, while in practice barge services are planned based on uncertain forecasts for transport demand. Future research could focus on how this uncertainty may be taken into account by the model. Reserving a portion of vessel capacity for unexpected increases in transport demand may be an opportunity. Similar to the concept of safety stock in inventory theory, the amount of capacity to be reserved should depend on the variability of the demand. Additional numerical experiments may be performed to analyze whether the model can still be solved efficiently for larger problem instances (increase in number of ports, vessels, clients or weeks).

Regarding the operational planning of drayage operations, several extensions of the integrated drayage problem may be investigated. Limits on the number of empty containers available at each container terminal could be imposed. This reduces the set of feasible solutions for the empty container allocation subproblem and further complicates the integrated drayage problem. Local search operators have to be adapted to avoid violations of the additional constraint. Furthermore, only a single container type and a single vehicle type are assumed in this thesis, while multiple types are used in practice. Future research could focus on how the solution algorithm may be adapted to take this variety in containers and vehicles into account. For some combinations of container and vehicle type, it may for example be feasible to transport two containers simultaneously by a single vehicle. Containers of different owners may be assumed, restricting the use of a container to a particular set of consignees and shippers. In a case of a heterogeneous fleet, different fixed costs may apply for each type of vehicle and some consignees and shippers may not be able to accommodate all types of vehicles due to practical limitations. Next, a multi-objective version of the problem may be proposed by considering three or more objectives. Minimizing the number of vehicles, total distance and total route duration have already been introduced in this thesis. An additional objective might be to balance the workload among vehicles. Such an objective is often introduced in vehicle routing problems in order to bring an element of fairness into play. A new solution approach to deal with this multi-objective problem would have to be introduced. With respect to the algorithm for the time-dependent problem, solution quality in case of links with different and more complex speed profiles could be investigated. Finally, in this thesis a static planning approach is considered. To increase the applicability of the modeling approach in practice, a dynamic version of the integrated drayage problem may be studied. In a dynamic problem context, not all problem information is known at the beginning of the planning period. Instead this information becomes available or is updated during the planning period. Examples include new requests arriving or existing requests being canceled during the day, changes in customer time windows and vehicle breakdowns. The existing planning should be updated in real-time to accommodate the new information.

Appendix A

Data overview for service network design model

This appendix provides an overview of the data used in the tactical planning model for service network design in intermodal barge transportation which is presented in Chapter 3. Cost data are mainly based on a recent report commissioned by the Dutch government agency 'Rijkswaterstaat' of the Ministry of Infrastructure and the Environment NEA (2009). Other sources include Vacca et al. (2007), Promotie Binnenvaart Vlaanderen (2008), Konings (2009), Caris (2011) and personal communication. The terminals at Antwerp right river bank and Antwerp left river bank are denoted respectively RRB and LRB.

A.1 Network

Table A.1: Distances d_{ij} (km)

	Genk	Meerhout	Deurne	RRB	LRB
Liege	41.2	77.7	125.2	134.5	139.5
Genk		36.5	84.0	93.3	98.3
Meerhout			47.5	56.8	61.8
Deurne				9.3	14.3
RRB					5.0

Table A.2: Travel times t_{ij} (h)

	Genk	Meerhout	Deurne	RRB	LRB
Liege	3	7	11	14	16.5
Genk		4	8	11	13.5
Meerhout			4	7	9.5
Deurne				3	5.5
RRB					2.5

Table A.3: Freight rates (€/TEU)

	Loaded (f^l_{ij})		Empty (f^e_{ij})	
	RRB	LRB	RRB	LRB
Liege	120	120	50	50
Genk	110	110	45	45
Meerhout	95	95	40	40
Deurne	80	80	35	35

Table A.4: Truck rates $\hat{c}_{ij}$ (€/TEU)

	Genk	Meerhout	Deurne	RRB	LRB
Liege	125	180	213	216	220
Genk		123	185	200	203
Meerhout			133	140	150
Deurne				100	110
RRB					80

A.2 Ports

Container handling costs:	$c_i^h = 13$ €/TEU	$\forall i \in N$
Port entry costs:	$c_i^e = 0$ €	$\forall i \in N$
Container handling time:	$t_i^h = 0.0417$ h/TEU	$\forall i \in N$
Mooring and unmooring time:	$t_i^m = 0.5$ h	$\forall i \in N$

Container storage costs: $c_p^s = 1$ €/(TEU × day) $\forall p \in P$

Maximum inventory level:
$$inv_p^{max} = \begin{cases} 20 & \forall p = \{1,2,3,4\} \\ \infty & \forall p = \{5,6\} \end{cases}$$

A.3 Vessels

Table A.5: Vessels

Capacity (TEU)	Charter and crew costs c^r_{char} (€/day)	Fuel and maintenance costs c^r_{fuel} (€/km)
100	2560	6.80
150	3615	7.27
300	5714	12.57

Appendix B

Detailed results: sequential solution approach

Detailed results of all algorithm variants for the sequential solution approach are presented in this appendix. Table B.1 shows the average number of vehicles used and average total distance traveled for each problem instance. Table B.2 shows the absolute gap for the number of vehicles used and the relative gap for the total distance traveled. To calculate the relative gap for the total distance, the distance of each solution is compared the lower bound for the corresponding number of vehicles ($LB_{d(k)}$).

Table B.1: Detailed results: sequential approach

Instance	1-DA		2-DA		1-DA_{TS}		2-DA_{TS}	
	V[a]	D[b]	V	D	V	D	V	D
1.1	7.00	1031	6.00	1067	7.00	1030	6.00	1065
1.2	7.00	967	6.00	1010	7.00	966	6.06	1008
1.3	6.06	973	6.00	973	6.06	972	6.00	972
2.1	6.00	1010	6.00	1009	6.00	1009	6.00	1008
2.2	6.22	969	6.00	970	6.32	964	6.00	968
2.3	6.00	921	6.00	921	6.00	920	6.00	921
3.1	6.00	823	6.00	823	6.00	823	6.00	823
3.2	6.00	750	6.00	751	6.00	749	6.00	749

	V[a]	D[b]	V	D	V	D	V	D
3.3	6.00	724	6.00	724	6.00	724	6.00	724
4.1	6.00	695	6.00	695	6.00	695	6.00	695
4.2	6.00	682	6.00	683	6.00	682	6.00	683
4.3	6.00	706	6.00	706	6.00	705	6.00	705
5.1	12.42	1792	12.00	1800	12.68	1781	12.00	1797
5.2	12.00	1821	12.00	1822	12.02	1818	11.92	1825
5.3	12.00	1647	11.00	1688	12.00	1647	11.00	1685
6.1	12.00	1640	11.00	1673	11.96	1639	11.00	1673
6.2	12.00	1655	11.00	1676	12.00	1654	11.00	1675
6.3	12.00	1787	11.02	1824	12.00	1785	11.00	1823
7.1	11.00	1410	11.00	1409	11.00	1409	11.00	1409
7.2	11.00	1299	10.78	1315	11.00	1297	10.76	1313
7.3	11.00	1288	10.00	1320	11.00	1288	10.00	1319
8.1	11.00	1348	11.00	1348	11.00	1345	11.00	1345
8.2	11.00	1294	10.38	1322	11.00	1293	10.56	1314
8.3	10.40	1162	10.00	1166	10.70	1156	10.00	1165
9.1	9.00	1934	9.00	1934	9.00	1934	9.00	1934
9.2	9.00	1970	9.00	1967	9.00	1965	9.00	1966
9.3	8.80	1833	8.00	1874	8.78	1831	8.00	1871
10.1	9.00	1938	8.00	1971	9.00	1938	8.00	1970
10.2	8.84	1849	8.00	1897	8.88	1847	8.00	1896
10.3	8.42	1888	8.00	1889	8.52	1886	8.00	1889
11.1	8.00	1605	8.00	1605	8.00	1605	8.00	1605
11.2	8.00	1666	8.00	1665	8.00	1663	8.00	1663
11.3	9.00	1495	8.12	1633	9.00	1492	8.06	1631
12.1	8.00	1469	7.06	1548	8.00	1467	7.02	1543
12.2	8.00	1548	8.00	1547	8.00	1548	8.00	1550
12.3	7.00	1345	7.00	1345	7.00	1344	7.00	1345
13.1	16.98	3363	16.00	3413	17.00	3358	16.00	3403
13.2	17.00	4044	17.00	4044	17.00	4040	16.98	4043

	V[a]	D[b]	V	D	V	D	V	D
13.3	17.00	3487	16.00	3513	17.00	3488	16.00	3514
14.1	16.00	3340	15.00	3418	16.00	3339	15.00	3412
14.2	17.00	3594	16.00	3626	17.00	3591	16.00	3623
14.3	16.00	3224	15.00	3276	16.00	3222	15.00	3273
15.1	15.00	2908	14.72	2939	15.00	2906	14.58	2951
15.2	14.98	2792	14.00	2831	14.96	2791	14.00	2826
15.3	15.94	2703	15.00	2739	15.94	2701	15.00	2735
16.1	14.60	2777	14.00	2793	14.40	2785	14.00	2794
16.2	14.00	2651	14.00	2650	14.00	2649	13.98	2649
16.3	14.00	2682	14.00	2682	14.00	2677	14.00	2676

[a] V: average number of vehicles used (over fifty runs)

[b] D: average total distance traveled (over fifty runs)

Table B.2: Detailed results: sequential approach - gaps

Instance	1-DA		2-DA		1-DA_{TS}		2-DA_{TS}	
	ΔV[a]	ΔD[b]	ΔV	ΔD	ΔV	ΔD	ΔV	ΔD
1.1	1.00	0.85	0.00	2.52	1.00	0.79	0.00	2.34
1.2	1.00	0.82	0.00	2.02	1.00	0.76	0.06	2.02
1.3	0.06	2.06	0.00	1.97	0.06	1.97	0.00	1.85
2.1	0.00	1.73	0.00	1.69	0.00	1.71	0.00	1.61
2.2	0.22	2.01	0.00	1.86	0.32	1.52	0.00	1.73
2.3	0.00	1.61	0.00	1.66	0.00	1.53	0.00	1.60
3.1	0.00	0.72	0.00	0.72	0.00	0.70	0.00	0.67
3.2	0.00	3.18	0.00	3.23	0.00	3.01	0.00	3.02
3.3	1.00	1.80	1.00	1.81	1.00	1.80	1.00	1.79
4.1	1.00	2.15	1.00	2.19	1.00	2.21	1.00	2.18
4.2	1.00	1.59	1.00	1.66	1.00	1.60	1.00	1.63
4.3	1.00	1.28	1.00	1.30	1.00	1.26	1.00	1.25

	ΔV^a	ΔD^b	ΔV	ΔD	ΔV	ΔD	ΔV	ΔD
5.1	1.42	2.43	1.00	2.53	1.68	1.99	1.00	2.36
5.2	1.00	2.85	1.00	2.90	1.02	2.71	0.92	2.96
5.3	1.00	2.27	0.00	3.80	1.00	2.27	0.00	3.61
6.1	1.00	2.43	0.00	4.29	0.96	2.36	0.00	4.25
6.2	1.00	1.38	0.00	2.70	1.00	1.32	0.00	2.59
6.3	1.00	2.95	0.02	4.61	1.00	2.85	0.00	4.50
7.1	1.00	3.84	1.00	3.81	1.00	3.80	1.00	3.80
7.2	1.00	2.55	0.78	3.55	1.00	2.37	0.76	3.38
7.3	1.00	2.34	0.00	4.29	1.00	2.37	0.00	4.21
8.1	1.00	3.93	1.00	3.94	1.00	3.70	1.00	3.69
8.2	1.00	4.06	0.38	6.05	1.00	3.93	0.56	5.49
8.3	1.40	3.49	1.00	3.89	1.70	2.82	1.00	3.86
9.1	1.00	0.99	1.00	0.96	1.00	0.96	1.00	0.95
9.2	0.00	1.02	0.00	0.86	0.00	0.77	0.00	0.79
9.3	0.80	1.24	0.00	2.01	0.78	1.11	0.00	1.86
10.1	1.00	1.27	0.00	1.93	1.00	1.28	0.00	1.86
10.2	0.84	1.59	0.00	3.31	0.88	1.52	0.00	3.25
10.3	0.42	0.90	0.00	0.86	0.52	0.83	0.00	0.90
11.1	0.00	1.09	0.00	1.09	0.00	1.07	0.00	1.08
11.2	0.00	1.77	0.00	1.71	0.00	1.56	0.00	1.57
11.3	1.00	0.84	0.12	7.05	1.00	0.67	0.06	6.73
12.1	1.00	0.96	0.06	5.80	1.00	0.80	0.02	5.45
12.2	1.00	0.96	1.00	0.91	1.00	0.98	1.00	1.06
12.3	0.00	1.84	0.00	1.84	0.00	1.78	0.00	1.81
13.1	2.98	1.70	2.00	2.82	3.00	1.54	2.00	2.52
13.2	1.00	2.33	1.00	2.32	1.00	2.23	0.98	2.27
13.3	2.00	1.41	1.00	2.05	2.00	1.44	1.00	2.05
14.1	2.00	1.92	1.00	4.20	2.00	1.89	1.00	4.03
14.2	2.00	2.25	1.00	2.86	2.00	2.18	1.00	2.77

