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A Reactive Decision Support System for Intermodal Freight Transportation

Yunfei Wang

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A Reactive Decision Support System for Intermodal Freight Transportation

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Abstract. Barge transportation is an important research topic that started to draw increasing scientific attention in the recent decade. Considered as sustainable, environment-friendly and economical, barge transportation has been identified as a competitive alternative for freight transportation, complementing the traditional road and rail modes. However, contributions related to barge transportation, especially in the context of intermodal transportation, are still scarce. The objective of this thesis is to contribute to fill this gap by proposing a reactive decision support system for freight intermodal barge transportation from the perspective of the carriers. The proposed system incorporates resource and revenue management concepts and principles to build the optimal set of scheduled services plans at the tactical level. Carriers may thus benefit from transportation plans offering increased flexibility and reliability. They could thus serve more demands and better satisfy customers. One novelty of the approach is the application of revenue management considerations (e.g., market segmentation and price differentiation) at both operational and tactical planning levels. The optimization problems are mathematically formalized and mixed integer linear programming (MILP) models are proposed, implemented and tested against various network settings and demand scenarios, for each decision level. At the tactical level, a new solution approach, combining adaptive large neighborhood search (ALNS) and Tabu search is designed to solve large scale MILP problems. An integrated simulation framework, including the tactical and the operational levels jointly, is proposed to validate the decision support system in different settings, in terms of physical network topology, revenue management parameters and accuracy degree of demand forecasts. To analyze the numerical results corresponding to the solutions of the optimization problems, several categories of performance indicators are proposed and used.

Keywords: Intermodal barge transportation, decision support system, revenue management, scheduled service network design, mixed integer linear programming, metaheuristics, network capacity allocation, discrete event simulation, performance indicators.

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Publications

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- Wang Y., Bilegan I.C., Crainic T.G., Artiba A. (2016). A Revenue Management Approach for Network Capacity Allocation of an Intermodal Barge Transportation System. In: A. Paias et al. (Eds.) ICCL 2016. LNCS, vol. 9855, pp. 243-257. DOI: 10.1007/978-3-319-44896-1_16.
- Wang Y., Bilegan I.C., Crainic T.G., Artiba A. (2014). Performance Indicators for Planning Intermodal Barge Transportation Systems. Transportation Research Procedia, 3, pp. 621-630. ISSN 2352-1465.

Working Papers

- Scheduled Service Network Design with Resource and Revenue Management Considerations for Intermodal Barge Transportation. Article manuscript in progress, to be submitted to Transportation Science, 2017.
- A Metaheuristic for Service Network Design with Revenue Management for Freight Intermodal Transportation. Data collection and analysis in progress, to be submitted.

International Conferences

- Crainic T.G., Bilegan I.C., Wang Y. (2016). Barge Scheduled Service Network Design with Resource and Revenue Management. INFORMS 2016 Annual Meeting, Nashville, United States, November.
- Crainic T.G., Bilegan I.C., Wang Y. (2016). Scheduled Service Network Design with Revenue Management Considerations: An Intermodal Barge Transportation

Application. Ninth Triennial Symposium on Transportation Analysis (TRISTAN IX), Aruba, June.

- Wang Y., Crainic T.G., Bilegan I.C., Artiba A. (2015). A Metaheuristic for Service Network Design with Revenue Management for Freight Intermodal Transport. CORS/INFORMS International Conference, Montreal, Canada, June.

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General Introduction

Barge transportation is an important research topic that started to draw increasing scientific attention in the recent decade. Considered as sustainable, environment friendly and economical, barge transportation has been identified as a competitive alternative for freight transportation, complementing the traditional road and rail modes. However, contributions related to barge transportation, especially in the context of intermodal transportation, are still scarce. The objective of this thesis is to contribute to fill this gap by proposing a Reactive Decision Support System (R-DSS) for freight intermodal barge transportation from the perspective of the carriers. To achieve the R-DSS, four related research problems are proposed and addressed in this thesis.

In the first phase of the study, we propose a revenue management model (DCA-RM) for the network capacity allocation problem of an intermodal barge transportation system, at operational level. In the proposed DCA-RM model, two RM policies (i.e., customer classification and price differentiation) are considered. In terms of customer classification, three categories of customers are identified according to their business relationships with the carriers. Their transport requests, therefore, are accordingly treated differently. The proposed DCA-RM model makes decisions to accept or reject a transport request by maximizing the expected revenue of current demand and potential future demands over a given time horizon, taking into account several categories of customers. The considered potential future demands are characterized by probability distribution functions, with respect to their volume. Sequential arrivals of transport requests are simulated to validate and assess the proposed DCA-RM model. A conventional model for dynamic capacity allocation considering only the feasibility, in terms of network capacity and delivery time constraints is used as alternative for comparison.

In the second part of the research, we propose what we believe to be, the first comprehensive Scheduled Service Network Design model for freight carriers that integrates both Resource and Revenue Management considerations (SSND-RRM). RM policies are equally considered in the proposed tactical planning model. To be more precise, customers are classified into several categories according to their business relationships with the carriers, and are dealt with following different (acceptance/denial) rules. In terms of resource management, design-balance constraints are considered to ensure the vehicle flow conservation at each terminal for each time instant. Vehicles repositioning is thus implicitly considered as the SSND-RRM problems are formulated as a cyclic model. In addition, upper bounds on the quantity of the resource are also formulated. Freight transshipment between services and freight holding at terminals are also considered, with their corresponding handling and holding costs. In order to validate RM policies consideration at tactical level for freight transportation and to assess the performances of the proposed model, we test the SSND-RRM model in various problem settings, in terms of demand distribution, network topology, fare classes and quality-of-service (e.g., delivery time). The optimization problems are solved by feeding a commercial solver.

As the optimization problems addressed at tactical level are NP-hard, we propose a metaheuristic (MH) to produce high-quality solutions for the SSND-RRM problems in reasonable time, in a third part of the research study. The proposed solution approach is composed of four phases. In the first phase, a constructive heuristic is proposed to obtain an initial feasible solution. The solutions are then iteratively improved in the second phase following a local search procedure. Adaptive large neighborhood search (ALNS) and tabu search are combined to guide the search. The other two phases: intensification and diversification are also included to deeply explore a given region of the solution space and to direct the search towards non-thoroughly-explored regions of the solution space, respectively. Moreover, new neighborhood structures are proposed to accelerate the search by ensuring the design-balance constraints and quick exploration simultaneously. Learning mechanisms are embedded into the proposed MH and used to guide the search. As no other solution approach to the proposed SSND-RRM problems exists in the literature, a commercial solver (IBM CPLEX) is used to compare with, in terms of computational time and solution quality.

The fourth research problem studied concerns a review of Performance Indicators (PIs) that could be used to evaluate the proposed R-DSS. PIs found in public sources and scientific literature are qualified with respect to their relevance to intermodal barge transportation systems. The analysis is extended with consideration of revenue management policies, a topic generally neglected in freight transportation. We then make a first step towards a taxonomy of PIs. Three categories of PIs, i.e., *economic impact*, *resource utilization* and *quality of service*, are defined based on their relevance and meaning from the perspective of both carriers and customers. New PIs, considering both resource and revenue management, in the context of freight transportation are also proposed for the three categories. We also propose a methodology to generate test instances, methodology adopted for the experiments throughout the whole thesis, and adequate for further studies of planning issues in a general context of freight barge transportation.

As a part of this fourth research question, we perform some validation tests of the proposed R-DSS, by designing an integrated simulation framework considering both tactical and operational levels. Given the estimated demands, physical network and potential services, we first solve the service network design problems at tactical level for a given schedule length. These selected services are then deployed repeatedly at the operational level during the planning horizon. Once the service plan is settled on space-time representation of the transportation network at the operational level, we simulate sequential arrivals of transport requests as an iterative process at operational level. Different cases are designed and tested to evaluate the proposed R-DSS with specified PIs. The proposed R-DSS is thus compared against traditional decision support systems (with no consideration of RM at tactical level).

In summary, this thesis is devoted to contribute to the design of a reactive decision support system, which deals with both tactical and operational levels of the transportation activities planning. The optimization problems are mathematically formalized and mixed integer programming (MIP) models are proposed, implemented and tested against various network settings and demand scenarios, for each decision level. RM policies are considered at both levels to enhance their interaction and information/knowledge exchange. Consequently, this will generate more consistent and robust decisions, in terms of (scheduled) service plans, resource utilization, flow distribution, etc. At the tactical level, a new solution approach, combining adaptive large neighborhood search (ALNS) and tabu search is designed to solve large scale SSND-RRM problems. The proposed models are validated and tested in different settings, in terms of physical network topology, revenue management parameters and accuracy degree of demand forecasts. To analyze the numerical results a taxonomy and some new performance indicators are proposed and used.

Chapter I

Introduction

Contents

I.1 Background, Motivation & Research Problems

Transportation, as one of the fundamental human activities, is vital to the development of the economy and society. In addition to providing the mobility of passengers and freights, it also affects our lives in various aspects, e.g., environment, land use, safety, health and society equity. Freight transportation, in particular, contributes to the activities of production, trade and consumption by ensuring the availability of raw materials and end products, in terms of required both physical movement and time condition [Crainic, 2000]. In 2012, almost 2100 billion tonne-kilometres (tkm) of inland freight were transported in the EU-28, and accounted for about 5% of gross domestic product (GDP) of EU-28 [Eurostat, 2015].

However, along with increased energy consumption and human intervention, the expansion of transportation is considered as one of the three major contributions to the climate change and arouses the awareness of human wellbeing and environment. The development of sustainable economy and the improvement of environment, therefore, drew the global attention over the last few decades. [European Commission, 2011], in the white paper of transport, set up a goal to reduce the emissions of greenhouse gases and pollutants by 20% in 2020 and 40% in 2030, compared to the 1990 levels. To achieve that, increasing the use of more eco-friendly transport mode, among other measures, e.g., developing renewable energy and increasing vehicle fuel efficiency, are encouraged by the European Commission.

Compared to the traditional road and rail mode, barge transportation is more eco-friendly, in terms of both energy consumption and noise emissions. To be more precise, its energy consumption per tonne-kilometer of transported goods is approximately 17% of that of road transport and 50% of rail transport. In addition, barge transportation also contributes to relieving the traffic congestion and reducing the number of accidents of the road and rail transport networks. Therefore, it offers a competitive alternative for the road and rail transport. However, according to [Eurostat, 2015], the majority of the EU-28 inland freight was transported by road (75.5%) in 2002. This share of inland freight transported by road was more than four times as high as the share transported by rail (18.3%), while only the remainder (6.2%) of the freight transported was carried by barges. [European Commission, 2011], in the white paper of transport, targeted to shift 30% of road freight over 300 km to either rail or barge by 2030, and more than 50% by 2050. In 2012, the corresponding percentage of each transport mode changed slightly, and became 75.1% (road), 18.2% (rail) and 6.7% (barge). A general upward trend was found in the share of inland freight transported along waterways during the period of 2002-2012 in the EU-28, but still far away from the targets set by European Commission. Meanwhile, compared to the traditional road and rail modes, which have been intensively studied (e.g., [Lium et al., 2009, Cordeau et al., 1998, Moccia et al., 2011]), studies targeting barge transportation are still scarce (e.g, [Sharypova, 2014, Fazi et al., 2015, Frémont and Franc, 2010, Konings, 2007, Konings et al., 2013, Notteboom, 2012, Taylor et al., 2005, Caris et al., 2011]).

Therefore, in this thesis, we make contributions to building a competitive and efficient transport system by making greater use of more energy-efficient mode, i.e., barge transportation, in the context of *intermodal freight transportation*. Generally defined as moving cargo from its origin to its destination by a sequence of at least two transport modes (e.g., [Crainic and Kim, 2007, Bektaş and Crainic, 2008, SteadieSeifi et al., 2014]), *intermodal freight transportation* performs the transfer of cargo from one mode to the next at an intermodal terminal without handling the cargo directly. The reduced direct handling of cargo is accomplished by containerization, which means transporting cargo in the containers with standardized dimensions, e.g., twenty-foot equivalent unit (often TEU). As cargo is transported in containers for most of the journey, the safety of cargo is enhanced, e.g., reducing the loss and damage of cargo. Benefiting from the standardized procedure, containerized intermodal transportation also encourages consolidation, and consequently produces economies of scale and generates less transport cost.

The original motivation of this thesis is the willingness of the inland waterway infrastructure managers, e.g., VNF, to work together along the Nord-Pas-de-Calais - Wallonie inland waterway from Dunkirk, France to Liege, Belgium (as shown in Figure I.1), and to offer *TaxiBarge* to the customers. The initial idea for *TaxiBarge* (as well as the name) has been brought forward by the Port of Dunkirk (GPMD) and VNF, who were then linked together in a contract for cooperation in order to better develop their traffics together. As illustrated by the name of this project, barges are used to offer services as taxis, which responding on demand (freight, not passenger) and often for a non-shared trip. To be more precise, a *TaxiBarge* responds to a particular customer and offers customized transport service where the pick-up (origin) and drop-off (destination) terminals are determined by the customer within the required delivery time. VNF and GPMD then invited the Belgian port of Liège (PAL) and the service publique de Wallonie (SPW) to join them, as they imagined the *TaxiBarge* service on the inland waterway between Dunkirk and Liege. A protocol of understanding and cooperation was signed between them, and communicated to the press. They then contacted i-Trans in order to find help for the realization and possible additional funding for the project. In order to complete the project and facilitate the progress (as well as finding of funding), the new innovation platform i-Fret then suggested to add a research part in the project. The cooperation between i-Trans/i-Fret and LAMIH was then established.

Figure I.1: Inland waterway network of Northern France, Belgium, Netherlands (Source: VNF[1])

The research conducted by LAMIH aims to promote the development of container traffic on barge in the region of Northern France and Belgium with a set of ports (maritime and inland waterway) involved, in the context of intermodal transportation. It is true that by offering *TaxiBarge*, carriers may benefit from its flexibility and have better customer satisfaction. However, as the services are customized, low capacity usage of those barges is normally expected and carriers have a high possibility to suffer lower income. The research topic then evolved. In the evolution, the idea of containerized multimodal transportation and barge transportation remains, but the offered services are evolved from customized services to consolidation-based services. In this thesis, barge is deployed for regular services to encourage consolidation, instead of responding on demand. Therefore, we propose a Reactive Decision Support System (R-DSS) methodology for intermodal freight transportation, aiming to improve the freight transportation planning and management, in terms of service design, resource utilization, demand uncertainty consideration, etc. The proposed R-DSS methodology is expected to have an application on the northern France inland waterway network.

[1]VNF:Voies Navigables de France; http://www.vnf.fr

A freight transportation system can be considered from two main perspectives: *demand* and *supply*. Demand comes from the *shippers* that need to move cargoes to different locations. These shippers are the purchasers of the freight transportation. Supply, on the other hand, is mainly provided by the infrastructures operators (e.g., intermodal terminals, locks and dams) and carriers, who move cargoes using resources (e.g., vessels and crews). In this thesis, we limit the scope of our research and take the perspective of a single carrier or a group of carriers cooperating with each other.

The structure of the proposed R-DSS is depicted in Figure I.2.

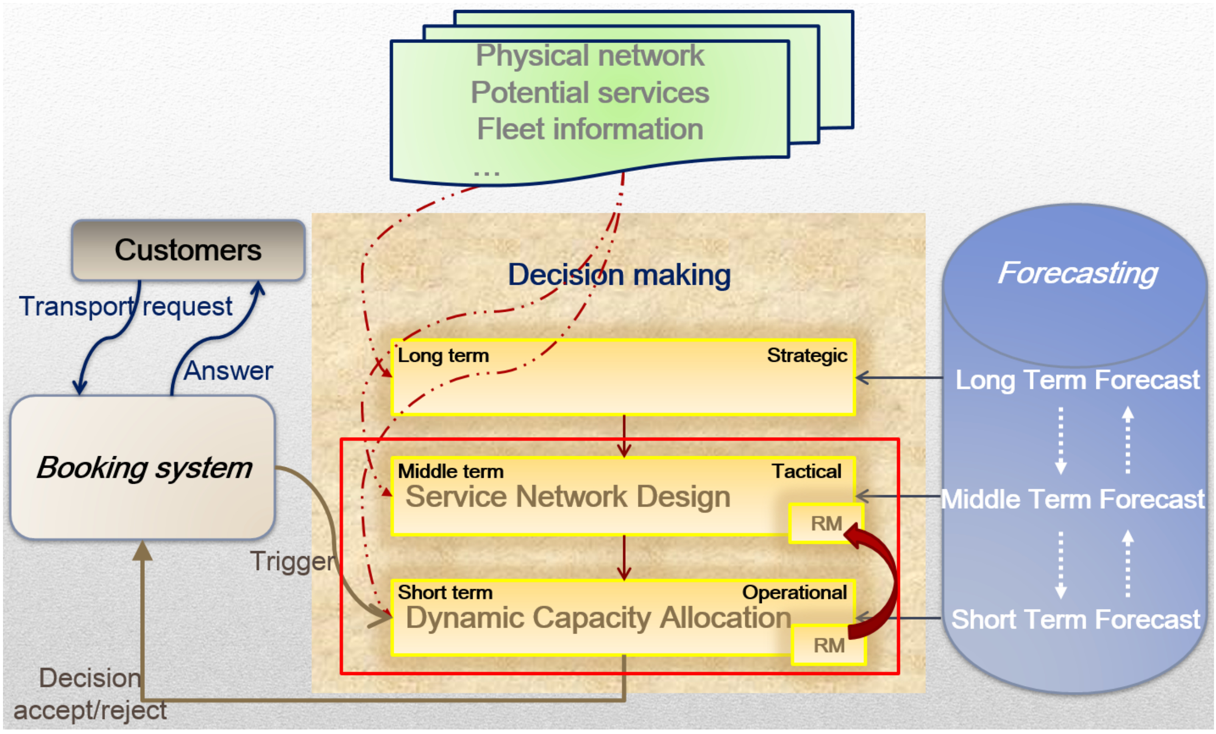

Figure I.2: Structure of the proposed reactive decision support system; Both tactical and operational planning levels are considered; Revenue Management (RM) policies are introduced [Bilegan and Crainic, 2012]

Decision making for transportation, conventionally, is composed of three levels, i.e., *strategic*, *tactical* and *operational*. This hierarchical structure of decision making corresponds to the planning horizon at each level: long term, middle term and short term, respectively. Note that, in addition to the characteristics of the decision making process at each level, there are also mutual influences among different levels.

At *strategic level*, the most aggregated level of planning, decisions are made to determine general policies, physical infrastructure/network, acquisition of major resources, etc.

At *tactical level*, decisions are made to ensure an efficient allocation and utilization of resources over the middle-term planning horizon. The network of services is designed to satisfy the forecasted demands, while minimizing total cost or maximizing the revenue. Typically, at tactical level, two types of major decisions, i.e., service selection and flow distribution, are made. The first determines the itinerary of each service (if selected) and the corresponding schedule. The second major type of decisions is the routing of demands from their origin to destination within the required delivery time (if considered) and the corresponding operations at terminals.

At *operational level*, decisions are made to allocate the network capacity, in a highly dynamic environment considering uncertainty of demands, damage or loss of cargo, delay of services, etc. In this planning level, the time factor plays an important role. The states of the transport network, berthing capacity in the terminals, transport requests, etc., vary through time. Therefore, the adjustment of routing is determined.

In addition, decision and information flows are also emphasized in the hierarchical structure. Decisions made at each level have influence on the lower level(s). For example, a solution to a strategic problem may determine the design and evolution of the physical network, e.g., where new terminals should be built, how big the berthing capacity should be, how many equipments should be prepared and which terminals should serve as a hub. Based on the determined physical network from strategic level, decisions are made to select which services to open with their corresponding schedule and itinerary at tactical level. At the middle-term planning level, the service network is build for a given schedule length, e.g., a week, which is then operated repeatedly and proposed to shippers for the duration of the next planing horizon, e.g., six months. The decision made at tactical level, i.e., a set of selected services characterized by schedule, itinerary and capacity, is then fed to the operational planning as input. Based on the determined service network, the routing of demands is decided and adjusted at operational level. The information flow, on the contrary, has influence upwards. Essential information, in terms of geographic location of terminals, customer definition, product definition, etc., at each level of the hierarchical structure is supplied to the higher level(s) for decision making processes.

As illustrated with the red rectangle in Figure I.2, the proposed R-DSS covers both the tactical and operational levels of the operations planning. To be more precise, given the physical network, potential services and forecasted demands, decisions about the optimal scheduled service plan are made for the carriers at tactical level. Those selected services are then deployed at operational level to face transport requests from the shippers (or *customers* in this thesis). At operational level, decisions in terms of the acceptance/denial of each transport request and the corresponding routing (for accepted demands), are made with the objective of revenue maximization. In order to limit the scope of this research, a set of assumptions are made as follows:

- The scope of this research is limited to freight transportation, especially containerized freight transportation;

- Demand forecasting is out of the scope of this thesis. Information related to demand forecasting is considered to be available for the decision making. Other required information, e.g., distance between terminals, speed of vehicles, handling time at terminals, fixed and variable costs, is also considered to be available for the scope of the study;

- No traffic congestion, delay of services or damage/loss of cargo is considered; Note that, the delay of services (here we are talking about short delays, not disaster ones) could be claimed as considered as part of the time of operations consumed by a service at terminals;

- No other transport modes are considered explicitly in this thesis. To synchronize the barge transport mode with other modes in the context of intermodal freight transportation, time dimension is considered. Both demands and services are represented with time-related characteristics;

- At tactical level:

  - To explicitly represent the movement of services and demands in time, and to synchronize the barge transport mode with other modes in the context of intermodal transportation, the middle-term planning problems are formulated on a time-space network. In Figure I.3, we present a physical network of four terminals with three services (Figure I.3a) and the corresponding services with schedules in a time-space network (Figure I.3b);
  - Different states of services and variety of demands are studied over the schedule length, which is composed of a certain number of time periods in the time-space network;
  - Operations at terminals, such as loading at origin, unloading at destination, and transshipment at intermediate stops of a demand, are considered within the time consumed by services and associated with corresponding costs;

- At operational level:

  - Services, that have already been selected and scheduled at the tactical planning level, are not going to be rescheduled at the operational level;
  - The capacities of scheduled services are also fixed since vehicles are already assigned to services and no extra-vehicles are considered to be available upon request;

– Transportation activities are also represented on a time-space network;

– The routing of demands is decided and fixed when the acceptance decision is made. No re-routing of demands is allowed in the first version of operational mode; Re-routing is allowed in a second version.

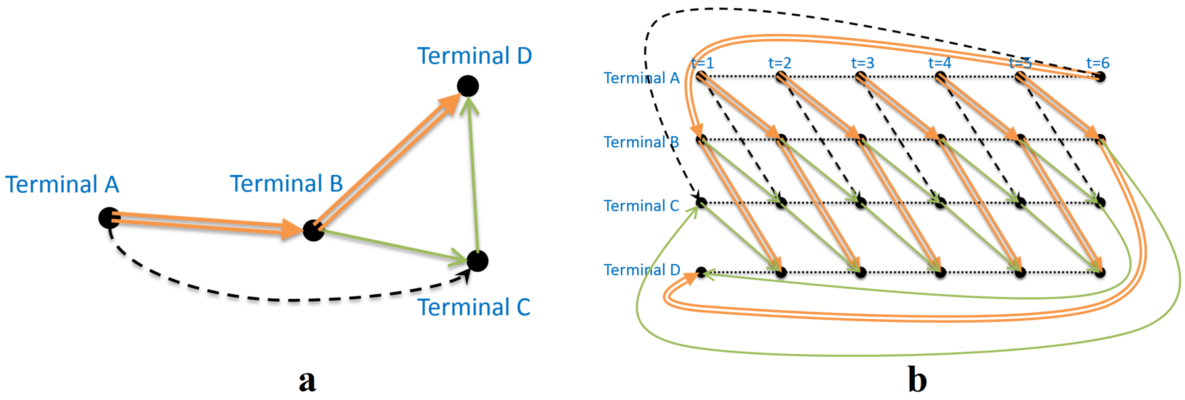

Figure I.3: a. An example of physical network of four terminals with three services defined; b. The corresponding three services with schedules presented in a time-space network

In this thesis, we offer the carriers a different perspective (*Revenue Management*) to make decisions for freight transportation. *Revenue Management*, which is composed of four subproblems: demand forecasting, inventory control, pricing and over-booking decisions, is broadly used in passenger transportation to manage trip prices and reservations at operational level [Armstrong and Meissner, 2010]. As a set of main characteristics (e.g., uncertain demands, scarce resources and market segmentation) required for efficiently applying RM polices are also identified in freight transportation, RM recently has been identified as a desirable feature for freight transportation, including barge intermodal transportation [van Riessen et al., 2015a]. It helps the carriers to tackle the challenge and pressure from the market competition, e.g., decreasing costs and improving customers satisfaction, and make more competitive decisions, in terms of revenue/profit, resource utilization, etc.