	ΔV[a]	ΔD[b]	ΔV	ΔD	ΔV	ΔD	ΔV	ΔD
14.3	2.00	2.32	1.00	3.79	2.00	2.27	1.00	3.69
15.1	1.00	3.04	0.72	3.70	1.00	2.95	0.58	3.91
15.2	1.98	1.99	1.00	2.70	1.96	1.93	1.00	2.51
15.3	2.94	1.98	2.00	3.11	2.94	1.91	2.00	2.94
16.1	1.60	3.59	1.00	4.17	1.40	3.88	1.00	4.18
16.2	1.00	3.50	1.00	3.48	1.00	3.44	0.98	3.43
16.3	1.00	4.50	1.00	4.47	1.00	4.29	1.00	4.24

[a] ΔV: average absolute gap for number of vehicles

[b] ΔD: average relative gap for distance traveled

Appendix C

Detailed results: integrated solution approach

Detailed results of all algorithm variants for the integrated solution approach are presented in this appendix. Table C.1 shows the average number of vehicles used and average total distance traveled for each problem instance. Table C.2 shows the absolute gap for the number of vehicles used and the relative gap for the total distance traveled. To calculate the relative gap for the total distance, the distance of each solution is compared the lower bound for the corresponding number of vehicles ($LB_{d(k)}$).

Table C.1: Detailed results: integrated approach

Instance	1-DA		2-DA		1-DA$_{TS}$		2-DA$_{TS}$	
	V[a]	D[b]	V	D	V	D	V	D
1.1	7.00	1017	6.06	1063	7.00	1014	6.00	1065
1.2	6.00	989	6.00	987	6.02	988	6.00	985
1.3	6.12	973	6.00	972	6.26	966	6.00	969
2.1	6.00	1001	6.00	1000	6.00	1001	6.00	1001
2.2	6.34	970	6.00	972	6.38	968	6.00	973
2.3	6.00	918	6.00	919	6.00	917	6.00	917
3.1	6.00	808	6.00	808	6.00	808	6.00	809
3.2	6.00	743	6.00	743	6.00	743	6.00	742

	V[a]	D[b]	V	D	V	D	V	D
3.3	6.00	699	6.00	699	6.00	699	6.00	699
4.1	6.00	692	6.00	692	6.00	692	6.00	692
4.2	6.00	679	6.00	679	6.00	679	6.00	679
4.3	6.00	696	6.00	696	6.00	696	6.00	696
5.1	12.00	1802	12.00	1792	12.00	1797	12.00	1789
5.2	12.00	1820	11.98	1821	12.00	1815	12.00	1815
5.3	11.98	1647	11.00	1681	12.00	1645	11.00	1678
6.1	12.00	1655	11.00	1682	12.00	1653	11.00	1678
6.2	11.76	1659	11.00	1665	11.82	1658	11.00	1663
6.3	12.00	1782	11.12	1806	12.00	1779	11.00	1806
7.1	11.00	1394	11.00	1397	11.00	1392	11.00	1393
7.2	11.00	1279	10.86	1285	11.00	1277	10.82	1286
7.3	11.00	1294	10.00	1320	11.00	1290	10.02	1315
8.1	11.00	1339	10.96	1339	11.00	1337	10.92	1342
8.2	11.00	1286	10.50	1307	11.00	1285	10.44	1309
8.3	10.00	1161	10.00	1160	10.00	1161	10.00	1158
9.1	9.00	1934	9.00	1930	9.00	1936	9.00	1931
9.2	9.00	1959	9.00	1955	9.00	1957	9.00	1956
9.3	8.48	1823	8.00	1843	8.54	1816	8.00	1842
10.1	9.00	1937	8.00	1962	9.00	1935	8.00	1961
10.2	8.68	1850	8.00	1876	8.76	1847	8.00	1873
10.3	8.54	1885	8.00	1885	8.52	1883	8.00	1885
11.1	8.00	1601	8.00	1602	8.00	1600	8.00	1600
11.2	8.00	1656	8.00	1655	8.00	1653	8.00	1654
11.3	8.74	1509	8.00	1567	8.56	1518	8.00	1565
12.1	8.00	1452	7.00	1516	8.00	1449	7.00	1521
12.2	8.00	1550	8.00	1550	8.00	1549	8.00	1551
12.3	7.00	1346	7.00	1343	7.00	1345	7.00	1346
13.1	16.00	3329	15.42	3354	16.00	3324	15.62	3340
13.2	17.00	4037	17.00	4038	17.00	4034	16.98	4033

	V[a]	D[b]	V	D	V	D	V	D
13.3	16.00	3502	16.00	3506	16.00	3498	16.00	3500
14.1	16.00	3354	15.00	3394	16.00	3351	15.00	3387
14.2	16.20	3623	16.00	3610	16.16	3615	16.00	3607
14.3	15.60	3253	15.00	3258	15.54	3252	15.00	3254
15.1	15.00	2896	14.74	2919	15.00	2891	14.80	2909
15.2	14.48	2803	14.00	2817	14.48	2803	14.00	2816
15.3	15.00	2725	15.00	2721	15.00	2725	15.00	2722
16.1	14.44	2733	14.00	2735	14.52	2731	14.00	2733
16.2	14.00	2647	14.00	2640	14.00	2639	14.00	2641
16.3	14.00	2670	13.98	2673	14.00	2668	14.00	2671

[a] V: average number of vehicles used (over fifty runs)

[b] D: average total distance traveled (over fifty runs)

Table C.2: Detailed results: integrated approach - gaps

Instance	1-DA		2-DA		1-DA_{TS}		2-DA_{TS}	
	ΔV[a]	ΔD[b]	ΔV	ΔD	ΔV	ΔD	ΔV	ΔD
1.1	1.00	2.03	0.06	5.10	1.00	1.70	0.00	5.13
1.2	0.00	4.12	0.00	3.86	0.02	3.98	0.00	3.69
1.3	0.12	5.34	0.00	4.99	0.26	4.94	0.00	4.70
2.1	0.00	2.64	0.00	2.58	0.00	2.65	0.00	2.63
2.2	0.34	3.59	0.00	3.63	0.38	3.45	0.00	3.73
2.3	0.00	3.02	0.00	3.05	0.00	2.90	0.00	2.92
3.1	0.00	3.09	0.00	3.04	0.00	3.11	0.00	3.13
3.2	1.00	5.18	1.00	5.10	1.00	5.11	1.00	4.99
3.3	1.00	2.46	1.00	2.45	1.00	2.44	1.00	2.47
4.1	1.00	3.94	1.00	4.00	1.00	3.96	1.00	4.00
4.2	1.00	2.36	1.00	2.42	1.00	2.46	1.00	2.38
4.3	1.00	3.19	1.00	3.18	1.00	3.14	1.00	3.19

	ΔV^a	ΔD^b	ΔV	ΔD	ΔV	ΔD	ΔV	ΔD
5.1	1.00	5.11	1.00	4.54	1.00	4.84	1.00	4.34
5.2	1.00	6.01	0.98	6.05	1.00	5.72	1.00	5.75
5.3	1.98	5.05	1.00	7.03	2.00	4.91	1.00	6.83
6.1	1.00	4.36	0.00	6.08	1.00	4.21	0.00	5.83
6.2	0.76	3.86	0.00	4.33	0.82	3.79	0.00	4.22
6.3	1.00	5.00	0.12	6.46	1.00	4.81	0.00	6.44
7.1	1.00	6.97	1.00	7.15	1.00	6.79	1.00	6.84
7.2	1.00	6.06	0.86	6.54	1.00	5.86	0.82	6.56
7.3	1.00	6.70	0.00	8.77	1.00	6.41	0.02	8.36
8.1	1.00	7.07	0.96	7.12	1.00	6.91	0.92	7.35
8.2	1.00	6.95	0.50	8.83	1.00	6.91	0.44	8.97
8.3	1.00	7.54	1.00	7.50	1.00	7.52	1.00	7.32
9.1	1.00	2.17	1.00	1.95	1.00	2.26	1.00	2.02
9.2	1.00	3.32	1.00	3.14	1.00	3.24	1.00	3.21
9.3	0.48	2.99	0.00	3.59	0.54	2.68	0.00	3.51
10.1	1.00	1.88	0.00	2.41	1.00	1.79	0.00	2.36
10.2	0.68	3.76	0.00	4.49	0.76	3.67	0.00	4.34
10.3	0.54	1.88	0.00	2.06	0.52	1.79	0.00	2.05
11.1	1.00	2.03	1.00	2.09	1.00	1.99	1.00	1.97
11.2	1.00	3.36	1.00	3.28	1.00	3.19	1.00	3.22
11.3	1.74	3.83	1.00	7.06	1.56	4.32	1.00	6.94
12.1	1.00	2.60	0.00	7.48	1.00	2.43	0.00	7.84
12.2	1.00	3.73	1.00	3.73	1.00	3.66	1.00	3.76
12.3	0.00	3.83	0.00	3.58	0.00	3.75	0.00	3.79
13.1	2.00	4.47	1.42	5.16	2.00	4.29	1.62	4.75
13.2	1.00	4.45	1.00	4.48	1.00	4.38	0.98	4.33
13.3	2.00	4.07	2.00	4.20	2.00	3.97	2.00	4.02
14.1	2.00	5.30	1.00	6.78	2.00	5.22	1.00	6.57
14.2	2.20	4.86	2.00	4.48	2.16	4.62	2.00	4.41

	ΔV[a]	ΔD[b]	ΔV	ΔD	ΔV	ΔD	ΔV	ΔD
14.3	1.60	5.27	1.00	5.50	1.54	5.24	1.00	5.39
15.1	2.00	6.11	1.74	6.83	2.00	5.92	1.80	6.48
15.2	1.48	5.36	1.00	5.91	1.48	5.37	1.00	5.89
15.3	2.00	5.85	2.00	5.70	2.00	5.86	2.00	5.74
16.1	1.44	5.59	1.00	5.84	1.52	5.48	1.00	5.76
16.2	2.00	6.84	2.00	6.54	2.00	6.48	2.00	6.57
16.3	1.00	6.69	0.98	6.80	1.00	6.59	1.00	6.72

[a] ΔV: average absolute gap for number of vehicles

[b] ΔD: average relative gap for distance traveled

Appendix D

Detailed results: bi-objective approach

Detailed results of the BI-DA* algorithm for each of the 48 problem instances are shown in Table D.1. For each instance the lower bound on the number of vehicles is shown in the second column. The following columns contain the average results of the non-dominated solutions over fifty runs for each number of vehicles starting from the lower bound. For each instance, three values are shown per column. The first value is the average distance while the second value indicates in how many runs a non-dominated solution for this number of vehicles was found. The third value represents the average relative gap with the specific lower bound on total distance for this number of vehicles.