The motivations to integrate the RM polices into the proposed DSS are threefold. First, RM polices offer the carriers a different viewpoint to make decisions for freight transportation. Instead of minimizing the cost, which may lower the satisfaction of the customers and consequently lose the market share, we focus on maximizing the revenue/profit. Second, some useful information derived from the operational level is considered at the tactical level as a result of the integration of RM polices. Therefore, the information flow is enhanced and more comprehensive decisions on the selection of services are supposed to be made consequently. Third, the integration of RM polices is also expected to alleviate the negative influence of demand uncertainty and make more robust plans for the carriers. A better utilization of resource is also expected.

In this thesis, new models are proposed, at both tactical and operational levels to address the service network design (SND) and dynamic capacity allocation (DCA) problems, respectively. In addition, a new solution technique is proposed to solve the service network design problems with consideration of resource and revenue management. Performance indicators (PIs) are studied and proposed to evaluate and analyze the the proposed models.

To build the R-DSS, a set of research questions have to be answered. Therefore, the R-DSS is decomposed into four main research topics as follows:

- How to integrate RM polices (which polices) with barge transportation at operational level in order to dynamically allocate the capacity of transport network facing real transport requests, in the context of intermodal freight transportation;
- How to integrate RM polices (which polices) and resource management consideration with barge transportation for the service network design problems and how the selected services might be synchronized with other transport modes, in the context of intermodal freight transportation;
- How to efficiently solve the scheduled service network design problems while simultaneously considering resource and revenue management;
- How to validate and evaluate the decision support system of barge transportation, in terms of models, solution methods, corresponding results and strategies; are there some indicators that give insight more than others;

To answer these questions, in the following of this chapter, we first present the research methodology in Section I.2; the detailed challenges of each research topic and the contributions of the thesis are then discussed in Section I.3. Note that, the problem characterization and detailed literature review related to each research topic are introduced in each corresponding chapter.

I.2 Research Methodology

In this section, we present the research methodology used to address the reactive decision support system introduced in the previous section. At the operational planning level, we propose a revenue management model (DCA-RM) for the network capacity allocation problem, extended on [Bilegan et al., 2015]. In addition to the consideration of *feasibility*, i.e., available network capacity within the required delivery time, the proposed DCA-RM model makes decisions to accept or reject a transport request by maximizing the expected revenue of current demand and potential future demands over a given time horizon, which is called the consideration of *profitability*. The sequential arrival of transport requests is simulated as an iterative process, and the decision on each transport request is made by solving the proposed DCA-RM model with a commercial solver. The total revenue obtained by applying the DCA-RM model through the simulation is calculated and compared with the total revenue obtained by applying a conventional model considering only the *feasibility*. Different negotiation strategies, dealing with the rejected transport requests, are also embedded in the DCA-RM model and discussed.

Aiming to improve the tactical planning for freight carriers in the context of intermodal barge transportation, we propose a *scheduled service network design with resource and revenue management* (SSND-RRM) model. By integrating the polices of RM, customers are classified into different categories according to their business relationships with the carriers and their behaviors. Accordingly, different treatment of demands from different categories of customers are modeled. Moreover, various fare classes according to the required delivery service types are also modeled as one of the characteristics of demands. Various problem settings, in terms of demand distribution, network topology, fare class and delivery service type, are tested to analyze the performance of the proposed SSND-RRM model. The optimization problems are also solved by feeding a commercial solver.

As the proposed SSND problems with the consideration of resource and revenue management are NP-hard, we propose a metaheuristic (MH) to produce high-quality solutions in reasonable time. The proposed solution approach is composed of four phases: a constructive heuristic to obtain an initial feasible solution, a metaheuristic to iteratively improve the solutions, intensification and diversification. The proposed metaheuristic is based on adaptive large neighborhood search [Ropke and Pisinger, 2006] and tabu search. Aiming to accelerate the search, new neighborhood structures considering design-balance constraints are proposed. Learning mechanisms are embedded in the whole algorithm to guide the search by identifying good characteristics/attributes of solutions. The obtained statistical information is also used to diversify and intensify the search when predefined conditions are met. As no other solution approaches to the new SSND-RRM model exists, IBM CPLEX is used as comparison, in terms of computational time and solution quality.

In order to qualify the reactive decision support system and evaluate the performance of the proposed models, performance indicators (PIs), which are broadly used in practice and research of transportation, are studied, discussed, classified and applied. We first study and analyze some of the performance indicators generally used for validating and evaluating service network design models in the literature. A first classification of these different performance indicators based on their relevance and meaning from the service providers' perspective is then proposed. Furthermore, additional performance indicators for the intermodal freight transportation problems with revenue management considerations are proposed. Some more representative performance indicators from each category are then selected and applied to assess the performance of the proposed reactive DSS. Insights into the generation of adequate test instances to study the planning issues in the general context of freight transportation systems are also provided.

I.3 Contributions of the Thesis

The fundamental contribution (or the first group of contributions) of this thesis is the integration of revenue management (RM) polices and the barge transportation system in the context of the intermodal freight transportation. RM, conventionally applied for passenger transportation at operational planning level, is considered when making decisions on operations planning at both tactical and operational levels in our research.

At operational level, we propose a DCA-RM model for the network capacity allocation problem of an intermodal barge transportation system in Chapter II. As RM polices are considered in the proposed DCA-RM model, one of the main challenges is to classify the customers. According to the business relationship, customers are classified into three categories: regular customers (R customers), who sign long-term contracts with the carriers, and thus whose demands (R demands) have to be accepted; on the other hand, the so-called spot-market customers (P or F customers), who request transportation less frequently and on an irregular basis, and thus whose demands may be partially accepted (P demands) or fully accepted/denied (F demands). Another challenge is to differentiate the products. To achieve that, a transport request is characterized by three time characteristics:

- The reservation time of a transport request, when it is submitted to the booking system;
- The available time of a transport request, when it is ready to be transported at its origin terminal on the carriers' transportation network;
- The due time of a transport request, its maximization. delivery time to its destination;

among other characteristics. The difference between the available time and the reservation time gives us the so-called *booking anticipation* of the transport request, and the *delivery type* (slow/fast) depends on the required transport distance from origin to destination and on the requested delivery time (the difference between the due time and the available time). A pricing policy, related to the booking anticipation and delivery type, is then applied to differentiate several product fares. The decision to accept or reject a transport request is made based on a probabilistic mixed integer optimization model maximizing the expected revenue of the carrier over a given time horizon. To maximize the expected revenue of carriers, a set of future potential demands are considered and probability distribution functions are used to account for their uncertainty of these future demands. In addition, a set of possible negotiation strategies for better satisfying the rejected customers are studied based on the proposed DCA-RM model.

In Chapter III, we propose, what we believe to be, the first comprehensive tactical planning model for freight carriers that integrates both revenue and resource management considerations. Customer classification and price differentiation, as considered RM polices, are integrated into the proposed SSND-RRM model. Instead of accepting all transport requests like most of the deterministic tactical planning models do, transport requests from spot-market customers, in the proposed SSND-RRM model, are allowed to be partially or fully rejected aiming to have better resource utilization and maximize the net profit of the carriers. The different treatments of customers are decided according to their corresponding customer categories. The same three customer categories as introduced at the operational level (Chapter II) apply. Different fare classes are also defined according to the required delivery types. Note that, at tactical level, the price policy is related to delivery type only. Booking anticipation is not considered because the reservation time is not used to characterize a transport request at tactical level. With respect to the resource management, design-balance constraints are considered to ensure the balance of incoming and outgoing vehicles at each terminal for each time instant. Repositioning of vehicles is also considered implicitly as the SSND-RRM problems are formulated as a cyclic model. In addition, the limits on the quantity of the resource is also formulated. Moreover, transshipment of the freight between different vehicles/services and holding them at terminals for given periods are considered, with corresponding handling and holding costs. The proposed SSND-RRM model is tested in various problem settings, in terms of demand distribution, network topology, fare class and quality-of-service (e.g., delivery time), to study and analyze its performance.

The next original contribution of this thesis is an efficient solution approach for solving the proposed SSND-RRM model (discussed in Chapter III). The proposed four-phase metaheuristic (MH) is introduced in Chapter IV. Design-balanced service network design problems, as shown in [Pedersen et al., 2009] and [Vu et al., 2013], are NP-hard. Further complexity to the SSND-RRM is added because of the additional demand selection associated to one of the customer categories defined in the SSND-RRM model (binary decision variables), competition of different categories of customers for the network capacity with different fares and trade-offs between opening more services with higher revenue and rejecting more demands with lower total costs. There are challenges even just to obtain feasible solutions. We then propose a constructive heuristic in the first phase to obtain initial solutions to the SSND-RRM. Once an initial solution is obtained from the first phase, the algorithm tries to improve it in the second phase, by iteratively exploring the search space of service selection, demand selection and the combination of both. The selection of search space is based on a modified adaptive large neighborhood search (ALNS) inspired by [Ropke and Pisinger, 2006] and tabu search. To explore the search space of service selection, several heuristics are proposed based on a *service cycle* related neighborhood structure. A *service cycle* is a set of consecutive services using the same type of vehicle back to the terminal where the sequence of service starts. Moves based on the new neighborhood structure guarantee the design-balance constraints and diversify the search simultaneously. To explore the search space of F-demand selection, several *F-selection heuristics* are proposed and different strategies are considered to accept or reject F demands. Learning mechanisms are embedded into the proposed MH, and used to guide the search and the other two phases (intensification and diversification).

Performance indicators (PIs) are broadly used to characterize the performance of transportation systems and to validate and evaluate models, solution methods, corresponding results and strategies. Some of these are found in public documents, usually providing global measures such as total flow volumes, profits and share values. While of great interest, such measures are not sufficient to support a fine analysis of different operation strategies, commercial policies and planning methods. Therefore, the contributions we make in Chapter V are as follows. First, we make the first step towards a taxonomy of PIs. Three categories of PIs, i.e., *economic impact*, *resource utilization* and *quality of service*, are classified based on their relevance and meaning from the perspective of both service provider and customer. Second, new PIs considering resource and revenue management in the context of freight transportation are proposed for all three categories. In addition, we also provide procedure employed to generate test instances, which are adopted for the experiments throughout the whole thesis, and adequate for further studies of the planning issues in a general context of freight barge transportation.

I.4 Structure of the Thesis

The thesis is composed of five chapters and the remaining is organized as follows. Chapter II introduces the proposed revenue management approach for dynamic capacity allocation of an intermodal barge transportation system. Chapter III presents the scheduled service network design with resource and revenue management considerations model for intermodal barge transportation. A metaheuristic for the SSND-RRM is then introduced in Chapter IV. In Chapter V, we study and classify performance indicators for planning intermodal barge transportation systems and present test for the assessment of the R-DSS methodology proposed.

Chapter II

A Revenue Management Approach for Network Capacity Allocation of an Intermodal Barge Transportation System

Contents

This chapter is dedicated to the operational level of planning for the proposed R-DSS. In this chapter, we first propose a revenue management model (DCA-RM) for the network capacity allocation problem of an intermodal barge transportation system. Accept/reject decisions are made based on a probabilistic mixed integer optimization model maximizing the expected revenue of the carrier over a given time horizon. Probability distribution functions are used to characterize future potential demands. The simulated booking system solves, using a commercial software, the capacity allocation problem for each new transportation request. A conventional model for dynamic capacity allocation considering only the available network capacity and the delivery time constraints is used as alternative when analyzing the results of the proposed model.

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Note that, in the proposed DCA-RM model, the routing of demand is decided and fixed when the corresponding acceptance decision is made. We then, in the second part of this chapter, extend the proposed DCA-RM model by integrating the re-routing of accepted demands. Preliminary experiments are conducted to examine the extended DCA-RM model.

II.1 Introduction

Barge transportation offers a competitive alternative for freight transportation, complementing the traditional road and rail modes. Moreover, considered as sustainable, environment-friendly and economical, barge transportation has been identified as instrumental for modal shift and the increased use of intermodality in Europe [European Commission, 2011]. Yet, studies targeting barge transportation are scarce, (e.g., [Fazi et al., 2015, Frémont and Franc, 2010, Konings, 2007, Konings et al., 2013, Notteboom, 2012, Taylor et al., 2005]), the ones considering the intermodal context being even more rare (e.g., [Tavasszy et al., 2015, van Riessen et al., 2015a, Zuidwijk, 2015, Ypsilantis and Zuidwijk, 2013]). An important and recent review of the scientific literature on multimodal freight transportation planning can be found in [SteadieSeifi et al., 2014].

Revenue Management (*RM*), broadly used in passenger transportation to manage trip prices and bookings (e.g., [Armstrong and Meissner, 2010]), has been identified as a desirable feature for freight transportation, including barge intermodal services [van Riessen et al., 2015a]. RM is expected to provide freight carriers with tools to better manage revenues and enhance service by, in particular, tailoring the service levels and tariffs to particular classes of customers. In [van Riessen et al., 2015b], the authors study revenue management in synchromodal container transportation to increase the revenue of the transportation providers. In their study, several delivery types are provided by carriers. Each type of delivery is associated with a fare class, characterized by a specific price and a specific due time. In [Li et al., 2015], authors propose a cost-plus-pricing policy to determine the price of delivery types in the context of intermodal *(truck, rail and barge)* freight transportation. The price associated with each delivery type is the sum of the operational cost and the targeted profit margin. The price of a delivery type depends on its urgency as well. Different scenarios, i.e., self-transporting, subcontracting, and a mix of the two, are studied, with different operational costs and targeted profit margins. However, in both [van Riessen et al., 2015b] and [Li et al., 2015], only one type of customers, who sign long-term contracts with the carriers, is considered. Consequently, no accepting or rejecting decision is made during the operational phase. In [Liu and Yang, 2015], customers are classified into two categories: contract sale (large shippers, which might be considered regular) customers, and free sale (scattered shippers) customers. A two-stage stochastic optimal model is then proposed to maximize the revenue. In the first stage, the revenue is maximized serving contract sale customers only. In the second stage, the slot capacity after serving contract sale customers is used to serve the scattered shippers customers through a dynamic pricing method for price settling and an inventory control method for slot allocation applied jointly in each period of free sale. The exploration of RM-related issues in freight transportation is still at the very early stages, however, as illustrated by the reviews related to air cargo operations [Feng et al., 2015], railway transportation [Armstrong and Meissner, 2010], and container synchromodal services [van Riessen et al., 2015a].

We aim to contribute to the field by proposing a DCA-RM model to address the network capacity allocation problem of an intermodal barge transportation system. As intermodal barge and rail systems share a number of characteristics, e.g., scheduled services, limited transport capacity (resource) and uncertain future demands, the approach is inspired by the work of [Bilegan et al., 2015] where the authors develop a model to dynamically allocate the rail capacity at operational level. In defining the revenue management problem for barge transportation we induce novel features to our modeling, however: we adapt it for the barge transportation space-time network, we enrich it by introducing different categories of customers with the definition of specific treatment for each of them, including particular accept/reject rules. An important feature offered by the new modeling lays in the proposal of a negotiation process based on the optimization model when dealing with rejected demands, as explained in more details further on. Customers are classified into different categories as follows. Regular customers, who sign long-term contracts with the carriers/providers, must be satisfied and thus all these regular category of demands have to be accepted. On the other hand, the so-called spot-market customers, who request transportation less frequently and on an irregular basis, may be rejected if needed. The accept/reject mechanism is settled according to an estimation of the profitability of each new incoming demand, given the availability of service capacities at the time of decision. In order to better consider customer behavior specificities, those spot-market customers are further classified into partially-spot customers, who would accept their requests to be partially accepted, and fully-spot customers, whose requests must be either accepted as a whole or not accepted at all. These acceptance rules are introduced and used in the new DCA-RM model (through specific decision variables). Moreover, based on the customer differentiation, and on the associated acceptance rules, different mechanisms are set out in a new negotiation process model which is implemented and used when dealing with rejected demands. At the authors best knowledge, this is the first contribution proposing to introduce RM techniques, e.g., price differentiation and customer classification, at the operational level planning of barge transportation activities.

The application of RM polices requires a booking system to manage transport requests, and the capability to forecast future demands. In our case, the simulated booking system performs an accept/reject decision for each new transport request, based on the results of the proposed optimization model maximizing the expected revenue of the carrier over a given time horizon. In case of acceptance, the corresponding optimal routing is also provided by the optimization. Probability distribution functions are used to characterize future potential demands for transportation and, thus, the proposed optimization model takes the form of a *probabilistic mixed integer program* (MIP). A commercial solver is used to address this model. Simulation is used to analyze the performance of the proposed optimization model and RM polices, through comparisons with a conventional dynamic capacity allocation model considering only the available network capacity and the delivery time constraints.

The remainder of this chapter is organized as follows. In the first part, we briefly describe the network capacity allocation problem and the considered RM concepts and strategies for intermodal barge transportation in Section II.2. The proposed DCA-RM model is introduced in Section II.3. Simulation and numerical results are discussed and analyzed in Section II.4. In the second part of this chapter, the extended DCA-RM model is presented in Section II.5 and validated with preliminary experiments. We conclude in Section II.6.

II.2 Problem Characterization

We first briefly present the general problem of dynamic capacity allocation for barge transportation. The mechanisms of the booking system are then discussed, together with the proposed RM polices. The associated notation is identified as well.

II.2.1 Dynamic Capacity Allocation Problem

Consolidation-based carriers, such as those operating barge services, plan and schedule their operations for the "next season" with the goal of jointly maximizing the revenue and satisfying the forecast regular demand, through efficient resource utilization and operations. Transport requests fluctuate greatly during actual operations, however, in terms of origins, destinations, volumes, etc., not to speak of those unforeseen demands the carrier will try to accommodate. The capability to answer customer expectations of the transport network is consequently continuously changing as well, together with its efficiency and profitability. Setting up some form of advanced booking system is the measure generally adopted to handle this complex situation.

Transport booking requests are traditionally answered on a first-come first-serve (FCFS) basis. Moreover, a transport request is (almost) always accepted provided the network currently has the capability to satisfy both the volume and the delivery time specified by the customer. This has the unwanted consequence that requests coming at a latter time might not be accepted, even though they present the potential to generate a higher revenue, due to a lack of transport capacity, resulting in the loss of additional revenue for the carrier.

RM-based booking systems operate according to different principles. The booking system considered in this chapter manages the transport capacity, and the decision to accept or reject a new demand, considering a set of potential future demands characterized by different fare classes. To make the final decision, the acceptance and rejection of the current demand are compared by optimizing the estimated total revenue of all demands, current and potential future ones. Therefore, in our model, a current transport request may be rejected if it appears less profitable compared with the estimated profit of future demands competing for the transport capacity. The resource is then reserved for the future demands, expecting a higher total revenue. On the other hand, when the booking system accepts the current transport request and more than one possible routing exist, a "better" capacity allocation plan can be obtained by considering the future demands. That is, the capacity available in the future might more closely match future demands, increasing the possibility of acceptance and the generation of additional revenue.

We formulate the dynamic capacity allocation problem on a space-time network over a time interval composed of $1, ..., T$ time instants. The nodes of the $G = (\mathcal{N}, \mathcal{A})$ network are obtained by duplicating the representation of the physical terminals at all time instants, i.e., a node $n(i, t) \in \mathcal{N}$ specifies the physical terminal i and the time instant t.

A set of already-selected services, each with given schedule, route and capacity, provides transportation among the nodes in $\mathcal{N}$. Note that, in this research, we assume that services have already been scheduled at the tactical planning level (i.e., when the Scheduled Service Network Design problem is solved) and are not to be rescheduled at the operational level. The capacities of scheduled services are also fixed since vehicles are already assigned to services and no extra-vehicles are considered to be available upon request. A service $s \in S$ is characterized by its transport capacity $cap(s)$ and set of legs $\eta(s)$. Leg $a_k(s) \in \eta(s)$ represents k^{th} leg of service between two consecutive stops (i.e., $i_k(s)$ and $i_{k+1}(s)$) of service s, and is characterized by its origin and destination terminals, $orig(a_k(s)), dest(a_k(s)) \in \mathcal{N}$, with the respective departure $dep(a_k(s))$ and arrival $arr(a_k(s))$ times. Let $cap(a_k(s)) = cap(s)$ identify the capacity of $a_k(s)$, and define $cap\_avl(a_k(s))$, the residual capacity of leg $a_k(s)$ after having routed the already accepted demands.

The set of arcs $\mathcal{A}$ is then made up of the sets $\mathcal{A}_K$ and $\mathcal{A}_H$ representing the transport and holding arcs, respectively. Set $\mathcal{A}_K$ is composed of all the defined service legs, while $\mathcal{A}_H$ arcs link two representations of the same terminal at two consecutive time periods.

Holding arcs represent the possibility of demand flows to wait at their respective origins or at intermediate terminals during their journey, to be picked up by services passing by at later periods.

II.2.2 RM Policies

Revenue Management groups together a set of concepts and techniques aimed to better integrate customer behavior knowledge into the optimal capacity allocation models. For instance, different fares are applied to well-differentiated products/services, and different market segments are identified and used with the overall objective to maximize expected revenue. To define RM polices for barge transportation systems, we introduce *customer classification* and *price differentiation*.

Customers are classified into three categories according to the business relationship: regular customers (R), who sign long-term contracts with the carrier or whom the carrier trusts; partially-spot customers (P), who contact the carrier infrequently and do not require that all their demand be accepted; fully-spot customers (F), who also require service irregularly but their demand must be accepted as a whole or not at all.

Let d be the current booking request. Let $\mathcal{D}'_d$ be the set of demands accepted before the arrival of d, and $\mathcal{D}''_d$ the set of forecasted future demands with direct interactions in time with d. A transport request $\mathfrak{d} \in \mathcal{D}'_d \cup \mathcal{D}''_d \cup \{d\}$ is then characterized by the volume to be transported in TEUs, $vol(\mathfrak{d})$; the origin and destination terminals, $orig(\mathfrak{d})$ and $dest(\mathfrak{d})$, respectively; the time $res(\mathfrak{d})$ it is submitted to the booking system; the time $avl(\mathfrak{d})$ it becomes available at its origin terminal and the corresponding anticipation time, $\Theta(\mathfrak{d}) = avl(\mathfrak{d}) - res(\mathfrak{d})$; the due time (latest delivery time) $out(\mathfrak{d})$ and the requested delivery time $\Delta(\mathfrak{d}) = out(\mathfrak{d}) - avl(\mathfrak{d})$; the unit tariff $f(\mathfrak{d})$ according to the fare class of the demand (defined bellow); and the category $cat(\mathfrak{d})$ of customers (R, P or F). Note that a future demand d'' is considered to be part of the set of potential future demands $\mathcal{D}''_d$ when it has "direct interactions" with the current booking request d, which is true when the two time conditions are satisfied:

- $res(d'') > res(d)$
- $[in(d''), out(d'')] \cap [in(d), out(d)] \neq \emptyset$.

Let $VMAX(d'')$ be the maximum volume a future demand request $d'' \in \mathcal{D}''_d$ may take, and $P_{d''}(x)$ the discrete probability distribution function indicating the probability that a given value $0 \leq x \leq VMAX(d'')$ occurs.

We define four fare classes for any pair of terminals in the physical network (and the distance separating them) as the combination of $\Theta(d)$, early or late booking, and $\Delta(d)$, slow or fast delivery requested. A demand with the highest fare class thus corresponds to a late booking and fast delivery request, while a demand with the lowest fare class corresponds to an early booking and slow delivery request.

The proposed RM policy for barge transportation is then to examine each new transport request, d, and decide on its acceptance, and routing through the network for accepted ones, by considering its *feasibility* and *profitability*, given the current status of the network and an estimation of future demands. The former means that currently there is sufficient capacity and time to satisfy d. The latter indicates that the expected total revenue given the acceptance of d is at least not worse than the one corresponding to rejecting it, taking into account the potential future demands. The model of Section II.3 is used to make these decisions.

A rejected request has no influence on the transport network. Similarly, the potential future demands are only used to calculate the expected total revenue, and do not impact the status of the network.

II.3 DCA-RM Model Formulation

We now present the Revenue Management decision model (DCA-RM) that is to be solved for every arriving request for transportation d. The decision variables are:

- $\xi(d)$: accept or reject d, where $\xi(d)$
  - equals 1 when $cat(d) = \text{R}$,
  - varies within [0, 1] when $cat(d) = \text{P}$,
  - takes the value 0 or 1 when $cat(d) = \text{F}$;
- $x(d, a_k(s))$: volume of demand d on arc $a_k(s)$;
- $maxvol(d'')$: maximum volume available on the network (at the decision time) to serve the potential future demand $d'' \in \mathcal{D}''_d$;
- $x(d'', a_k(s))$: volume of the potential future demand $d'' \in \mathcal{D}''_d$ on arc $a_k(s)$.

Obviously, $\xi(d')$ and $x(d', a_k(s))$ variables are fixed on all arcs for the already accepted demands, which we denote d', $d' \in \mathcal{D}'_d$.