It is important to note that only non-dominated solutions provided by each run of the algorithm are used to construct Table D.1. However, this does not imply that the average of the non-dominated solutions for a particular number of vehicles is lower than the average of the non-dominated solutions for a lower number of vehicles. In case a non-dominated solution with a high number of vehicles is only found for a subset of the runs, it might occur that the average distance of these non-dominated solutions is higher than the average distance of the non-dominated solutions with fewer vehicles. This is for example the case for instance 1.1 where the average distances of the non-dominated solutions with 10 and 11 vehicles are higher than the average distance of the solutions with 9 vehicles.

Table D.1: Detailed results of the BI-DA* algorithm

Inst.	LB	Distance / number of solutions / gap with $LB_{d(k)}$											
	=k	k	k+1	k+2	k+3	k+4	k+5	k+6	k+7	k+8	k+9	k+10	k+11
1.1	6	1065	1015	1006	1000	1001	1004						
		50	50	50	50	14	1						
		5.21	1.83	1.48	1.08	0.98	1.06						
1.2	6	985	958	950	949	950							
		50	50	50	27	1							
		3.66	1.92	1.18	0.97	0.77							
1.3	6	971	935	921	910	908	907	909					
		50	50	50	48	31	24	1					
		4.85	3.12	2.41	1.63	1.39	0.99	0.82					
2.1	6	1001	984	979	977	979							
		50	50	50	37	5							
		2.62	1.42	0.86	0.52	0.47							
2.2	6	973	949	946	946	948							
		50	50	45	16	1							
		3.72	1.84	1.60	1.24	0.82							
2.3	6	917	904	903	902	903							
		50	50	42	19	6							
		2.92	1.88	1.70	1.45	1.19							
3.1	6	808	794	790	788	791							
		50	50	50	31	1							
		3.11	2.25	2.05	1.52	1.48							
3.2	5		743	728	721	717	716	720					
			50	50	50	43	27	1					
			5.13	4.01	3.56	2.93	2.16	1.85					
3.3	5		699	696	694	696							
			50	50	32	4							
			2.45	1.95	1.40	1.26							

Inst.	LB	k	k+1	k+2	k+3	k+4	k+5	k+6	k+7	k+8	k+9	k+10	k+11
4.1	5		691	685	683	683							
			50	50	41	2							
			3.89	3.07	2.24	1.69							
4.2	5		679	676	677	677							
			50	44	5	1							
			2.38	1.83	1.50	0.80							
4.3	5		696	691	692	692							
			50	44	12	1							
			3.20	2.02	1.69	1.06							
5.1	11		1790	1765	1754	1748	1741	1737	1735	1735	1737	1735	
			50	50	49	50	47	39	19	13	7	1	
			4.43	3.28	2.80	2.48	2.01	1.69	1.44	1.28	1.20	0.86	
5.2	11	1866	1814	1788	1773	1763	1756	1753	1753	1752	1752		
		1	50	50	50	49	48	38	27	15	3		
		8.26	5.68	4.41	3.67	3.09	2.70	2.39	2.24	2.02	1.79		
5.3	10		1679	1638	1622	1615	1611	1609	1608	1613			
			50	50	50	48	45	28	8	1			
			6.88	4.44	3.51	2.96	2.51	2.10	1.72	1.73			
6.1	11	1678	1646	1633	1626	1624	1624	1627					
		50	50	50	45	32	8	2					
		5.85	3.81	2.83	2.22	1.77	1.46	1.27					
6.2	11	1663	1646	1642	1640	1639	1640						
		50	50	46	35	20	5						
		4.21	3.06	2.67	2.36	2.05	1.85						
6.3	11	1807	1778	1761	1752	1748	1746	1745	1744	1745	1744	1750	
		49	50	50	49	46	32	26	17	7	2	1	
		6.48	4.78	3.75	3.13	2.71	2.41	2.11	1.85	1.64	1.31	1.33	
7.1	10		1394	1367	1354	1351	1350	1349	1349				
			50	50	50	46	30	21	6				
			6.98	4.88	3.83	3.39	3.09	2.77	2.42				

Inst.	LB	k	k+1	k+2	k+3	k+4	k+5	k+6	k+7	k+8	k+9	k+10	k+11
7.2	10	1322	1277	1263	1257	1253	1253	1254	1256				
		10	50	50	44	33	24	4	1				
		9.42	5.91	4.64	3.90	3.33	2.97	2.67	2.42				
7.3	10	1317	1289	1279	1272	1269	1269	1268	1268	1269			
		49	50	50	50	35	22	12	7	1			
		8.55	6.28	5.39	4.68	4.33	4.10	3.83	3.60	3.27			
8.1	10	1396	1336	1322	1314	1309	1308	1308	1311	1309			
		4	50	50	50	43	20	15	5	2			
		11.74	6.86	5.58	4.72	4.03	3.63	3.29	3.09	2.51			
8.2	10	1328	1285	1270	1263	1260	1259	1259	1259	1259			
		28	50	50	47	45	20	9	3	1			
		10.59	6.85	5.49	4.63	4.12	3.80	3.35	2.98	2.54			
8.3	9		1159	1146	1143	1142	1142						
			50	50	36	16	2						
			7.36	5.80	5.07	4.52	3.98						
9.1	8		1932	1910	1899	1893	1894						
			50	50	50	49	3						
			2.03	1.48	1.12	0.83	0.70						
9.2	8		1957	1921	1911	1907	1904	1908					
			50	50	50	37	19	1					
			3.21	2.18	1.97	1.81	1.43	1.33					
9.3	8	1841	1793	1781	1775	1776							
		50	50	50	43	4							
		3.46	1.87	1.54	1.05	0.75							
10.1	8	1960	1934	1923	1919	1920							
		50	50	47	39	5							
		2.29	1.75	1.30	0.80	0.41							
10.2	8	1873	1835	1814	1808	1803	1808						
		50	50	50	45	32	6						
		4.32	3.22	2.24	1.79	1.20	1.06						

Inst.	LB	k	k+1	k+2	k+3	k+4	k+5	k+6	k+7	k+8	k+9	k+10	k+11
10.3	8	1884	1868	1871									
		50	50	21									
		2.03	0.80	0.44									
11.1	7		1600	1580	1576	1575							
			50	50	43	12							
			1.99	1.01	0.87	0.44							
11.2	7		1653	1625	1613	1611	1611	1615					
			50	50	50	27	9	2					
			3.14	2.27	1.77	1.67	1.57	1.59					
11.3	7		1563	1485	1469								
			50	50	50								
			6.79	2.48	1.34								
12.1	7	1521	1449	1450									
		49	50	12									
		7.83	2.40	1.85									
12.2	7	1610	1550	1538	1534	1536							
		1	50	49	35	1							
		7.03	3.69	2.78	2.19	1.84							
12.3	7	1343	1327	1323	1325								
		50	50	35	14								
		3.59	2.41	1.65	1.22								
13.1	14		3376	3319	3291	3276	3269	3271	3268		3276		
			21	50	49	45	28	18	8		1		
			5.77	4.14	3.22	2.62	2.21	2.08	1.75		1.36		
13.2	16	4091	4031	3979	3945	3921	3904	3896	3888	3887	3886	3883	3891
		2	50	50	50	50	47	44	43	29	18	16	2
		5.18	4.30	3.34	2.66	2.19	1.79	1.56	1.33	1.24	1.12	0.92	1.00
13.3	14			3500	3460	3451	3450	3453	3454				
				50	50	42	24	6	3				
				4.01	2.74	2.32	2.03	1.86	1.61				

Inst.	LB	k	k+1	k+2	k+3	k+4	k+5	k+6	k+7	k+8	k+9	k+10	k+11
14.1	14		3388	3331	3317	3312	3311	3311					
			50	50	49	35	15	8					
			6.59	4.59	3.92	3.44	3.09	2.73					
14.2	14			3608	3579	3567	3560	3557	3555	3555	3559		
				50	50	46	43	29	22	7	1		
				4.43	3.51	3.07	2.71	2.41	2.14	1.86	1.67		
14.3	14		3251	3223	3210	3202	3199	3200	3201				
			50	49	49	39	28	13	5				
			5.29	4.25	3.64	3.17	2.83	2.63	2.37				
15.1	13		2990	2893	2851	2824	2810	2801	2798	2796	2798		
			12	50	50	50	46	46	29	14	8		
			9.16	5.98	4.58	3.59	2.95	2.45	2.16	1.89	1.69		
15.2	13		2814	2780	2759	2755	2753	2752	2756				
			50	50	50	38	27	18	3				
			5.82	4.48	3.62	3.22	2.85	2.51	2.34				
15.3	13			2720	2690	2680	2675	2675	2678				
				50	50	48	35	20	6				
				5.65	4.37	3.76	3.27	2.89	2.57				
16.1	13		2732	2706	2696	2693	2697	2695					
			50	50	44	25	7	1					
			5.70	4.36	3.56	2.92	2.49	1.75					
16.2	12			2638	2611	2599	2594	2595	2599				
				50	50	48	36	13	3				
				6.48	5.00	4.07	3.39	2.86	2.47				
16.3	13		2667	2629	2612	2603	2603	2603	2607				
			50	50	49	36	24	8	1				
			6.58	4.92	4.04	3.43	3.08	2.67	2.36				

Appendix E

Detailed results: minimization of total route duration

Table E.1: Detailed results: route duration

Instance	V^a	ΔV^b	Dur^c	ΔDur^d
1.1	6.00	0.00	2685	1.26
1.2	6.00	0.00	2571	1.93
1.3	6.00	0.00	2559	1.45
2.1	6.00	0.00	2591	1.12
2.2	6.00	0.00	2605	0.99
2.3	6.00	0.00	2567	0.67
3.1	6.00	0.00	2531	1.45
3.2	6.00	1.00	2370	1.33
3.3	6.00	1.00	2302	1.83
4.1	6.00	1.00	2317	1.23
4.2	6.00	1.00	2339	0.71
4.3	6.00	1.00	2333	1.27
5.1	12.00	1.00	4943	1.47

Instance	V^a	ΔV^b	Dur^c	ΔDur^d
5.2	12.00	1.00	5040	1.93
5.3	11.00	1.00	4833	2.32
6.1	11.00	0.00	4893	1.70
6.2	11.00	0.00	4868	1.32
6.3	11.00	0.00	5038	2.03
7.1	11.00	1.00	4694	2.06
7.2	10.76	0.76	4513	2.35
7.3	10.00	0.00	4540	2.80
8.1	10.84	0.84	4604	1.90
8.2	10.36	0.36	4567	2.89
8.3	10.00	1.00	4261	2.31
9.1	9.00	1.00	3571	0.75
9.2	9.00	1.00	3586	1.29
9.3	8.00	0.00	3455	0.82
10.1	8.00	0.00	3667	0.76
10.2	8.00	0.00	3476	1.80
10.3	8.00	0.00	3466	0.86
11.1	8.00	1.00	3349	0.86
11.2	8.00	1.00	3363	1.30
11.3	8.00	1.00	3258	3.27
12.1	7.00	0.00	3139	3.87
12.2	8.00	1.00	3208	1.98
12.3	7.00	0.00	2987	2.09
13.1	15.48	1.48	6579	2.81
13.2	16.92	0.92	7361	1.24
13.3	16.00	2.00	6750	2.42
14.1	15.00	1.00	6529	3.42
14.2	16.00	2.00	6843	2.23
14.3	15.00	1.00	6398	2.89
15.1	14.52	1.52	6349	2.26

Instance	V[a]	ΔV[b]	Dur[c]	ΔDur[d]
15.2	14.00	1.00	6063	2.69
15.3	14.98	1.98	6030	3.05
16.1	14.00	1.00	6012	1.98
16.2	14.00	2.00	5906	2.80
16.3	14.00	1.00	5945	2.78