The objective function of the model with respect to the current demand d maximizes the sum of its corresponding revenue and the expected revenue computed on the basis of future demand forecasts:

$$\max\ (f(d) \cdot \xi(d) \cdot vol(d) + \phi) \tag{II.1}$$

where

$$\phi = \sum_{d'' \in \mathcal{D}''_d} f(d'') \sum_{x=0}^{maxvol(d'')} x P_{d''}(x) \tag{II.2}$$

Following [Bilegan et al., 2015], ϕ is linearized by introducing additional binary decision variables $y_{d''j}$ for each potential future demand d'', where the integer-valued j takes all the values between 1 and $VMAX(d'')$. Note that $VMAX(d'')$ represents the maximum possible volume of a booking request, which translates mathematically, in terms of probability distribution, as $P_{d''}(j) = 0$ when $j \geq VMAX(d'') + 1$. The binary decision variables $y_{d''j}$ are defined to be equal to 1, if no more than volume j of capacity is available on the network to serve the potential future demand d'' and 0 otherwise. In order to make this definition consistent, for each future demand d'', at most one of the variables $y_{d''j}$ may take the value 1 (since this will correspond to the maximum capacity available on the network to serve that specific demand). Thus, the objective function becomes:

$$\max\ (f(d) \cdot \xi(d) \cdot vol(d) + \sum_{d'' \in \mathcal{D}''_d} f(d'') \sum_{1 \leq j \leq VMAX(d'')} y_{d''j} \sum_{x=0}^{j} (x P_{d''}(x))) \tag{II.3}$$

since $maxvol(d'')$ is defined as follows:

$$maxvol(d'') = \sum_{1 \leq j \leq VMAX(d'')} j y_{d''j} \tag{II.4}$$

with

$$\sum_{1 \leq j \leq VMAX(d'')} y_{d''j} \leq 1 \tag{II.5}$$

and

$$y_{d''j} \in \{0, 1\}. \tag{II.6}$$

Following this definition, note that the optimal value of $maxvol(d'')$ is computed (II.4) as a result of the optimization problem. Thus, this optimal value is obtained when maximizing the expected revenue corresponding to current demand d on the network, taking into account the entire remaining available capacity and the overall profitability of the whole set of potential future demands on that specific time window.

The constraints of the model are the usual flow conservation relations at nodes and the capacity restrictions imposed by the service network. The latter take the form defined by (II.7) for each service leg

$$\sum_{d'' \in \mathcal{D}''_d} x(d'', a_k(s)) + v(d, a_k(s)) \leq cap\_avl(a_k(s)), \quad \forall a_k(s) \in \mathcal{A}_K \tag{II.7}$$

while the flow conservation constraints for all nodes $n(i,t) \in N_{IT}$ are:

$$\sum_{a \in \mathcal{A}^+(n(i,t))} x(d,a) - \sum_{a \in \mathcal{A}^-(n(i,t))} x(d,a) = \begin{cases} \xi(d)vol(d) & \text{if } i = orig(d) \\ -\xi(d)vol(d) & \text{if } i = dest(d) \\ 0 & \text{otherwise} \end{cases} \tag{II.8}$$

and

$$\sum_{a \in \mathcal{A}^+(n(i,t))} x(d'',a) - \sum_{a \in \mathcal{A}^-(n(i,t))} x(d'',a) = \begin{cases} maxvol(d'') & \text{if } i = orig(d'') \\ -maxvol(d'') & \text{if } i = dest(d''), \forall d'' \in \mathcal{D}''_d \\ 0 & \text{otherwise} \end{cases} \tag{II.9}$$

where $\mathcal{A}^+(n(i,t))$ and $\mathcal{A}^-(n(i,t))$ stand for the sets of outgoing and incoming arcs, respectively, of node $n(i,t) \in \mathcal{N}$.

Finally, the constraints defining the range of the decision variables are:

$$\xi(d) = \begin{cases} 1, & \text{if } cat(d) = R \\ [0,1], & \text{if } cat(d) = P \\ \{0,1\}, & \text{if } cat(d) = F \end{cases} \tag{II.10}$$

$$x(d,a) \geq 0, \quad \forall a \in \mathcal{A} \tag{II.11}$$

$$x(d'', a) \geq 0, \quad \forall d'' \in \mathcal{D}''_d, \ \forall a \in \mathcal{A} \tag{II.12}$$

II.4 Simulation, Numerical Results and Analysis

To validate the proposed DCA-RM model, we use computer simulation. We simulate the sequential arrival of current demands as an iterative process. As shown in Figure II.1, before launching the iterative process, an initialization phase is required. Services (with specified itinerary, schedule and capacity) selected at the tactical planning level are given as inputs for the initialization to decide the capacity of the transportation network at operational level. The demand forecasts are also considered to be known and given in the initialization. Note that, as the length of the simulation is longer than the scheduled length at tactical level, the selected services are applied repeatedly over the simulation according to their schedules. We then start to simulate the sequential arrival of current demands. In the simulation, we randomly generate no more than one current demand for one time instant. For each current demand, we solve the corresponding optimization problem. According to the optimal solution, we make the decision to accept/reject the current demand, and update the status of the network in terms of remaining available capacity. Then, if the simulation has not been finished, a new iteration is performed.

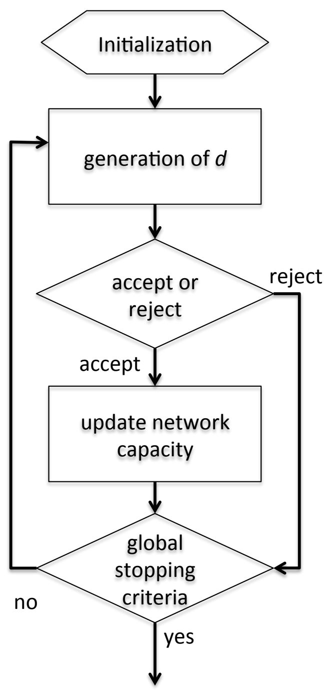

Figure II.1: Procedure of the simulation

Several scenarios are used to test and validate the proposed model. We first set up a scenario with scarce resources and a very limited number of origin-destination (OD) pairs of transport requests. By using this scenario, we analyze the impact of different price ratios applied when different fares are introduced, corresponding to different classes of booking and delivery delays required by the customers. A second scenario, with a more comprehensive problem setting in terms of number of services, number of possible OD pairs of demands, is devised. This second scenario is settled to discuss the performance of the DCA-RM model with respect to different levels of transportation capacity on the network, as well as with respect to the accuracy of demand forecasts. Based on the second scenario, possible strategies of negotiation, when a regular demand is rejected, are equally considered, and numerical results are analyzed. The remaining of this section is organized as follows. We briefly introduce the scenario settings for the simulation in Subsection II.4.1. We then illustrate and analyze the numerical results in Subsection II.4.2.

II.4.1 Scenario Settings

For all scenarios, four consecutive terminals, i.e., A, B, C and D, are considered to be located along the inland waterway with travel times for barges between any two consecutive terminals assumed to be the same. As for the service travel times, all the scheduled stops of a service (including at its origin and destination), are assumed to have identical durations as well, these delays corresponding to the time consumption for operations at port (e.g., loading/unloading containers). The maximum capacity of services is identical within one set of experiments but is varied from one scenario to another. The residual capacities of service legs are sequentially updated according to the accepted demands and their optimal routing. Holding arcs of containers at terminals have unlimited capacity.

Let us recall that any current demand d is characterized by its $res(d)$, $vol(d)$, $orig(d)$, $dest(d)$, $avl(d)$, $out(d)$, $f(d)$ and $cat(d)$. We discretize the time so that no more than one reservation request ($res(d)$) may arrive at each time instant during the simulation; $vol(d)$ is a discrete random value between 0 and VMAX (the same maximum volume is assumed for any demand) following a given probability distribution function; $vol(d) = 0$ indicates that there is no booking request for the current time instant. The origin-destination pair, thus the values of $orig(d)$ and $dest(d)$, are uniformly generated out of the set of possible OD corresponding to a scenario. Both anticipation $\Theta(d)$ and delivery time $\Delta(d)$ are randomly selected from a predefined pool of possible values, following the uniform distribution; the generation of the latter is equally related to the distance between the $orig(d)$ and the $dest(d)$ of the demand. The $avl(d)$ and $out(d)$ are then computed accordingly. Thresholds for the anticipation and delivery time are predefined to split the demands into early/late reservation and slow/fast delivery types, respectively. For a given distance of an OD, a basic fare p is predefined. The unit transportation price (per container) is then defined as $f(d) = p \cdot r_\Theta \cdot r_\Delta$, where r_Θ and r_Δ are the anticipation ratio and the delivery ratio respectively, and whose values will be set to define particular instances. Their corresponding values for early reservation and slow delivery are both set to 1, the others being integer values (factors) greater than one, corresponding to larger fares charged on high contribution demands requesting higher quality-of-service transportation. Finally, $cat(d)$ is randomly generated among R, P and F following the uniform distribution.

For each current demand d, the corresponding set of potential future demands is generated following the same generation procedure, except for its volume. Indeed, since the objective function is defined based on the mathematical expectation of the potential revenue of future demands, this computation is performed considering all the possible volumes (from 0 to VMAX), weighted by their probabilities. The summation is bounded, however, by the maximum available capacity (at decision time) on the network to satisfy each specific future demand d'' ($maxvol(d'')$). Following the same idea, note that the categories (i.e., R, P or F) of future demands are not needed either when generating the potential future demands. By doing so, an estimated value of the expected revenue is obtained by simulation and used to make the decision of accepting or rejecting the current demand d.

For all the scenarios in the simulation, a FCFS accept/reject policy is conducted as comparison. No potential future demands are considered for the FCFS model. A current demand d is accepted when at least one feasible route exists in the space-time network, without considering the expected revenue and hence, without considering its profitability.

The characteristics of the first scenario are:

- Length of the simulated time horizon is 300 time instants;
- There are 15 identical services defined, starting every 20 time instants, from A to D with an intermediate stop at B;
- 3 different ODs are considered: AB, BD and AD;
- Different experiments are conducted, with different values of the anticipation ratio (r_Θ) for late reservation and the values of the delivery ratio (r_Δ) for fast delivery: 1, 2, 3 and 4.

The characteristics of the second scenario are:

- Length of the simulated time horizon is 600 time instants;
- There is a total of 30 services running on the network, 15 in each direction: from A to D and from D to A; they all stop at all terminals;
- All 12 possible ODs are considered;
- Different experiments are conducted, with different capacities of services: 5, 10 and 20 TEUs;
- Different experiments are conducted, based on different forecast accuracies: good accuracy, underestimation, overestimation.

II.4.2 Numerical Results and Analysis

As described before, we vary the values of anticipation ratio (r_Θ) for late reservation and the values of the delivery ratio (r_Δ) for fast delivery in the first scenario. For example, when $r_\Theta = r_\Delta = 2$, the price ratio (r) of early reservation with slow delivery, early reservation with fast delivery, late reservation with slow delivery and late reservation with fast delivery is denoted as $r = 1:2:2:4$. Experiments are also conducted when $r_\Theta = r_\Delta = 1, 3$ or 4. For each tested price ratio, the simulation was carried out 20 times with random transport requests, which are generated following the procedure described in the previous subsection. The total revenue obtained by the DCA-RM model and by the FCFS policy is recorded for each simulation, and the ratio of total revenue of DCA-RM/FCFS is then calculated. In the simulation, we also counted the number of rejected transport requests, which are denied according to the DCA-RM model due to unprofitability or infeasibility .

The average results obtained on the first scenario are illustrated in Figure II.2. Figure II.2 (a) presents the ratio between the total revenue obtained with the DCA-RM model and the total revenue obtained with the FCFS policy, corresponding to different price ratios. Figure II.2 (b) presents the corresponding ratios of the number of nonprofitable rejected requests over the total number of rejected requests when applying the DCA-RM model. On the horizontal axis, r indicates the tested price ratios. As expected, better revenue is always obtained by applying the DCA-RM model when compared with the FCFS policy. When we increase the price ratio r, the difference in profitability of low-fare compared to high-fare demands grows as well. A low-fare demand, which has a feasible routing in the transport network, has then a higher chance to be less profitable

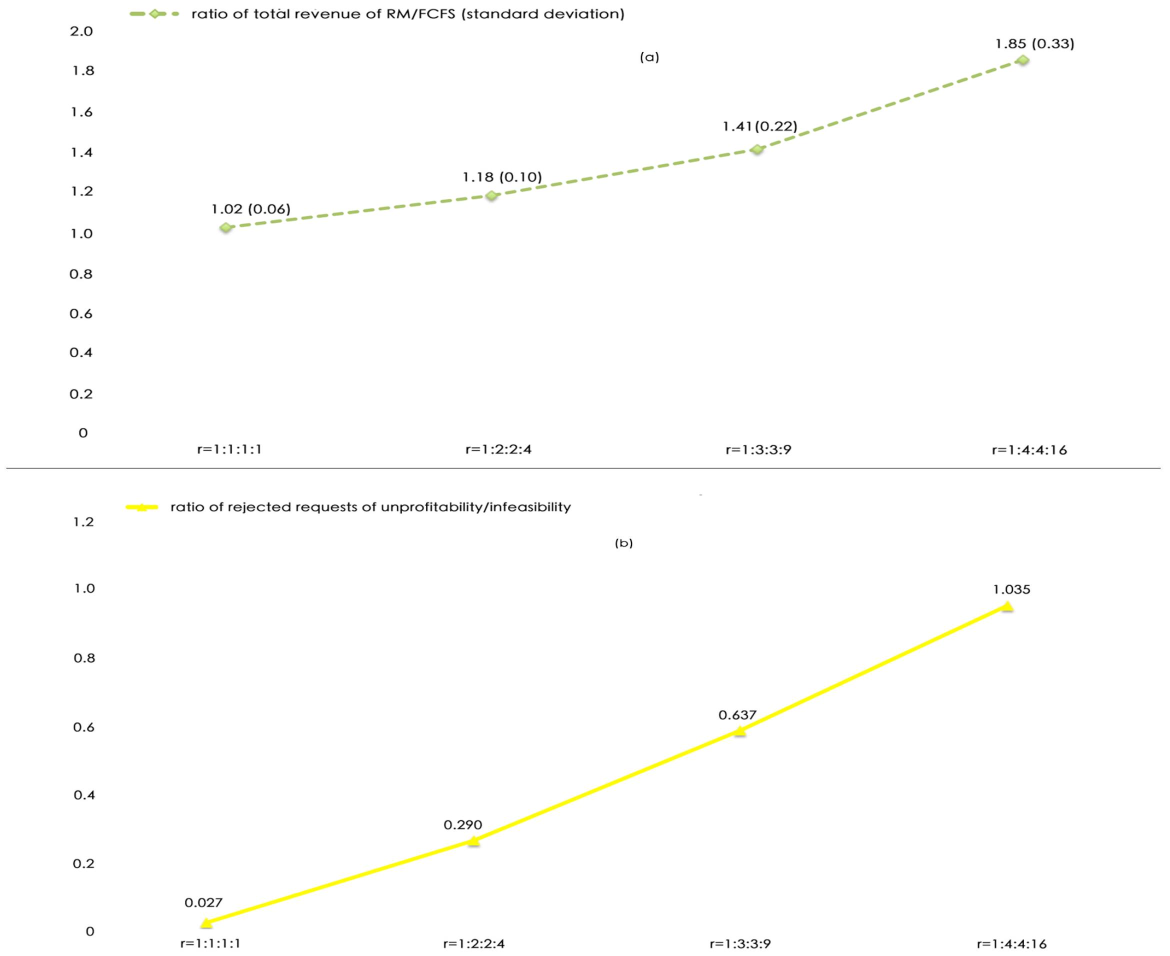

Figure II.2: Effect of price differentiation on revenue (a) and on rejected requests (b)

compared to a potential future high-fare demand (even if its probability to occur is low) and consequently will be rejected or not fully accepted. Therefore, as shown in Figure II.2 (b), when we increase the price ratio r, more demands are rejected because of this economic discrimination (unprofitability). Consequently, a boost in revenue, as illustrated in Figure II.2 (a), is obtained when we increase the values of anticipation and delivery price ratios. As the presented average values are calculated over 20 instances, an insight about the consistency of the simulation (with the corresponding standard deviation in the parenthesis) is also given in Figure II.2 (a).

Note that, even without any price differentiation, the DCA-RM model still generates better solutions in terms of total revenue (Figure II.2 (a), when r=1:1:1:1). In fact, the consideration of future demands equally aids in finding a better routing solution when a demand is accepted. This better routing makes room in the space-time network for potentially infeasible future demands, and hence convert them to feasible, which is transformed accordingly into extra revenue.

The ratios between the total revenues generated when applying the DCA-RM model

Table II.1: Ratio of total revenue of RM/FCFS

	Service Cap.=20	Service Cap.=10	Service Cap.=5
Simulate:Estimate=0.5	1.0093 (0.02)	1.0637 (0.06)	1.3293 (0.14)
Simulate:Estimate=1.0	1.0469 (0.03)	1.3134 (0.10)	1.5082 (0.16)
Simulate:Estimate=1.5	1.1426 (0.06)	1.4139 (0.13)	1.5245 (0.16)

and when applying the FCFS policy within the second scenario are presented in Table II.1. To examine the sensitivity of the DCA-RM model to different forecast accuracy situations, we carry out three different sets of simulation related to the accuracy of the demand forecasts, in terms of total volume. In these simulations, if the arrival process of demands to the booking system follows the same probability distribution function as considered in the objective function of the DCA-RM model, we say the demand forecast is accurate (Simulate:Estimate=1.0). Simulate:Estimate=1.5 indicates that the demands are underestimated by a factor of 0.67, while Simulate:Estimate=0.5 indicates that the demands are overestimated by a factor of 2. The behavior of the DCA-RM model with respect to different levels of maximum service capacity is also studied. The values 20, 10 and 5 TEUs for the maximum service capacities are tested in three independent sets of experiments. For each tested accuracy of demand forecast and service capacity, the simulation was carried out 20 times. The results presented in this table are the average values over 20 test instances with corresponding standard deviation given in the parenthesis.

As expected, the DCA-RM model generates higher total revenue than FCFS when the demand forecast is accurate. Moreover, even when demands are not coming as expected (overestimation or underestimation), DCA-RM model still defeats its competitor. The better performance of the DCA-RM model is found to overcome the influence of underestimation. Underestimated demand forecast here implies more booking requests than expected, which can be relatively interpreted as a situation with scarce resource. Another observation from Table II.1 is that the less network capacity we have, the better the DCA-RM model responds. Therefore, the best revenue ratio (1.5245) is obtained when the resource is scarce and the demand forecast is underestimated.

The reason why the DCA-RM model generates better solutions can be as follows: fully or partially denying demands (due to the different customer categories) create the possibility of saving the precious resource for more profitable (due to higher contribution fares) future demands; to accept a demand, the best routing is decided by taking into account the potential future demands. Consequently, the better routing of current demand may convert some of the potentially infeasible future demands into feasible demands. Note that, three cases (out of 20), when Service Cap.=20 and Simulate:Estimate=0.5, are observed with a ratio of total revenue of RM/FCFS less than 1, which means FCFS model generated better solution than the DCA-RM model. This kind of situation may

Table II.2: Number of rejected demands of RM/FCFS

	Service Cap.=20	Service Cap.=10	Service Cap.=5
Simulate:Estimate=0.5	8.63/6.89	30.05/19.55	67.15/58.60
Simulate:Estimate=1.0	29.8/26.55	110.5/106.55	182.55/184.90
Simulate:Estimate=1.5	95.95/96.50	242.45/234.80	324.40/328.25

happen when future demands are not coming as expected, especially less demands are coming. In that case, some transport requests are rejected because they are considered as unprofitable at the decision time, but the reserved capacity by the DCA-RM model is not fulfilled later with those expected more profitable demands. It then results into the unexpected revenue performance (worse than the FCFS). The existence of this kind of situation implies the importance of demand forecast when applying the RM polices in practice, which is not the focus in my thesis. However, by applying the proposed DCA-RM model, even the demand forecast is overestimated, better total revenue is still obtained in general.

Due to the introduction of RM techniques, some demands are rejected due to their profitability, even if they are feasible at the decision time. Therefore, compared to the FCFS models, more demands are expected to be rejected by the DCA-RM model. However, according to Table II.2, the number of rejected demands when applying the DCA-RM model is less than the corresponding number of rejected demands with the FCFS policy in some cases. This observation indicates that the reserved capacity is taken by future "infeasible" demands and results in better customer satisfaction. Moreover, given the same level of accuracy of demand forecast, less demands are rejected with higher network capacity. However, the difference between the two competitors is slight. For the DCA-RM model, almost one third of the denied transport requests correspond to regular (R) customers.

Therefore, we design another set of simulations including a negotiation phase for only the rejected R category customers. As shown in Figure II.3, the negotiation phase is triggered once a demand from an R customer is rejected. According to the result of negotiation (succeed/fail), the remaining available capacity of the transportation network is updated. According to our problem setting, two main reasons may result in the rejection of R customers: first, no enough capacity in the network at decision time; and second, the given delivery time constraint is too tight. Therefore, three possible negotiation strategies, Nego_RM, Nego_FCFS and Nego_PP, are combined with the proposed RM approach. The first two strategies try to make the best use of the available capacity in the network, while the third one tries to loose the delivery time constraint. To be more precise, both Nego_RM and Nego_FCFS strategies consider the rejected R demand as a P demand. However, the former tries to fit this demand in the transport network

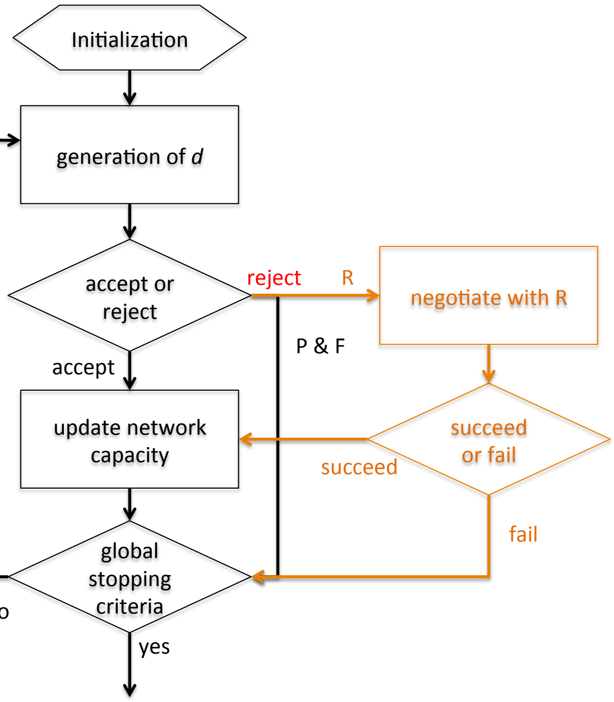

Figure II.3: Procedure of the simulation combined with negotiation phase

considering estimated future demands (DCA-RM model), while the later tries to accept this demand on the transport network in a greedy manner (FCFS model). Instead of changing the category of the demand, the Nego_PP strategy still treats an R customer as regular. In order to transport it, the delivery delay of this demand is extended and a lower unit price is charged (as penalty). For all the tests, a FCFS policy is also carried on as comparison. The effect of different negotiation strategies for rejected R type demands on the total revenue and the percentage of successful negotiation is illustrated in Table II.3.

In Table II.3, Price Ratio r indicates the tested values of both $r_\ominus$ for late reservation and $r_\triangle$ for fast delivery are equal to 2, 3 or 4. Revenue/FCFS indicates the ratio of total revenue obtained by DCA-RM model with (or without) negotiation phase related to FCFS, and Successful Nego shows the percentage of successful negotiation corresponding to each strategy. For each tested negotiation strategy and price ratio, the simulation was carried out 20 times, and the average values are presented with their corresponding values of standard deviation. As shown in the table, even combined with negotiation, DCA-RM model still generates better solutions than FCFS. For a given price ratio, Nego_RM always generates slightly better solutions, in terms of total revenue, compared with Nego_FCFS. On the other hand, the latter always has better performance in negotiation than the former. Therefore, carriers can choose the appropriate strategies according to the requirements

Table II.3: Effect of different negotiation strategies for rejected R customers

Price Ratio	Nego. Strategies	Revenue/FCFS	Successful Nego. (%)
r=1:2:2:4	RM	1.1361 (0.12)	0
	Nego_RM	1.1737 (0.07)	12.82
	Nego_ FCFS	1.1540 (0.08)	18.36
	Nego_PP	1.0248 (0.07)	50.31
r=1:3:3:9	RM	1.3208 (0.17)	0
	Nego_RM	1.3733 (0.11)	16.42
	Nego_ FCFS	1.3476 (0.11)	20.67
	Nego_PP	1.1904 (0.13)	57.14
r=1:4:4:16	RM	1.5300 (0.21)	0
	Nego_RM	1.5905 (0.18)	16.14
	Nego_ FCFS	1.5379 (0.19)	22.44
	Nego_PP	1.3466 (0.14)	56.81

of their regular customers. In case that R customers have a relative loose constraint on the delivery time, Nego_PP succeeds more than 50% in the negotiation process for all tested price ratios. One may argue that there exists other possible ways to compensate. In fact, we do not claim the proposed negotiation strategies are the best solutions. Instead, we put the emphasis on the fact that with the proposed RM approach, we offer to the carriers a panel of possible ways to simultaneously increase the satisfaction of regular customers and make more revenue. Different negotiation strategies may be adopted based on different types of behavior characterizing regular customers.