[a] V: average number of vehicles used

[b] ΔV: average absolute gap for number of vehicles

[c] Dur: average total route duration

[d] ΔDur: average relative gap for total route duration

Appendix F

Detailed results: time-dependent travel times

Table F.1: Detailed results: time-dependent travel times

Instance	V[a]	ΔV[b]	Dur[c]	ΔDur[d]
TD 1.1	7.00	0.00	2807	2.99
TD 1.2	7.00	1.00	2920	1.44
TD 1.3	7.00	1.00	2862	2.87
TD 2.1	7.00	1.00	2871	1.44
TD 2.2	6.00	0.00	2697	2.87
TD 2.3	7.00	1.00	2740	2.24
TD 3.1	6.00	0.00	2556	2.56
TD 3.2	6.00	0.00	2625	2.67
TD 3.3	7.00	1.00	2785	2.42
TD 4.1	6.00	0.00	2533	2.11
TD 4.2	6.00	1.00	2435	2.08
TD 4.3	6.00	1.00	2418	1.83
TD 5.1	12.68	1.68	5457	3.66
TD 5.2	13.00	1.00	5549	2.36

Instance	V^a	ΔV^b	Dur^c	ΔDur^d
TD 5.3	13.00	1.00	5496	3.23
TD 6.1	13.00	1.00	5607	4.39
TD 6.2	12.00	1.00	5410	5.82
TD 6.3	12.00	1.00	5401	4.87
TD 7.1	11.08	0.08	4971	3.79
TD 7.2	11.90	0.90	5073	2.42
TD 7.3	11.58	0.58	5024	2.53
TD 8.1	11.00	1.00	4830	4.63
TD 8.2	11.00	1.00	4825	5.30
TD 8.3	11.00	1.00	4777	5.78
TD 9.1	10.00	1.00	4299	2.06
TD 9.2	11.00	1.00	4642	0.98
TD 9.3	10.00	0.00	4194	2.78
TD 10.1	10.00	1.00	4276	1.58
TD 10.2	9.00	1.00	3854	1.45
TD 10.3	9.00	1.00	3863	2.55
TD 11.1	9.00	1.00	3709	3.57
TD 11.2	8.94	0.94	3524	2.62
TD 11.3	9.00	1.00	3710	2.18
TD 12.1	8.00	1.00	3410	3.06
TD 12.2	8.00	1.00	3445	3.28
TD 12.3	9.00	1.00	3700	2.25
TD 13.1	19.00	3.00	7931	4.21
TD 13.2	18.00	2.00	7737	2.98
TD 13.3	18.74	2.74	7731	3.21
TD 14.1	18.92	2.92	7931	5.65
TD 14.2	18.00	2.00	7728	5.15
TD 14.3	17.98	2.98	7521	5.39
TD 15.1	15.60	1.60	6683	4.40
TD 15.2	16.62	2.62	7031	4.26

Instance	V[a]	ΔV[b]	Dur[c]	ΔDur[d]
TD 15.3	15.94	1.94	6679	4.23
TD 16.1	15.00	2.00	6460	6.77
TD 16.2	15.00	1.00	6690	6.01
TD 16.3	15.00	2.00	6649	6.40

[a] V: average number of vehicles used

[b] ΔV: average absolute gap for number of vehicles

[c] Dur: average total route duration

[d] ΔDur: average relative gap for total route duration

Bibliography

Abrache, J., Crainic, T. G., Gendreau, M., 1999. A new decomposition algorithm for the deterministic dynamic allocation of empty containers. Tech. Rep. CRT-99-49, Center for Research on Transportation, University of Montreal, Montreal, Canada.

Ahn, B.-H., Shin, J.-Y., 1991. Vehicle-routeing with time windows and time-varying congestion. Journal of the Operational Research Society 42 (5), 393–400.

Baldacci, R., Bodin, L., Mingozzi, A., 2006. The multiple disposal facilities and multiple inventory locations rollon-rolloff vehicle routing problem. Computers & Operations Research 33 (9), 2667–2702.

Balseiro, S. R., Loiseau, I., Ramonet, J., 2011. An ant colony algorithm hybridized with insertion heuristics for the time dependent vehicle routing problem with time windows. Computers & Operations Research 38 (6), 954–966.

Bandeira, D. L., Becker, J. L., Borenstein, D., 2009. A DSS for integrated distribution of empty and full containers. Decision Support Systems 47 (4), 383–397.

Beaujon, G. J., Turnquist, M. A., 1991. A model for fleet sizing and vehicle allocation. Transportation Science 25 (1), 19–45.

Bent, R., Van Hentenryck, P., 2004. A two-stage hybrid local search for the vehicle routing problem with time windows. Transportation Science 38 (4), 515–530.

Bent, R., Van Hentenryck, P., 2006. A two-phase hybrid algorithm for pickup and delivery vehicle routing problems with time windows. Computers & Operations Research 33 (4), 875–893.

Berbeglia, G., Cordeau, J.-F., Laporte, G., 2010. Dynamic pickup and delivery problems. European Journal of Operational Research 202 (1), 8–15.

Blum, C., Puchinger, J., Raidl, G. R., Roli, A., 2011. Hybrid metaheuristics in combinatorial optimization: A survey. Applied Soft Computing 11 (6), 4135–4151.

Boile, M., Theofanis, S., Baveja, A., Mittal, N., 2008. Regional repositioning of empty containers: A case for inland depots. Transportation Research Record: Journal of the Transportation Research Board 2066 (1), 31–40.

Boile, M. P., Mittal, N., Golias, M., Theofanis, S., 2006. Empty marine container management: Addressing a global problem locally. In: Transportation Research Board 85th Annual Meeting Compendium of Papers CD-ROM. Washington DC.

Bourbeau, B., Crainic, T. G., Gendron, B., 2000. Branch-and-bound parallelization strategies applied to a depot location and container fleet management problem. Parallel Computing 26 (1), 27–46.

Braekers, K., Caris, A., Janssens, G. K., 2011a. A deterministic annealing algorithm for a bi-objective full truckload vehicle routing problem in drayage operations. In: The State of the Art in the European Quantitative Oriented Transportation and Logistics Research - 14th Euro Working Group on Transportation & 26th Mini Euro Conference & 1st European Scientific Conference on Air Transport, volume 20 of Procedia - Social and Behavioral Sciences. Poznan, Poland, pp. 344–353.

Braekers, K., Caris, A., Janssens, G. K., 2012a. Bi-objective optimization of drayage operations in the service area of intermodal terminals. Transportation Research Part E: Logistics and Transportation Review, Submitted, 1st review.

Braekers, K., Caris, A., Janssens, G. K., 2012b. Integrated planning of loaded and empty container movements. OR Spectrum, Forthcoming (DOI:10.1007/s00291–012–0284–5).

Braekers, K., Caris, A., Janssens, G. K., 2012c. Optimal shipping routes and vessel size for intermodal barge transport with empty container repositioning. Computers in Industry, Forthcoming (DOI:10.1016/j.compind.2012.06.003).

Braekers, K., Caris, A., Janssens, G. K., 2012d. Time-dependent routing of drayage operations in the service area of intermodal terminals. In: The International Workshop on Harbour, Maritime & Multimodal Logistics Modelling and Simulation (HMS 2012). Vienna, Austria, Forthcoming.

Braekers, K., Janssens, G. K., Caris, A., 2009. Integrating empty container allocation with vehicle routing in intermodal transport. In: The International Workshop on

Harbour, Maritime & Multimodal Logistics Modelling and Simulation (HMS 2009). Puerto de La Cruz, Spain, pp. 132–139.

Braekers, K., Janssens, G. K., Caris, A., 2010. A deterministic annealing algorithm for simultaneous routing of loaded and empty containers. In: Proceedings of the Industrial Simulation Conference. Budapest, Hungary, pp. 172–176.

Braekers, K., Janssens, G. K., Caris, A., 2011b. Challenges in managing empty container movements at multiple planning levels. Transport Reviews 31 (6), 681–708.

Branch, A. E., 2006. Export practice and management, 5th Edition. Thomson Learning, London.

Bräysy, O., Berger, J., Barkaoui, M., Dullaert, W., 2003. A threshold accepting metaheuristic for the vehicle routing problem with time windows. Central European Journal of Operations Research 11 (4), 369–387.

Bräysy, O., Dullaert, W., Hasle, G., Mester, D., Gendreau, M., 2008a. An effective multistart deterministic annealing metaheuristic for the fleet size and mix vehicle routing problem with time windows. Transportation Science 42 (3), 371–386.

Bräysy, O., Gendreau, M., 2002. Tabu search heuristics for the vehicle routing problem with time windows. TOP 10 (2), 211–237.

Bräysy, O., Gendreau, M., 2005a. Vehicle routing problem with time windows, Part I: Route construction and local search algorithms. Transportation Science 39 (1), 104–118.

Bräysy, O., Gendreau, M., 2005b. Vehicle routing problem with time windows, Part II: Metaheuristics. Transportation Science 39 (1), 119–139.

Bräysy, O., Hasle, G., Dullaert, W., 2004. A multi-start local search algorithm for the vehicle routing problem with time windows. European Journal of Operational Research 159 (3), 586–605.

Bräysy, O., Hotokka, P., Dullaert, W., Nagata, Y., 2008b. An adaptive diversification heuristic for the fleet size and mix vehicle routing problem with time windows. In: Proceedings of the EU/MEeting 2008: Metaheuristics for Logistics and Vehicle Routing. Troyes, France.

Campbell, A. M., Savelsberg, M. W. P., 2004. Efficient insertion heuristics for vehicle routing and scheduling problems. Transportation Science 38 (3), 369–378.

Caris, A., 2011. Simulation and optimisation of intermodal barge transport networks. 4OR: A Quarterly Journal of Operations Research 9 (2), 211–214.

Caris, A., Janssens, G. K., 2009. A local search heuristic for the pre- and end-haulage of intermodal container terminals. Computers & Operations Research 36 (10), 2763–2772.

Caris, A., Janssens, G. K., 2010. A deterministic annealing algorithm for the pre- and end-haulage of intermodal container terminals. International Journal of Computer Aided Engineering and Technology 2 (4), 340–355.

Caris, A., Macharis, C., Janssens, G. K., 2008. Planning problems in intermodal freight transport: Accomplishments and prospects. Transportation Planning & Technology 31 (3), 277–302.

Caris, A., Macharis, C., Janssens, G. K., 2011. Network analysis of container barge transport in the port of Antwerp by means of simulation. Journal of Transport Geography 19 (1), 125–133.

Caris, A., Macharis, C., Janssens, G. K., 2012. Corridor network design in hinterland transportation systems. Flexible Services and Manufacturing 24 (3), 294–319.

Caseau, Y., Laburthe, F., 1999. Heuristics for large constrained vehicle routing problems. Journal of Heuristics 5 (3), 281–303.

Chang, H., Jula, H., Chassiakos, A., Ioannou, P., 2006. Empty container reuse in the Los Angeles/Long Beach Port Area. In: Proceedings of the National Urban Freight Conference. METRANS Transportation Center, Long Beach, CA.

Chang, H., Jula, H., Chassiakos, A., Ioannou, P., 2008. A heuristic solution for the empty container substitution problem. Transportation Research Part E: Logistics and Transportation Review 44 (2), 203–216.

Chao, I. M., 2002. A tabu search method for the truck and trailer routing problem. Computers & Operations Research 29 (1), 33–51.

Cheang, B., Lim, A., 2005. A network flow based method for the distribution of empty containers. International Journal of Computer Applications in Technology 22 (4), 198–204.

Cheung, R. K., Chen, C.-Y., 1998. A two-stage stochastic network model and solution methods for the dynamic empty container allocation problem. Transportation Science 32 (2), 142–162.

Choong, S. T., Cole, M. H., Kutanoglu, E., 2002. Empty container management for intermodal transportation networks. Transportation Research Part E: Logistics and Transportation Review 38 (6), 423–438.

Chou, C.-C., Gou, R.-H., Tsai, C.-L., Tsou, M.-C., Wong, C.-P., Yu, H.-L., 2010. Application of a mixed fuzzy decision making and optimization programming model to the empty container allocation. Applied Soft Computing 10 (4), 1071–1079.

Chu, Q., 1995. Dynamic and stochastic models for container allocation. Phd thesis, Department of Ocean Engineering, Massachusetts Institute of Technology.

Corberan, A., Fernandez, E., Laguna, M., Marti, R., 2002. Heuristic solutions to the problem of routing school buses with multiple objectives. Journal of the Operational Research Society 53 (4), 427–435.

Cordeau, J.-F., Laporte, G., 2003. A tabu search heuristic for the static multi-vehicle dial-a-ride problem. Transportation Research Part B: Methodological 37 (6), 579–594.