II.5 Extended DCA-RM Model

In the proposed DCA-RM model, once a transport request is accepted, simultaneously the routing of this demand is decided and fixed. However, as the existence of anticipation time $\Theta(\mathfrak{d})$, re-routing the previously-accepted demands is possible and has the potential to make better plans, in terms of resource utilization and total revenue.

Therefore, we extend the proposed DCA-RM model by integrating the re-routing of accepted demands. To achieve that, a demand $\mathfrak{d}$, in addition to other characteristics discussed in Subsection II.2.2, is also characterized by $dep(\mathfrak{d})$, which indicates the earliest departure time of any fragment of $\mathfrak{d}$. To be more precise, given an accepted transport request $d' \in \mathcal{D}'_d$, the value of $\xi(d')$ has been fixed since the DCA-RM model decided to accept d'. When the booking of the current transport request d occurs, if any fragment of d' has been or is ready to be transported away from its origin terminal $orig(d')$, namely $dep(d') \leq res(d)$, d' are not allowed to be re-routed, which means values of $x(d', a)$

variables are fixed on all arcs; Otherwise (i.e., $dep(d') > res(d)$), d' will be re-routed when the DCA-RM model makes decision to accept or reject the current transport request d, which means the values of $x(d', a)$ variables have to be computed again. We define $\tilde{\mathcal{D}}(d) = \{d' \mid dep(d') > res(d)\}$ as a subset of $\mathcal{D}'_d$.

To consider those variables, the model presented in Section II.3 is then extended in the following way. The constraints (II.7) should be replaced by:

$$\sum_{d' \in \tilde{\mathcal{D}}(d)} x(d', a_k(s)) + \sum_{d'' \in \mathcal{D}''_d} x(d'', a_k(s)) + x(d, a_k(s)) \leq cap\_avl(a_k(s)), \quad \forall a_k(s) \in A_K \tag{II.13}$$

Two more sets of constraints, with respect to flow conservation and range of decision variables, are added as well to the previous model.

$$\sum_{a \in \mathcal{A}^+(n(i,t))} x(d', a) - \sum_{a \in \mathcal{A}^-(n(i,t))} x(d', a) = \begin{cases} \xi(d')vol(d') & \text{if } i = orig(d') \\ -\xi(d')vol(d') & \text{if } i = dest(d'), \forall d' \in \tilde{\mathcal{D}}(d) \\ 0 & \text{otherwise} \end{cases} \tag{II.14}$$

and

$$x(d', a) \geq 0, \quad \forall d' \in \tilde{\mathcal{D}}(d), \ \forall a \in \mathcal{A}. \tag{II.15}$$

In order to examine the extended DCA-RM model, we conduct preliminary experiments. The same set of simulations described in Section II.4 is used here and a new scenario is designed and characterized as follows:

- Length of the simulated time horizon is 600 time instants;
- There is a total of 30 services running on the network, 15 in each direction: from A to D and from D to A; they all stop at all terminals;
- All 12 possible ODs are considered;
- The value of anticipation ratio (r_Θ) for late reservation and the value of the delivery

ratio (r_Δ) for fast delivery are both set at 2;

- The capacity of services is 20 TEUs;
- Demand forecast is considered to be accurate;
- Different experiments are conducted, based on different approaches to accept or reject demands: DCA-RM model without re-routing of accepted demands (RM), extended DCA-RM model with re-routing of accepted demands (RM_ReRoute) and conventional FCFS model considering only feasibility (FCFS).

The simulation was carried out 20 times and the accumulated total revenue (average value at each simulated time instant) is chosen as performance indicator to evaluate the new model, and the results are displayed in Figure II.4.

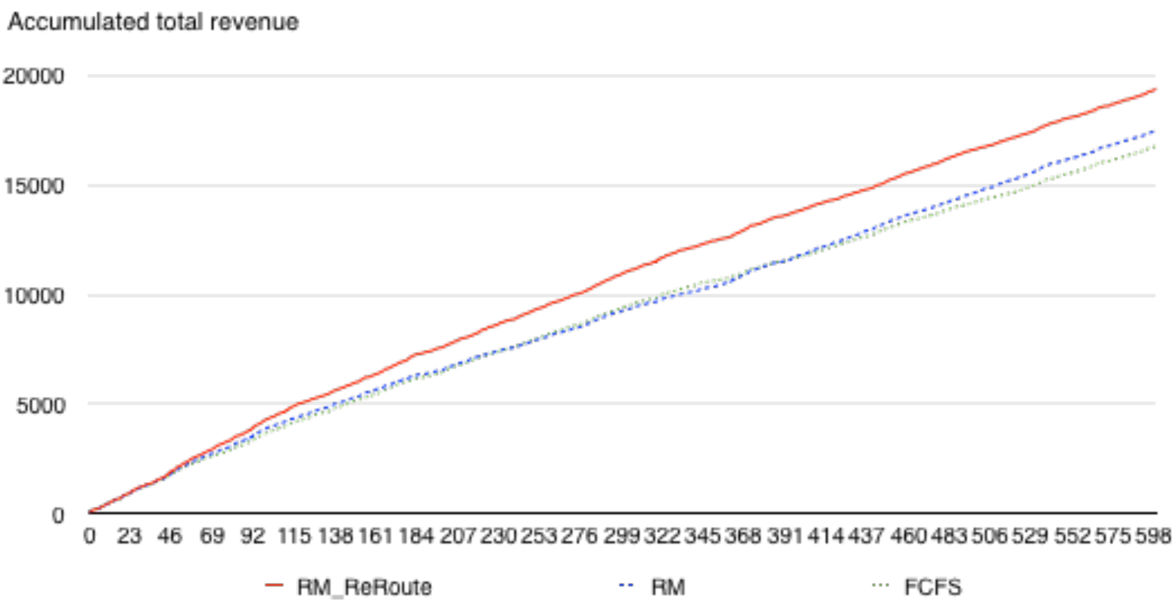

Figure II.4: Performance of the extended DCA-RM model; The accumulated total revenues of RM_ReRoute, RM and FCFS are presented

As the greedy acceptance mechanism considers no future demands and profitability, FCFS model performs better on a very short term than both RM and RM_ReRoute. FCFS model and RM model then iteratively have the lead (compared with each other) in the accumulated total revenue before time instant $t = 380$, as the warm up of the simulation. After that, RM model gradually has better performance than FCFS. Before time instant $t = 50$, RM and RM_ReRoute have the same total revenue. The decisions to accept or reject each transport request of both RM and RM_ReRoute before that time are the same, but with different routings. After $t = 50$, better total revenue is obtained by RM_ReRoute benefiting from the consideration of re-routing of accepted demands.

Following the time in the simulation, the difference between these three models, in terms of accumulated total revenue, is getting bigger.

Recall that the DCA-RM model decides the routing of a demand simultaneously when the acceptance decision of that demand is made. Once the routing of a demand is decided, it is then fixed. A set of related future demands are also considered, when making routing plans, so that an intelligent transport capacity allocation is expected with respect to better resource utilization and profitability. We call a routing procedure like this: *predictive routing*, as the decision is made based on a prediction of the future demands. However, the quality of *predictive routing* mainly depends on the accuracy of the forecast. The more accurate the forecast is, the better the routing plan will be. To route demands, the extended DCA-RM model follows the *predictive routing* procedure, but allows the re-routing of some accepted demands. From the perspective of those accepted demands, forecasts are regularly updated, as the information of some "future" demands is confirmed. The routing decisions of those accepted demands are then updated regularly corresponding to the confirmed information of "future" demands. An accepted demand keeps being re-routed until the departure of its very first container. By taking into account the re-routing of accepted demands (a more intelligent routing), better transport capacity allocation is expected. According to the results, it is obvious that the extended DCA-RM model (RM_ReRoute in Figure II.4) performs better and generates higher total revenue compared with DCA-RM model (RM in Figure II.4) throughout the simulation.

As Figure II.4 presents the average accumulated total revenue of each model based on 20 test instances, we then offer more insights of each test instance by presenting the possible performance patterns of these three tested models in Figure II.5.

As shown in Figure II.5, there are three possible performance patterns: (a) $RM\_ReRoute > RM > FCFS$, (b) $RM > RM\_ReRoute > FCFS$ and (c) $RM\_ReRoute > FCFS > RM$, in terms of total revenue when the simulation is finished. To be more precise, these three patterns happened 17 times, 2 times and 1 time, in turn, among the 20 test instances. In addition to the expected pattern (a), two more patterns (b) and (c) are also observed. As shown in Figure II.5 (b), RM_ReRoute generates less total revenue than RM after the simulation in this pattern. We notice that, after $t = 514$, the accumulated total revenue of RM_ReRoute no more increases. This kind of situation happens, when current demands in the simulation are encountered either infeasible or unprofitable consecutively for the RM_ReRoute. The same reason also explains the flat segment of RM in Figure II.5 (c). However, as shown in Figure II.5 (c), after the abnormal situation, the curve of the RM is gradually shrinking its difference compared to FCFS. If the simulation is carried out for longer, RM is expected to have a better total revenue than FCFS. We also have the same expectation for RM_ReReoute to obtain the best total revenue among

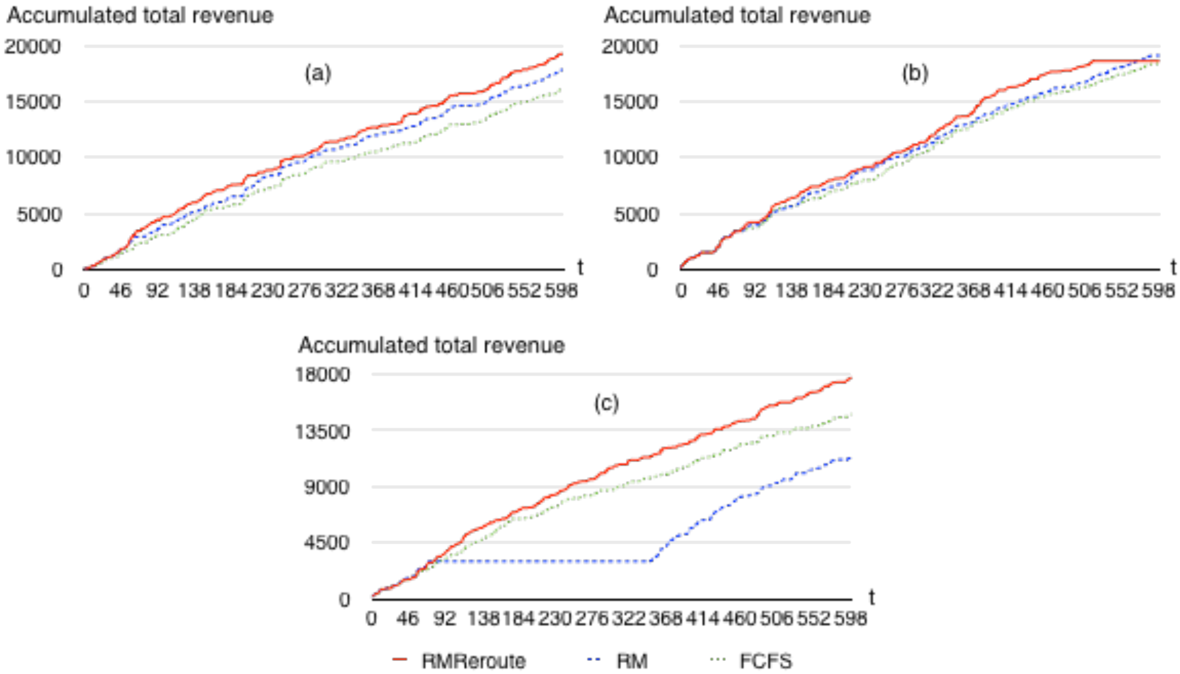

Figure II.5: Examples of the three possible performance patterns of RM_ReRoute, RM and FCFS

these three models in Figure II.5 (b).

Note that, as more decision variables are considered, more computational time is consumed to solve the extended DCA-RM model. Therefore, in the rest of the thesis, as the purpose is to validate the concept of RM introduction into the proposed reactive decision support system, experiments are conducted based on the first version of the DCA-RM model.

II.6 Conclusions

In this chapter, we present a Revenue Management (RM) approach for dynamic capacity allocation of the intermodal barge transportation network. A new model is proposed considering the RM polices.

Customers in a deregulated market have different behaviors, requires and willingness to pay. To model that, in our research, we classify the customer-demand from 2 dimensions. The first one is contractual category. According to their business relationships with the carriers, in our research, we assume that customers are classified into two categories, Regular and Spot. Regular customers, are those customers who sign long-term contracts with carriers and whose demands must be accepted, if feasible; and Spot customers, are those customers who come to the carriers with transport requests from time to time and consequently whose demands could be rejected. The Spot customers are further classified into two categories, P and F: P stands for partially acceptance, which means to be accepted as much as possible, and F stands for fully acceptance, which means to be either fully accepted or rejected. The second dimension to classify customer-demand is its required service quality and booking anticipation, which means customers are asking for normal/slow delivery or fast delivery, with early or late reservation. Note that, this customer-demand classification is applied throughout the whole thesis.