Cordeau, J.-F., Laporte, G., 2005. Tabu search heuristics for the vehicle routing problem. In: Sharda, R., Voß, S., Rego, C., Alidaee, B. (Eds.), Metaheuristic Optimization via Memory and Evolution. Vol. 30 of Operations Research/Computer Science Interfaces Series. Kluwer Academic Publishers, Boston, MA, pp. 145–163.

Cordeau, J.-F., Laporte, G., Mercier, A., 2004. Improved tabu search algorithm for the handling of route duration constraints in vehicle routing problems with time windows. Journal of the Operational Research Society 55 (5), 542–546.

Cordeau, J.-F., Laporte, G., Potvin, J.-Y., Savelsbergh, M. W. P., 2007a. Transportation on demand. In: Barnhart, C., Laporte, G. (Eds.), Transportation. Vol. 14 of Handbooks in Operations Research and Management Science. Elsevier, pp. 429–466.

Cordeau, J.-F., Laporte, G., Ropke, S., 2008. Recent models and algorithms for one-to-one pickup and delivery problems. In: Golden, B., Raghavan, S., Wasil, E. (Eds.), The Vehicle Routing Problem: Latest Advances and New Challenges. Vol. 43 of Operations Research/Computer Science Interfaces Series. Springer, pp. 327–357.

Cordeau, J.-F., Laporte, G., Savelsbergh, M. W. P., Vigo, D., 2007b. Vehicle routing. In: Barnhart, C., Laporte, G. (Eds.), Transportation. Vol. 14 of Handbooks in Operations Research and Management Science. Elsevier, pp. 367–428.

Crainic, T. G., 2000. Service network design in freight transportation. European Journal of Operational Research 122 (2), 272–288.

Crainic, T. G., 2002. Long-haul freight transportation. In: Hall, R. W. (Ed.), Handbook of Transportation Science, 2nd Edition. Kluwer Academic Publishers, pp. 451–516.

Crainic, T. G., Dejax, P., Delorme, L., 1989. Models for multimode multicommodity location problems with interdepot balancing requirements. Annals of Operations Research 18 (1), 279–302.

Crainic, T. G., Delorme, L., 1993. Dual-ascent procedures for multicommodity location-allocation problems with balancing requirements. Transportation Science 27 (2), 90–101.

Crainic, T. G., Delorme, L., Dejax, P., 1993a. A branch-and-bound method for multicommodity location with balancing requirements. European Journal of Operational Research 65 (3), 368–382.

Crainic, T. G., Di Francesco, M., Zuddas, P., 2007. An optimization model for empty container reposition under uncertainty. In: Proceedings of Tristan VI: Sixth Triennial Symposium on Transportation Analysis. Phuket Island, Thailand.

Crainic, T. G., Gendreau, M., Dejax, P., 1993b. Dynamic and stochastic models for the allocation of empty containers. Operations Research 41 (1), 102–126.

Crainic, T. G., Gendreau, M., Soriano, P., Toulouse, M., 1993c. A tabu search procedure for multicommodity location/allocation with balancing requirements. Annals of Operations Research 41 (4), 359–383.

Crainic, T. G., Kim, K. H., 2007. Intermodal transportation. In: Barnhart, C., Laporte, G. (Eds.), Transportation. Vol. 14 of Handbooks in Operations Research and Management Science. Elsevier, pp. 467–537.

Crainic, T. G., Laporte, G., 1997. Planning models for freight transportation. European Journal of Operational Research 97 (3), 409–438.

Currie, R. H., Salhi, S., 2004. A tabu search heuristic for a full-load, multi-terminal, vehicle scheduling problem with backhauling and time windows. Journal of Mathematical Modelling and Algorithms 3 (3), 225–243.

Dabia, S., Ropke, S., Van Woensel, T., de Kok, T., 2011. Branch and cut and price for the time dependent vehicle routing problem with time windows. Working Paper 361, Eindhoven University of Technology, Eindhoven, the Netherlands.

de Brito, M. P., Konings, R., 2006. The reverse logistics of empty maritime containers. In: Logistics in Global Economy - Challenges and trends, 1st International Conference of Logistics. Gdansk, Poland, pp. 1–11.

de Brito, M. P., Konings, R., 2008. Container management strategies to deal with the East-West flows imbalance. In: Nectar Cluster Meeting on Freight Transport and Intermodality. Delft, the Netherlands.

de Jong, C., Kant, G., van Vliet, A., 1996. On finding minimal route duration in the vehicle routing problem with multiple time windows. Tech. rep., Department of Computers Science, Utrecht University, Utrecht, the Netherlands.

Dean, B. C., 2004. Shortest paths in FIFO time-dependent networks: Theory and algorithms. Tech. rep., Division of Computer Science, Massachusetts Institute of Technology, Cambridge, MA.

Deidda, L., Di Francesco, M., Olivo, A., Zuddas, P., 2008. Implementing the street-turn strategy by an optimization model. Maritime Policy & Management 35 (5), 503–516.

Dejax, P. J., Crainic, T. G., 1987. A review of empty flows and fleet management models in freight transportation. Transportation Science 21 (4), 227–248.

Desaulniers, G., Lavigne, J., Soumis, F., 1998. Multi-depot vehicle scheduling problems with time windows and waiting costs. European Journal of Operational Research 111 (3), 479–494.

Desrochers, M., Lenstra, J. K., Savelsbergh, M. W. P., Soumis, F., 1988. Vehicle routing with time windows: Optimization and approximation. In: Golden, B. L., Assad, A. A. (Eds.), Vehicle Routing: Methods and Studies. North-Holland, Amsterdam.

Desrosiers, J., Sauvé, M., Soumis, F., 1988. Lagrangian relaxation methods for solving the minimum fleet size multiple traveling salesman problem with time windows. Management Science 34 (8), 1005–1022.

Di Francesco, M., 2007. New optimization models for empty container management. Phd thesis, Faculty of Engineering (Land Engineering), University of Cagliari.

Di Francesco, M., Crainic, T. G., Zuddas, P., 2009. The effect of multi-scenario policies on empty container repositioning. Transportation Research Part E: Logistics and Transportation Review 45 (5), 758–770.

Di Francesco, M., Manca, A., Olivo, A., Zuddas, P., 2006. Optimal management of heterogeneous fleets of empty containers. In: Proceedings of the International Conference on Information Systems, Logistics and Supply Chain. Lyon, France, pp. 922–931.

Donati, A. V., Montemanni, R., Casagrande, N., Rizzoli, A. E., Gambardella, L. M., 2008. Time dependent vehicle routing problem with a multi ant colony system. European Journal of Operational Research 185 (3), 1174–1191.

Dong, J.-X., Song, D.-P., 2009. Container fleet sizing and empty repositioning in liner shipping systems. Transportation Research Part E: Logistics and Transportation Review 45 (6), 860–877.

Du, Y., Hall, R., 1997. Fleet sizing and empty equipment redistribution for center-terminal transportation networks. Management Science 43 (2), 145–157.

Dueck, G., Scheuer, T., 1990. Threshold accepting: A general purpose optimization algorithm appearing superior to simulated annealing. Journal of Computational Physics 90 (1), 161–175.

Ehrgott, M., 2005. Multicriteria Optimization, 2nd Edition. Springer, Berlin.

Ehrgott, M., Gandibleux, X., 2002. Multiobjective combinatorial optimization. In: Ehrgott, M., Gandibleux, X. (Eds.), Multiple Criteria Optimization-State of the Art Annotated Bibliographic Surveys. Vol. 52 of International Series in Operations Research and Management. Kluwer Academic Publishers, Boston, MA, pp. 369–444.

Ehrgott, M., Gandibleux, X., 2004. Approximative solution methods for multiobjective combinatorial optimization. TOP 12 (1), 1–90.

Erera, A. L., Morales, J. C., Savelsbergh, M. W. P., 2005. Global intermodal tank container management for the chemical industry. Transportation Research Part E: Logistics and Transportation Review 41 (6), 551–566.

Erera, A. L., Morales, J. C., Savelsbergh, M. W. P., 2009. Robust optimization for empty repositioning problems. Operations Research 57 (2), 468–483.

Erera, A. L., Smilowitz, K., 2008. Intermodal drayage routing and scheduling. In: Ioannou, P. (Ed.), Intelligent Freight Transportation. Automation and Control Engineering Series. CRC Press, Boca Raton, FL, pp. 171–188.

Ermol'ev, Y. M., Krivets, T. A., Petukhov, V. S., 1976. Planning of shipping empty seaborne containers. Cybernetics and Systems Analysis 12 (4), 644–646.

Escudero, A., nuzuri, J. M., Arango, C., Onieva, L., 2011. A satellite navigation system to improve the management of intermodal drayage. Advanced Engineering Informatics 25 (3), 427–434.

Feng, C.-M., Chang, C.-H., 2008. Empty container reposition planning for intra-Asia liner shipping. Maritime Policy & Management 35 (5), 469–489.

Feng, C.-M., Chang, C.-H., 2010. Optimal slot allocation with empty container reposition problem for Asia ocean carriers. International Journal of Shipping and Transport Logistics 2 (1), 22–43.

Figliozzi, M. A., 2012. The time dependent vehicle routing problem with time windows: Benchmark problems, an efficient solution algorithm, and solution characteristics. Transportation Research Part E: Logistics and Transportation Review 48 (3), 616–636.

Fleischmann, B., Gietz, M., Gnutzmann, S., 2004. Time-varying travel times in vehicle routing. Transportation Science 38 (2), 160–173.

Ford, L. R., Fulkerson, D. R., 1956. Solving the transportation problem. Management Science 3 (1), 24–32.

Francis, P., Zhang, G., Smilowitz, K., 2007. Improved modeling and solution methods for the multi-resource routing problem. European Journal of Operational Research 180 (3), 1045–1059.

Gao, Q., 1997. Models for intermodal depot selection. Phd thesis, Department of Ocean Engineering, Massachusetts Institute of Technology.

Garcia-Najera, A., Bullinaria, J. A., 2011. An improved multi-objective evolutionary algorithm for the vehicle routing problem with time windows. Computers & Operations Research 38 (1), 287–300.

Gendreau, M., Potvin, J.-Y., Bräysy, O., Hasle, G., Løkketangen, A., 2008. Metaheuristics for the vehicle routing problem and its extensions: A categorized bibliography. In: Golden, B., Raghavan, S., Wasil, E. (Eds.), The Vehicle Routing Problem: Latest Advances and New Challenges. Vol. 43 of Operations Research/Computer Science Interfaces Series. Springer, pp. 143–169.

Gendreau, M., Tarantilis, C. D., 2010. Solving large-scale vehicle routing problems with time windows: the state-of-the-art. Technical Report CIRRELT-2010-04, CIRRELT, Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation, Montreal, Canada.

Gendron, B., Crainic, T. G., 1993. Parallel implementations of a branch-and-bound algorithm for multicommodity location with balancing requirements. INFOR 31 (3), 151–165.

Gendron, B., Crainic, T. G., 1995. A branch-and-bound algorithm for depot location and container fleet management. Location Science 3 (1), 39–53.

Gendron, B., Crainic, T. G., 1997. A parallel branch-and-bound algorithm for multicommodity location with balancing requirements. Computers & Operations Research 24 (9), 829–847.

Gendron, B., Potvin, J.-Y., Soriano, P., 2003a. A parallel hybrid heuristic for the multicommodity capacitated location problem with balancing requirements. Parallel Computing 29 (5), 591–606.

Gendron, B., Potvin, J.-Y., Soriano, P., 2003b. A tabu search with slope scaling for the multicommodity capacitated location problem with balancing requirements. Annals of Operations Research 122 (1), 193–217.

Ghoseiri, K., Ghannadpour, S. F., 2010. Multi-objective vehicle routing problem with time windows using goal programming and genetic algorithm. Applied Soft Computing 10 (4), 1096–1107.

Glover, F., 1986. Future paths for integer programming and links to artificial intelligence. Computers & Operations Research 13 (5), 533–549.

Glover, F., 1989. Tabu search - Part I. ORSA Journal on Computing 1 (3), 190–206.

Glover, F., 1990. Tabu search - Part II. ORSA Journal on Computing 2 (1), 4–32.

Gronalt, M., Hartl, R. F., Reimann, M., 2003. New savings based algorithms for time constrained pickup and delivery of full truckloads. European Journal of Operational Research 151 (3), 520–535.

Gronalt, M., Hirsch, P., 2007. Log-truck scheduling with a tabu search strategy. In: Doerner, K. F., Gendreau, M., Greistorfer, P., Guthjahr, W. J., Hartl, R. F., Reimann, M. (Eds.), Metaheuristics - Progress in Complex Systems Optimization. Springer, New York, NY, pp. 64–88.

Groothedde, B., Ruijgrok, C., Tavasszy, L., 2005. Towards collaborative, intermodal hub networks: A case study in the fast moving consumer goods market. Transportation Research Part E: Logistics and Transportation Review 41 (6), 567–583.

Hadjar, A., Soumis, F., 2009. Dynamic window reduction for the multiple depot vehicle scheduling problem with time windows. Computers & Operations Research 36 (7), 2160–2172.

Haghani, A., Jung, S., 2005. A dynamic vehicle routing problem with time-dependent travel times. Computers & Operations Research 32 (11), 2959–2986.

Hashimoto, H., Yagiura, M., Ibaraki, T., 2008. An iterated local search algorithm for the time-dependent vehicle routing problem with time windows. Discrete Optimization 5 (2), 434–456.

Hill, A. V., Benton, W. C., 1992. Modeling intra-city time-dependent travel speeds for vehicle scheduling problems. Journal of the Operations Research Society 43 (4), 343–351.

Holmberg, K., Joborn, M., Lundgren, J. T., 1998. Improved empty freight car distribution. Transportation Science 32 (2), 163–173.

Homberger, J., Gehring, H., 2005. A two-phase hybrid metaheuristic for the vehicle routing problem with time windows. European Journal of Operational Research 162 (1), 220–238.

Hughes, R. E., Powell, W. B., 1988. Mitigating end effects in the dynamic vehicle allocation model. Management Science 34 (7), 859–879.

Huth, T., Mattfeld, D. C., 2009. Integration of vehicle routing and resource allocation in a dynamic logistics network. Transportation Research Part C: Emerging Technologies 17 (2), 149–162.

Huth, T., Mattfeld, D. C., 2011. Myopic and anticipated planning in stochastic swap container management. International Journal of Operations Research 8 (1), 3–22.

Ichoua, S., Gendreau, M., Potvin, J.-Y., 2003. Vehicle dispatching with time-dependent travel times. European Journal of Operational Research 144 (2), 379–396.

Ileri, Y., Bazaraa, M., Gifford, T., Nemhauser, G., Sokol, J., Wikum, E., 2006. An optimization approach for planning daily drayage operations. Central European Journal of Operations Research 14 (2), 141–156.

Imai, A., Nishimura, E., Current, J., 2007. A Lagrangian relaxation-based heuristic for the vehicle routing with full container load. European Journal of Operational Research 176 (1), 87–105.

Imai, A., Rivera, F., 2001. Strategic fleet size planning for maritime refrigerated containers. Maritime Policy & Management 28 (4), 361–374.

Ioannou, P., Chassiakos, A., Jula, H., Chang, H., Valencia, G., 2006. Development of methods for handling empty containers with applications in the Los Angeles/Long Beach Port Area. Final Report Project 04-05, METRANS Transportation Center, Long Beach, CA.

Jabali, O., Van Woensel, T., de Kok, A. G., Lecluyse, C., Peremans, H., 2009. Time-dependent vehicle routing subject to time delay perturbations. IIE Transactions 41 (12), 1049–1066.

Jansen, B., Swinkels, P. C. J., Teeuwen, G. J. A., van Antwerpen de Fluiter, B., Fleuren, H. A., 2004. Operational planning of a large-scale multi-modal transportation system. European Journal of Operational Research 156 (1), 41–53.

Janssens, G. K., Caris, A., Ramaekers, K., 2009. Time Petri nets as an evaluation tool for handling travel time uncertainty in vehicle routing solutions. Expert Systems with Applications 36 (3), 5987–5991.

Jaszkiewicz, A., 2004. On the computational efficiency of multiple objective metaheuristics. The knapsack problem case study. European Journal of Operational Research 158 (2), 418–433.

Jozefowiez, N., Semet, F., Talbi, E.-G., 2008. Multi-objective vehicle routing problems. European Journal of Operational Research 189 (2), 293–309.

Jula, H., Chassiakos, A., Ioannou, P., 2003. Empty container interchange report: Methods for modeling and routing of empty containers in the Los Angeles and Long Beach port area. Final report, Center for the Commercial Deployment of Transportation Technologies, California State University, Long Beach, CA.

Jula, H., Chassiakos, A., Ioannou, P., 2006. Port dynamic empty container reuse. Transportation Research Part E: Logistics and Transportation Review 42 (1), 43–60.

Jula, H., Dessouky, M., Ioannou, P., Chassiakos, A., 2005. Container movement by trucks in metropolitan networks: modeling and optimization. Transportation Research Part E: Logistics and Transportation Review 41 (3), 235–259.

Jung, S., Haghani, A., 2001. A genetic algorithm for the time dependent vehicle routing problem. Transportation Research Record: Journal of the Transportation Research Board 1771, 164–171.

Knowles, J. D., Thiele, L., Zitzler, E., 2006. A tutorial on the performance assessment of stochastic multiobjective optimizers. Technical Report TIK-Report No. 214, Computer Engineering and Networks Laboratory, ETH Zurich, Zurich, Switzerland.

Kochel, P., Kunze, S., Nielander, U., 2003. Optimal control of a distributed service system with moving resources: Application to the fleet sizing and allocation problem. International Journal of Production Economics 81-82, 443–459.

Kok, A. L., Hans, E. W., Schutten, J. M. J., 2011. Optimizing departure times in vehicle routes. European Journal of Operational Research 210 (3), 579–587.

Konings, R., 2003. Network design for intermodal barge transport. Journal of the Transportation Research Board 1820, 17–25.

Konings, R., 2005. Foldable containers to reduce the costs of empty transport? A costbenefit analysis from a chain and multi-actor perspective. Maritime Economics & Logistics 7, 223–249.

Konings, R., 2006. Hub-and-spoke networks in container-on-barge transport. Transportation Research Record: Journal of the Transportation Research Board 1963, 23–32.

Konings, R., 2007. Opportunities to improve container barge handling in the port of Rotterdam from a transport network perspective. Journal of Transport Geography 15 (6), 443–454.

Konings, R., 2009. Intermodal barge transport: Network design, nodes and competitiveness. Phd thesis, Delft University of Technology (TRAIL Thesis Series nr. T2009/11).

Konings, R., Thijs, R., 2001. Foldable containers: a new perspective on reducing container-repositioning costs. European Journal of Transport and Infrastructure Research 1 (4), 333–352.

Koo, P. H., Lee, W. S., Jang, D. W., 2004. Fleet sizing and vehicle routing for container transportation in a static environment. OR Spectrum 26 (2), 193–209.

Kuo, Y., Wang, C.-C., Chuang, P.-Y., 2009. Optimizing goods assignment and the vehicle routing problem with time-dependent travel speeds. Computers & Industrial Engineering 57 (4), 1385–1392.

Lai, K. K., Lam, K., Chan, W. K., 1995. Shipping container logistics and allocation. Journal of the Operational Research Society 46, 687–697.

Lam, S.-W., Lee, L.-H., Tang, L.-C., 2007. An approximate dynamic programming approach for the empty container allocation problem. Transportation Research Part C: Emerging Technologies 15 (4), 265–277.

Law, A. M., 2007. Simulation modeling and analysis, 4th Edition. McGraw-Hill, New York, NY.

Le, D. H., 2003. The logistics of empty cargo containers in the Southern California region. Final report, METRANS Transportation Center, Long Beach, CA.

Le-Griffin, D. H., Griffin, M. T., 2010. Managing empty container flows through short sea shipping and regional port systems. International Journal of Shipping and Transport Logistics 2 (1), 59–75.

Lecluyse, C., Van Woensel, T., Peremans, H., 2009. Vehicle routing with stochastic time-dependent travel times. 4OR: A Quarterly Journal of Operations Research 7 (4), 363–377.

Li, J.-A., Leung, S. C. H., Wu, Y., Liu, K., 2007. Allocation of empty containers between multi-ports. European Journal of Operational Research 182 (1), 400–412.

Li, J.-A., Liu, K., Leung, S. C. H., Lai, K. K., 2004. Empty container management in a port with long-run average criterion. Mathematical and Computer Modelling 40 (1-2), 85–100.

Lopez, E., 2003. How do ocean carriers organize the empty containers reposition activity in the USA? Maritime Policy & Management 30 (4), 339–355.

Macharis, C., Bontekoning, Y. M., 2004. Opportunities for OR in intermodal freight transport research: A review. European Journal of Operational Research 153 (2), 400–416.

Malandraki, C., Daskin, M. S., 1992. Time dependent vehicle routing problems: Formulations, properties and heuristic algorithms. Transportation Science 26 (3), 185–200.

Malandraki, C., Dial, R. B., 1996. A restricted dynamic programming heuristic algorithm for the time dependent traveling salesman problem. European Journal of Operational Research 90 (1), 45–55.

Maras, V., 2008. Determining optimal transport routes of inland waterway containers ships. Transportation Research Record: Journal of the Transportation Research Board 2062, 50–58.

Mes, M., van der Heijden, M., Schuur, P., 2010. Look-ahead strategies for dynamic pickup and delivery problems. OR Spectrum 32 (2), 395–421.

Mes, M., van der Heijden, M., van Harten, A., 2007. Comparison of agent-based scheduling to look-ahead heuristics for real-time transportation problems. European Journal of Operational Research 181 (1), 59–75.

Mingozzi, A., Bianco, L., Ricciardelli, S., 1995. An exact algorithm for combining vehicle trips. In: Daduna, J. R., Branco, I., Paixao, J. M. (Eds.), Computer-aided Transit Scheduling. Lecture Notes in Economics and Mathematical Systems 430. Springer, Berlin, pp. 145–172.

Mitrović-Minić, S., Krishnamurti, R., 2006. The multiple TSP with time windows: vehicle bounds based on precedence graphs. Operations Research Letters 34 (1), 111–120.

Moon, I.-K., Ngoc, A.-D., Hur, Y.-S., 2010. Positioning empty containers among multiple ports with leasing and purchasing considerations. OR Spectrum 32 (3), 765–786.

Nagata, Y., Bräysy, O., 2009. A powerful route minimization heuristic for the vehicle routing problem with time windows. Operations Research Letters 37 (5), 333–338.

Namboothiri, R., Erera, A. L., 2004. A set partitioning heuristic for local drayage routing under time-dependent port delay. In: Proceedings of the IEEE International Conference on Systems, Man and Cybernetics. Den Haag, the Netherlands, pp. 3921–3926.

Namboothiri, R., Erera, A. L., 2008. Planning local container drayage operations given a port access appointment system. Transportation Research Part E: Logistics and Transportation Review 44 (2), 185–202.

NEA, 2009. Kostenkengetallen binnenvaart 2008 (in dutch). Tech. rep., Rijkswaterstaat, Dienst Verkeer en Scheepvaart (NL), Zoetermeer, the Netherlands.

Nikolakopoulos, A., Sarimveis, H., 2007. A threshold accepting heuristic with intense local search for the solution of special instances of the traveling salesman problem. European Journal of Operational Research 177 (3), 1911–1929.

Nilsson, I., 2002. The empty container management problem. Tech. rep., Department of Naval Architecture and Ocean Engineering, Chalmers University of Technology, Gothenborg, Sweden.

Notteboom, T., 2004. Container shipping and ports: An overview. Review of Network Economics 3 (2), 86–106.

Notteboom, T., 2007. Inland waterway transport of containerised cargo: from infancy to a fully-fledged transport mode. Journal of Maritime Research 4 (2), 68–80.

Notteboom, T., Rodrigue, J.-P., 2005. Port regionalization: Towards a new phase in port development. Maritime Policy & Management 32 (3), 297–313.

Olivo, A., Zuddas, P., Di Francesco, M., Manca, A., 2005. An operational model for empty container management. Maritime Economics & Logistics 7 (3), 199–222.

Ombuki, B., Ross, B. J., Hanshar, F., 2006. Multi-objective genetic algorithms for vehicle routing problems with time windows. Applied Intelligence 24 (1), 17–30.

Pacheco, J., Marti, R., 2006. Multi-objective genetic algorithms for vehicle routing problems with time windows. Journal of the Operational Research Society 57 (1), 29–37.

Parragh, S. N., Doerner, K. F., Hartl, R. F., 2010. Variable neighborhood search for the dial-a-ride problem. Computers & Operations Research 37 (6), 1129–1138.

Parragh, S. N., Doerner, K. F., Hartl, R. F., Gandibleux, X., 2009. A heuristic two-phase solution approach for the multi-objective dial-a-ride problem. Networks 54 (4), 227–242.

Pillac, V., Gendreau, M., Guéret, C., Medaglia, A. L., 2011. A review of dynamic vehicle routing problems. Technical Report CIRRELT-2011-62, CIRRELT, Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation, Montreal, Canada.

Port of Antwerp, 2009. Annual report 2009. Tech. rep., Antwerp Port Authority, Antwerp, Belgium.
URL `http://www.portofantwerp.com/annualreport/2009/en/downloads.php`

Potts, R. B., 1970. Movement of empty containers within Australia. Tech. rep., Operations Research Society of Victoria, Melbourne, Australia.

Potvin, J.-Y., Rousseau, J.-M., 1995. An exchange heuristic for routeing problems with time windows. Journal of the Operational Research Society 46 (12), 1433–1446.

Promotie Binnenvaart Vlaanderen, 2008. Waterway maps.
URL `http://www.binnenvaart.be/en/waterwegen/waterwegenkaarten.asp`

Savelsberg, M. W. P., 1990. An efficient implementation of local search algorithms for constrained routing problems. European Journal of Operational Research 47 (1), 75–85.

Savelsbergh, M. W. P., 1992. The vehicle routing problem with time windows: Minimizing route duration. ORSA Journal on Computing 4 (2), 146–154.

Shen, W. S., Khoong, C. M., 1995. A DSS for empty container distribution planning. Decision Support Systems 15 (1), 75–82.

Sheskin, D. J., 1997. Handbook of Parametric and Nonparametric Statistical Procedures. CRC Press, Boca Raton, FL.

Shintani, K., Imai, A., Nishimura, E., Papadimitriou, S., 2007. The container shipping network design problem with empty container repositioning. Transportation Research Part E: Logistics and Transportation Review 43 (1), 39–59.

Shintani, K., Konings, R., Imai, A., 2010. The impact of foldable containers on container fleet management costs in hinterland transport. Transportation Research Part E: Logistics and Transportation Review 46 (5), 750–763.

Sifa, Z., Jiandong, C., Xiaomin, L., Keqiang, L., 2011. Urban pickup and delivery problem considering time-dependent fuzzy velocity. Computers & Industrial Engineering 60 (4), 821–829.

Smilowitz, K., 2006. Multi-resource routing with flexible tasks: an application in drayage operations. IIE Transactions 38 (7), 577–568.

Soler, D., Albiach, J., Martnez, E., 2009. A way to optimally solve a time-dependent vehicle routing problem with time windows. Operations Research Letters 37 (1), 37–42.

Song, D.-P., 2007. Characterizing optimal empty container reposition policy in periodic-review shuttle service systems. Journal of the Operational Research Society 58 (1), 122–133.

Song, D.-P., Carter, J., 2008. Optimal empty vehicle redistribution for hub-and-spoke transportation systems. Naval Research Logistics 55 (2), 156–171.

Song, D.-P., Carter, J., 2009. Empty container repositioning in liner shipping. Maritime Policy & Management 36 (4), 291–307.

Song, D.-P., Dong, J.-X., 2008. Empty container management in cyclic shipping routes. Maritime Economics & Logistics 10 (4), 335–361.

Song, D.-P., Dong, J.-X., 2011. Effectiveness of an empty container repositioning policy with flexible destination ports. Transport Policy 18 (1), 92–101.

Song, D.-P., Dong, J.-X., Roe, M., 2010. Optimal container dispatching policy and its structure in a shuttle service with finite capacity and random demands. International Journal of Shipping and Transport Logistics 2 (1), 44–58.

Song, D.-P., Earl, C. F., 2008. Optimal empty vehicle repositioning and fleet-sizing for two-depot service systems. European Journal of Operational Research 185 (2), 760–777.

Song, D.-P., Zhang, Q., 2010. A fluid flow model for empty container repositioning policy with a single port and stochastic demand. SIAM Journal on Control and Optimization 48 (5), 3623–3642.

Srour, J. F., 2010. Dissecting drayage - an examination of structure, information, and control in drayage operations. Phd thesis, Erasmus University Rotterdam.

Sung, K., Bell, M. G. H., Seong, M., Park, S., 2000. Shortest paths in a network with time-dependent flow speeds. European Journal of Operational Research 121 (1), 32–39.

Tan, K. C., Chew, Y. H., Lee, L. H., 2006a. A hybrid multi-objective evolutionary algorithm for solving truck and trailer vehicle routing problems. European Journal of Operational Research 172 (3), 855–885.

Tan, K. C., Chew, Y. H., Lee, L. H., 2006b. A hybrid multiobjective evolutionary algorithm for solving vehicle routing problem with time windows. Computational Optimization and Applications 34 (1), 115–151.

Tarantilis, C. D., Kiranoudis, C. T., Vassiliadis, V. S., 2004. A threshold accepting metaheuristic for the heterogeneous fixed fleet vehicle routing problem. European Journal of Operational Research 152 (1), 148–158.

The Tioga Group, 2002. Empty ocean container logistics study. Final Empty Containers Report 050702, The Gateway Cities Council of Governments, the Port of Long Beach and the Southern California Association of Governments.

Theofanis, S., Boile, M., 2009. Empty marine container logistics: facts, issues and management strategies. GeoJournal 74 (1), 51–65.

Toth, P., Vigo, D., 2002. The vehicle routing problem. SIAM Monographs on Discrete Mathematics and Applications. SIAM, Philadelphia, PA.

UNCTAD, 2011. Review of maritime transport. Tech. Rep. UNCTAD/RMT/2011, United Nations Conference on Trade and Development, New York, NY.

Vacca, I., Bierlaire, M., Salani, M., 2007. Optimization at container terminals: Status, trends and perspectives. In: Proceedings of the 7th Swiss Transport Research Conference. Ascona, Switzerland.

van den Berg, R., Langen, P. W. D., 2011. Towards an 'ILT' centred value proposition in container transport? In: European Conference on Shipping, Intermodalism & Ports - ECONSHIP 2011: Maritime Transport: Opportunities & Threats in the Post-crises world. Chios, Greece.

Van Der Bruggen, L. J. J., Lenstra, J. K., Schuur, P. C., 1993. Variable-depth search for the single-vehicle pickup and delivery problem with time windows. Transportation Science 27 (3), 298–311.

Van Landeghem, H. R. G., 1988. A bi-criteria heuristic for the vehicle routing problem with time windows. European Journal of Operational Research 36 (2), 217–226.

Van Woensel, T., Kerbache, L., Peremans, H., Vandaele, N., 2007. A queueing framework for routing problems with Time-Dependent travel times. Journal of Mathematical Modelling and Algorithms 6 (1), 151–173.

Van Woensel, T., Kerbache, L., Peremans, H., Vandaele, N., 2008. Vehicle routing with dynamic travel times: A queueing approach. European Journal of Operational Research 186 (3), 990–1007.

Veenstra, A., 2005. Empty container reposition: the port of Rotterdam case. In: Flapper, S., Nunen, J., Wassenhove, L. (Eds.), Managing Closed-Loop Supply Chains. Springer Berlin Heidelberg, Berlin, pp. 65–76.

Wang, B., Wang, Z., 2007. Research on the optimization of intermodal empty container reposition of land-carriage. Journal of Transportation Systems Engineering and Information Technology 7 (3), 29–33.

Wang, X., Regan, A. C., 2002. Local truckload pickup and delivery with hard time window constraints. Transportation Research Part B: Methodological 36 (2), 97–112.

White, W. W., 1972. Dynamic transshipment networks: An algorithm and its application to the distribution of empty containers. Networks 2 (3), 211–236.

Wieberneit, N., 2008. Service network design for freight transportation: A review. OR Spectrum 30 (1), 77–112.

Wohlgemuth, S., Clausen, U., 2009. Design and optimization of dynamic routing problems with time dependent travel times. In: Fleischmann, B., Borgwardt, K.-H., Klein, R., Tuma, A. (Eds.), Operations Research Proceedings 2008 - Selected Papers of the Annual International Conference of the German Operations Research Society (GOR) University of Augsburg, September 3-5, 2008. Springer Berlin Heidelberg, Dordrecht, pp. 331–336.

Woxenius, J., 2007. Generic framework for transport network designs: Applications and treatment in intermodal freight transport literature. Transport Reviews 27 (6), 733–749.

Yun, W. Y., Lee, Y. M., Choi, Y. S., 2011. Optimal inventory control of empty containers in inland transportation system. International Journal of Production Economics 133 (1), 451–457.

Zhang, G., Smilowitz, K., Erera, A. L., 2011a. Dynamic planning for urban drayage operations. Transportation Research Part E: Logistics and Transportation Review 47 (5), 764–777.

Zhang, R., Yun, W. Y., Kopfer, H., 2010. Heuristic-based truck scheduling for inland container transportation. OR Spectrum 32 (3), 787–808.

Zhang, R., Yun, W. Y., Moon, I. K., 2009. A reactive tabu search algorithm for the multi-depot container truck transportation problem. Transportation Research Part E: Logistics and Transportation Review 45 (6), 904–914.

Zhang, R., Yun, W. Y., Moon, I. K., 2011b. Modeling and optimization of a container drayage problem with resource constraints. International Journal of Production Economics 133 (1), 351–359.

Zitzler, E., Knowles, J., Thiele, L., 2008. Quality assessment of Pareto set approximations. In: Branke, J., Deb, K., Miettinen, K., Slowinski, R. (Eds.), Multiobjective Optimization: Interactive and Evolutionary Approaches. Vol. 5252 of Lecture Notes in Computer Science. Springer, Berlin, pp. 373–404.

Zitzler, E., Laumanns, M., Bleuler, S., 2004. A tutorial on evolutionary multiobjective optimization. In: Gandibleux, X., Sevaux, M., Sörensen, K., T'Kindt, V. (Eds.), Metaheuristics for Multiobjective Optimisation. Vol. 535 of Lecture Notes in Economics and Mathematical Systems. Springer, Berlin, pp. 3–38.

Zitzler, E., Thiele, L., 1999. Multiobjective evolutionary algorithms: A comparative case study and the strength Pareto approach. IEEE Transactions on Evolutionary Computation 3 (4), 257–271.

Zitzler, E., Thiele, L., Laumanns, M., Fonseca, C. M., Grunert da Fonseca, V., 2003. Performance assessment of multiobjective optimizers: An analysis and review. IEEE Transactions on Evolutionary Computation 7 (2), 117–132.

Samenvatting

Sinds de introductie van containers ongeveer vijftig jaar geleden, is het gebruik ervan voor het transport van goederen continu toegenomen. Voordelen van het transporteren van goederen per container zijn de standardisatie van zowel ladingen als materieel, kortere laad- en lostijden en verminderde veiligheids- en schaderisico's. Als gevolg van deze voordelen, productiviteitswinsten in de sector en de toenemende globalisatie, kende containertransport een gemiddeld jaarlijks groeipercentage van 8.2% tussen 1990 en 2010.

Doordat containers relatief makkelijk van de ene naar de andere transportmodus overgeslagen kunnen worden, zorgt het toenemende gebruik van containers ook voor een stimulans voor intermodaal container transport. Bij intermodaal container transport worden goederen per container getransporteerd door middel van minstens twee transportmodi, zonder de goederen te behandelen tijdens de overslag. Het langste gedeelte van het transport wordt afgelegd via één of meerdere duurzame transportmodi zoals binnenvaart, spoorvervoer of zeevaart. Het eerste en laatste gedeelte, het voor- en natransport, wordt meestal uitgevoerd per vrachtwagen.

Naast bovenvermelde voordelen, zorgt het toenemende gebruik van containers voor een aantal nieuwe planningsproblemen zoals het bepalen van de grootte van de containervloot, de keuze tussen het aankopen of leasen van containers en de herpositionering van lege containers. Vooral het laatste probleem is erg complex. Dankzij het onevenwicht tussen de in- en uitvoer van goederen in een regio, zal in bepaalde regio's over verloop van tijd een overschot aan containers ontstaan, terwijl elders een tekort heerst. Op globaal niveau worden lege containers daarom geherpositioneerd tussen zeehavens, met als gevolg dat ongeveer 20% van alle maritieme containertransporten leeg zijn. Op regionaal niveau, in het achterland van een zeehaven, is het herpositioneren van lege containers eveneens vereist. Beladen containers worden getransporteerd van de zeehaven naar hun finale bestemming (importeurs) via wegtransport, binnenvaart, spoorvervoer of een combinatie van deze modi. Omgekeerd worden beladen containers getransporteerd van exporteurs naar de zeehaven. Omdat exporteurs en importeurs vaak niet op dezelfde locatie gelegen zijn, is het nodig om lege containers te herpositioneren tussen importeurs, exporteurs, intermodale containerterminals, binnenlandse containerdepots en containerterminals en -depots in de haven. Schattingen voor deze lege transporten variëren tussen de 40 en 50% van alle continentale containertransporten.

In tegenstelling tot het transport van beladen containers, zijn er meestal geen opbrengsten verbonden aan lege containertransporten. Het reduceren van deze activiteiten is daarom een belangrijk middel van rederijen en transportbedrijven om hun kosten te minimaliseren. Verder leidt het reduceren van het aantal lege containertransporten tot een vermindering van de externe effecten van transport, zoals congestie en luchtvervuiling, hetgeen het herpositioneringsprobleem eveneens relevant maakt vanuit een maatschappelijk standpunt.

In dit doctoraat wordt de herpositionering van lege containers in het achterland van een zeehaven bestudeerd. Aangezien lege containers worden getransporteerd over hetzelfde transportnetwerk en met dezelfde transportmiddelen als beladen containers, wordt gefocust op de integratie van beladen en lege containerbewegingen om de kosten van het herpositioneren te minimaliseren. Twee aspecten van het probleem worden geanalyseerd in dit onderzoek. Het eerste aspect betreft het ontwikkelen van een dienstennetwerk voor het transport van beladen en lege containers via binnenvaart tussen een zeehaven en een aantal havens in het achterland. Het tweede aspect betreft de integratie van beladen en lege containerbewegingen tijdens het voor- en natransport tussen intermodale containerterminals en importeurs en exporteurs. Het eerste aspect heeft betrekking op het tactische planningsniveau terwijl het tweede aspect betrekking heeft op het operationele planningsniveau.

Het eerste gedeelte van dit doctoraat behandelt een tactisch planningsprobleem in de containerbinnenvaart, namelijk het bepalen van de aan te bieden binnenvaartdiensten tussen een zeehaven en een aantal kleinere havens in het achterland die via een enkele waterstroom met elkaar worden verbonden. Een mathematisch model, toegepast op de situatie van het Albertkanaal en de haven van Antwerpen, wordt voorgesteld. Dit model bepaalt de optimale routes (de te bezoeken havens) voor één of meerdere schepen, het aantal te transporteren containers en de bijhorende kosten en opbrengsten voor een gegeven transportvraag, scheepscapaciteit en servicefrequentie. Verder kan de beste combinatie van capaciteit en servicefrequentie bepaald worden door verschillende scenario's te vergelijken. Het model kan gebruikt worden in de context van twee verschillende beslissingsnemers, binnenvaartoperatoren enerzijds en zeerederijen die deur-tot-deur transport aanbieden anderzijds. In het geval van binnenvaartoperatoren is de doelstelling het maximaliseren van de winst. Een niet-winstgevende transportvraag mag worden geweigerd en de herpositionering van lege containers wordt niet expliciet in rekening gebracht omdat binnenvaartoperatoren hier niet voor verantwoordelijk zijn. In het geval van zeerederijen die deur-tot-deur transport aanbieden is de beslissingsnemer tevens de eigenaar van de containers en bijgevolg wel verantwoordelijk voor de herpositionering ervan. De doelstelling is om de kosten te minimaliseren terwijl aan elke transportvraag wordt voldaan. Resultaten tonen aan dat wanneer reeds rekening wordt gehouden met de herpositionering van lege containers bij het bepalen van de aan te bieden diensten, kostenbesparingen kunnen worden gerealiseerd.

In het tweede gedeelte van dit doctoraat wordt een operationeel probleem met betrekking tot het wegtransport van beladen en lege containers tussen containerterminals, importeurs en exporteurs in een bepaalde regio bestudeerd. Beladen containers moeten worden getransporteerd van exporteurs naar containerterminals en van containerterminals naar importeurs. Verder vragen exporteurs lege containers en zijn lege containers beschikbaar bij importeurs. Ten slotte wordt verondersteld dat aan elke containerterminal een containerdepot gelegen is, waar een voorraad lege containers beschikbaar is en waar lege containers tijdelijk opgeslagen kunnen worden. Het probleem bestaat uit het vinden van een efficiënte rittenplanning voor een set van voertuigen waarbij alle beladen containertransporten worden uitgevoerd, aan de vraag naar lege containers van exporteurs wordt voldaan en alle lege containers beschikbaar bij importeurs worden opgehaald. Zowel het transport van beladen als van lege containers is onderhevig aan tijdsvensters. Bijkomend is enkel de oorsprong (bestemming) van een aangeboden (gevraagde) lege container vooraf gekend. Een sequentiële en een geïntegreerde oplossingsmethode worden voorgesteld en met elkaar vergeleken. Bij de sequentiële oplossingsmethode worden in een eerste stap de uit te voeren lege containertransporten bepaald. In tweede instantie worden voertuigroutes gecreëerd die alle beladen en lege containertransporten uitvoeren. Bij de geïntegreerde oplossingsmethode worden beide types van beslissingen tegelijkertijd genomen. Dit leidt tot een complexer probleem maar resulteert in betere oplossingen. Aangezien het exact oplossen van het probleem via een van beide methoden niet mogelijk is voor probleeminstanties van realistische grootte, wordt een metaheuristiek voorgesteld. Deze metaheuristiek is gebaseerd op 'deterministic annealing' en leidt tot quasi-optimale oplossingen. Resultaten voor een set van artificiële probleeminstanties worden besproken. Verschillende doelstellingsfuncties worden hierbij verondersteld. Resultaten tonen aan dat een geïntegreerde oplossingsmethode significant betere oplossingen geeft dan een sequentiële oplossingsmethode. Verder blijkt dat het uitvoeren van directe wissels, i.e. het direct transporteren van lege containers tussen importeurs en exporteurs zonder tussenstop bij een containerdepot, een grote positieve invloed heeft op de resultaten. Ten slotte wordt een uitbreiding van het probleem bestudeerd waarbij de reistijd tussen twee locaties niet langer constant is maar afhangt van het tijdstip van de dag. Op die manier kan congestie in rekening worden gebracht.

Publications and conference participation

Journal publications

Braekers, K., Janssens, G. K., Caris, A., 2011. Challenges in managing empty container movements at multiple planning levels. Transport Reviews 31(6), 681–708.

Braekers, K., Caris, A., Janssens, G. K., 2012. Integrated planning of loaded and empty container movements. OR Spectrum. Forthcoming (DOI:10.1007/s00291-012-0284-5).

Braekers, K., Caris, A., Janssens, G. K., 2012. Optimal shipping routes and vessel size for intermodal barge transport with empty container repositioning. Computers in Industry. Forthcoming (DOI:10.1016/j.compind.2012.06.003).

Braekers, K., Caris, A., Janssens, G. K., 2012. Bi-objective optimization of drayage operations in the service area of intermodal terminals. Transportation Research Part E: Logistics and Transportation Review. Submitted, 1st review.

Publications in conference proceedings

Braekers, K., Janssens, G. K., Caris A., 2009. Review on the comparison of external costs of intermodal transport and unimodal road transport. In: The BIVEC-GIBET Transport Research Day 2009. Brussels, Belgium, May 27, pp. 875–890.

Braekers, K., Janssens, G. K., Caris A., 2009. Integrating empty container allocation with vehicle routing in intermodal transport. In: The International Workshop on Harbor, Maritime & Multimodal Logistics Modeling and Simulation (HMS 2009). Puerto de la Cruz, Spain, September 23-25, pp. 132–139.

Braekers, K., Janssens, G. K., Caris A., 2010. A deterministic annealing algorithm for simultaneous routing of loaded and empty containers. In: The Industrial Simulation Conference (ISC 2010). Budapest, Hungary, June 7-9, pp. 172–176.

Braekers, K., Janssens, G. K., Caris A., 2010. Determining optimal shipping routes for barge transport with empty container repositioning. In: The European Simulation and Modelling Conference (ESM 2010). Diepenbeek, Belgium, October 25-27, pp. 338–344.

Braekers, K., Caris, A., Janssens, G. K., 2011. A deterministic annealing algorithm for a bi-objective full truckload vehicle routing problem in drayage operations. In: The State of the Art in the European Quantitative Oriented Transportation and Logistics Research - 14th Euro Working Group on Transportation & 26th Mini Euro Conference & 1st European Scientific Conference on Air Transport, volume 20 of Procedia - Social and Behavioral Sciences. Poznan, Poland, September 6-9, pp. 344-353.

Janssens, G. K., Braekers, K., 2011. An exact algorithm for the full truckload pick-up and delivery problem with time windows: concept and implementation details. In: The European Simulation and Modelling Conference (ESM 2011). Guimaraes, Portugal, October 24-26, pp. 257–262.

Braekers, K., Caris, A., Janssens, G. K., 2012. Optimal shipping routes and vessel size for intermodal barge transport with empty container repositioning. In: Nectar Cluster Meeting on Decision Support in Intermodal Transport. Brussels, Belgium, January 12-13.

Braekers, K., Caris, A., Janssens, G. K., 2012. Time-Dependent routing of drayage operations in the service area of intermodal terminals. In: The International Workshop on Harbor, Maritime & Multimodal Logistics Modeling and Simulation (HMS 2012). Vienna, Austria, September 19-21, Forthcoming.

Other conference participation (abstract)

Braekers, K., Janssens, G. K., Caris A., 2009. Modeling approaches for empty container management. ORBEL - 23th Annual Conference of the Belgian Operations Research Society. Louvain, Belgium, February 5-6.

Braekers, K., Janssens, G. K., Caris A., 2010. A deterministic annealing algorithm for the simultaneous routing of loaded and empty container movements. 24th European Conference on Operational Research (EURO XXIV). Lisbon, Portugal, July 11-14.

Braekers, K., Janssens, G. K., Caris A., 2010. Integrating empty container allocation with vehicle routing decisions. ORBEL - 24th Annual Conference of the Belgian Operations Research Society. Liege, Belgium, January 28-29.

Braekers, K., Caris A., Janssens, G. K., 2011. A deterministic annealing algorithm for simultaneous routing of loaded and empty containers. ORBEL - 25th Annual Conference of the Belgian Operations Research Society. Ghent, Belgium, February 10-11.

Braekers, K., Caris A., Janssens, G. K., 2012. Service network design with empty container repositioning in intermodal barge transportation. ORBEL - 26th Annual Conference of the Belgian Operations Research Society. Brussels, Belgium, February 2-3.

Braekers, K., Caris A., Janssens, G. K., 2012. Deterministic annealing algorithm for a time-dependent routing problem in drayage operations. First Annual Conference of the EURO Working Group on Vehicle Routing and Logistics Optimization (VeRoLog 2012). Bologna, Italy, June 18-20.