We conduct a set of experiments to validate the RM approach. Compared with the first-come first-serve (FCFS) based booking strategy, the DCA-RM model always generates better total revenue, even with inaccurate demand forecast. Another observation is that facing scarce resource (small transport capacity), the DCA-RM model easily outscores its competitor, and this trend grows when resource levels decrease. We also discuss a set of possible negotiation strategies combined with the proposed DCA-RM model, and conclude that with slightly lower total revenue the decision support still offers the possibility to better satisfy loyal (regular) customers and generate more revenue compared with FCFS.

An extended DCA-RM model considering re-routing of accepted demands is then proposed and studied. According to the numerical results, the extended DCA-RM model generates better total revenue, compared to the first version of the DCA-RM model. Extensive experiments should be conducted to further study and validate this extended DCA-RM model.

Encouraged by these preliminary results, we are also considering to study how the penalty or compensation for those denied demands (R, P and F) should be further integrated into the new DCA-RM model proposed.

Chapter III

Scheduled Service Network Design with Revenue Management Considerations for Intermodal Barge Transportation

Contents

In this chapter, we consider the problem of container barge transportation in the context of intermodal freight transportation at the middle-term planning level. A new Scheduled Service Network Design model with Resource and Revenue management (SSND-RRM) is proposed. The same RM policies applied at the operational level (i.e., customer classification and fare differentiation) in Chapter II, are considered in this model. Given the information about the physical network, potential services and forecasted demands, the objective of the proposed SSND-RRM model is to build a scheduled service network maximizing the net profit of the carriers. The model is solved with a commercial solver and various problem settings, in terms of demand distribution, network topology, fare class and quality-of-service (e.g., delivery time), are designed and tested to evaluate it. According to the results, it is promising to consider RM policies at tactical level.

Based on the material included in this chapter, a working paper is in preparation for submission to *Transportation Science*. Different parts of this research have been presented at several international conferences.

III.1 Introduction

Intermodal freight transportation is generally defined as moving cargo by a series of at least two transportation modes, being transferred from one mode to the next at intermodal terminals, e.g., ports and rail yards, without handling the cargo directly (e.g., [Bektaş and Crainic, 2008, Crainic and Kim, 2007, SteadieSeifi et al., 2014]). Intermodal cargo is thus generally loaded into containers for most of its journey.

Consolidation-based carriers perform the largest share of intermodal transportation, rail and navigation companies being particularly active in the long-distance segment. Carriers aim to maximize net profits and meet shipper demand and requirements, by setting up a resource- and cost-efficient service network and schedule given the forecast demand. The so-called *tactical* operations *planning* process yields this network and schedule.

The *scheduled service network design* (*SSND*) problem class is the methodology of choice to build this tactical plan [Crainic and Kim, 2007]. It selects the transportation services and schedule the carrier that will operate, and propose them to shippers for the next *season* (e.g., six months). The schedule is built for a given *schedule length* (e.g., a week), which is then operated repeatedly for the duration of the season. SSND with *resource management* models, *SSND-RM*, also include the determination of the resource (e.g., vessels, locomotives, etc.) routes supporting the selected services (e.g., [Andersen et al., 2009a, Crainic et al., 2014]).

Most service network design cases and models in the literature consider a single category of customers, making up what is generally identified as *regular demand*, which is expected to represent most of what is serviced during any "normal" period. SSND models are thus set to minimize the cost of performing the service, which may account for both operations and the cost of time for resources and cargo. We take a different view and consider several categories of customers, including regular and so-called spot demands, as well as several tariffs and operation classes, aiming for the maximization of the net revenue through the possibility to capture more demand, or higher priced demand, by offering a different service network. We thus integrate *revenue management* (*RM*) considerations into tactical planning SSND-RM models.

Although identified as a desirable feature for freight transportation [van Riessen et al., 2015a], RM is rather new to the freight transport planning literature, as illustrated by the reviews related to air cargo operations [Feng et al., 2015], railway transportation [Armstrong and Meissner, 2010], and container synchromodal services [van Riessen et al., 2015a]. Moreover, the few contributions focusing on revenue management and freight transportation [Bilegan et al., 2015, Wang et al., 2015] focus on the operational level, the tactical level being rarely envisaged [Crevier et al., 2012].

Our goal is to contribute closing this gap by studying the incorporation of RM considerations, usually tackled at the operational planning level, into tactical planning models for consolidation-based freight transportation carriers. Our interest goes beyond the modeling and algorithmic challenges, to exploring the impact of this integration on the structure of the service network (e.g., should the carrier increase the offer of service in order to later be able to capture spot demand?) and the selection of customer demands to service.

We perform this study within the context of intermodal barge transportation, a field relatively neglected in the literature. We thus present a *scheduled service network design with resource and revenue management* (*SSND-RRM*) model for the tactical planning of such carriers, and study its behavior and the structural characteristics of the solutions obtained through an extensive experimentation campaign.

The contributions of the chapter are:

- Introduce what we believe to be the first comprehensive tactical planning model for freight carriers that integrates revenue (and resource) management considerations;

- Provide a proof-of-concept by using an off-the-shelf software to solve the corresponding mixed-integer linear programming (MILP) formulation for realistically dimensioned barge intermodal transportation instances;

- Analyze the impact of various problem settings, in terms of, e.g., demand distribution, network topology, and fare and quality-of-service (e.g., delivery time, etc.) classes, on the structure of the scheduled service network and the carrier revenues.

The chapter is organized as follows. Section III.2 presents the relevant literature review on service network design and revenue management topics. Section III.3 describes the problem setting and discusses issues related to combining tactical planning and RM. Section III.4 is dedicated to the revenue management modeling at the tactical level and the proposed SSND-RRM formulation. The experimental plan and the analysis of the numerical results are described in Section III.5, and we conclude in Section III.6.

III.2 Literature Review

The section is dedicated to a brief tour of the relevant literature with the goal of relating our work to the field. We touch on barge transportation, service network design for consolidation-based freight carriers, and revenue management. [Bontekoning et al., 2004, Macharis and Bontekoning, 2004, Bektaş and Crainic, 2008, SteadieSeifi et al., 2014] offer general reviews on planning intermodal freight transportation systems.

Barge transportation, or, more generally, river and canal freight navigation, is economical in terms of unit transportation cost and eco-friendly in terms of environmental impacts. Although slower than other land-based transportation modes, barges may thus play an important role in intermodal transportation, both in exchanges between maritime ports and the hinterland and among river ports. This role is expanding in Europe, where the [European Commission, 2011] identifies barge transportation as the instrumental for modal shift and encouraged its use for intermodal freight transport, as well as elsewhere, most notably in China [Notteboom, 2012]. Yet, compared to other transportation modes, studies focusing on barge transportation, particularly in the context of intermodal transportation, are still very few. In most cases, one may class these contributions into one of two categories. The first category includes descriptive analyses of intermodal transportation, including barge transport, within a territory or corridor (e.g., [Frémont and Franc, 2010, Caris et al., 2012, Zuidwijk, 2015]). One may also mention within this group, the work of [Konings et al., 2013], who identify the need for a hub-and-spoke network structure for intermodal barge transport linked to major sea ports, with the port of Rotterdam as illustration, and that of [van Riessen et al., 2015a], who examine the issues and research opportunities related to synchromodal container assignment to available transportation modes and carriers in the same context. The second group of contributions addresses mostly operational issues in ports (e.g., [Taylor et al., 2005, Konings, 2007, Douma et al., 2011]), and in routing and dispatching out of ports (e.g., [Fazi et al., 2015, Braekers et al., 2013]).

There is a rather rich literature on service network design for consolidation-based freight carriers [Crainic, 2000], reviewed by, e.g., [Crainic, 2003] for long-haul transportation, [Cordeau et al., 1998] for rail, [Christiansen et al., 2004, Christiansen et al., 2007] for maritime, and [Crainic and Kim, 2007] for intermodal transportation. Scheduled service network design aims to generate the tactical operations plan for a consolidation-based freight carrier to, generally, minimize its costs or, more rarely, maximize revenues. The main decisions making up the models address the selection of services and their schedules, the determination of the terminal policies such as classification and consolidation of cargo and vehicles and the formation of convoys (when relevant), and the optimization of the cargo flow distribution on the resulting network to satisfy the multi-commodity demand.

SSND with resource management models include explicitly into the tactical planning models some high-level representation of the management of key resources, e.g., power units, vehicles or crews, necessary to operate the selected services. Encountered initially in articles targeting particular applications (e.g., [Lai, M.F. and Lo, H.K., 2004, Armacost et al., 2002, Smilowitz et al., 2003]), the SSND-RM problem is formally modeled by [Pedersen et al., 2009] as a network design problem with *design-balance* constrains, the latter imposing that the numbers of services (or resources) entering and leaving terminal-representing nodes be balanced. Extensions are presented by [Andersen et al., 2009b, Andersen et al., 2009a, Crainic et al., 2014] who, among other contributions, model the time-dependency of decision through time-space networks, enrich the range of resource management concerns, and emphasize the circular nature of the routes resources must follow to support the selected services.

We found only one publication addressing the tactical planning of an intermodal barge fleet [Sharypova et al., 2012]. The authors propose a SSND-RM model for the particular case of direct services (no intermediate stops), unique customer and service types, a single container type, and two homogeneous vehicle fleets representing barges and trucks. The authors propose a continuous-time formulation with particular care being paid to the modeling of the terminal service synchronization and the associated load/unload/transfer operations. The numerical results obtained on very small instances are encouraging, particularly in showing the interest of SSND-RM for planning barge transportation systems. The formulation we propose, based on a discrete-time representation, takes into account a significantly richer set of problem characteristics, as well as explicitly including revenue management aspects.

Indeed, none of these contributions found in the literature addressed the issue of revenue management. Revenue, or yield, management was initially developed for passenger air transportation, and was latter applied more broadly to passenger rail transportation, hotel room management, etc. (e.g., [Kasilingam, 1997]).The benefits observed in these domains appear promising for the freight transport industry as well. Yet, one cannot simply transpose the models and procedures from one industry to the other. Thus, e.g., [Kasilingam, 1997] present the characteristics and complexities of air cargo transportation (see for a review of air cargo operations [Feng et al., 2015]) from the perspective of RM by emphasizing the differences between air cargo and air passenger transportation. The author point out, in particular, that a correct and relevant model of RM for freight transportation requires the comprehensive understanding of customers' behavior, the consecutive identification of customer categories, the so-called *customer classification*, and the definition of different products and fares charged, i.e., the *fare differentiation*.

The contributions integrating RM and freight transportation of which we are aware address operational-level issues only. Thus, [Crevier et al., 2012] propose a bi-level mixed-integer formulation to jointly determine fares and the capacity utilization of a given set of services proposed by a rail freight carrier. [Bilegan et al., 2015] also present a RM model applied to rail freight transportation in which different fare classes are defined with respect to how early the booking is performed and how long the delivery time is. [Armstrong and Meissner, 2010] survey RM applied to railway transportation.

RM-related concepts are found in a number of tactical-planning studies for various transportation modes, e.g., the possibility not to service all the demand (e.g., [Braekers et al., 2013, Andersen and Christiansen, 2009, Thapalia et al., 2012]), the maximization of the net revenue, and the possibility for demands to be only partially accepted (e.g., [Teypaz et al., 2010, Agarwal and Ergun, 2008, Gelareh and Pisinger, 2011]), and the segmentation of the transportation requests according the obligation to service them [Stålhane et al., 2014].

We did not find, however, contributions integrating scheduled service network design, resource management and revenue management. We propose such an integrated model in Section III.4 for the intermodal transportation problem described next.

III.3 Problem Statement

We address the problem of setting up the tactical plan of an intermodal freight transportation carrier to maximize its revenues, while satisfying the estimated demand and requirements of its customers, and making the best use of its resources. The *tactical plan* thus determines the transportation services and schedule, together with the assignment of resources to the selected services, that the carrier will operate for the next cycle of activities, the next "season" (six months, for example), to answer this demand. The transportation plan actually specifies how operations are to be performed for a given time length, e.g., a week, that we call *schedule length*. The plan is then operated repeatedly for the duration of the season.

We therefore describe the problem we address along three dimensions. For the first dimension, we focus on the physical network and resources of a barge/coastal navigation carrier performing intermodal transportation, including the port infrastructure and facilities, the containers that need to be moved and the vessels that transport them. For the second one, we describe the customers of the system, that is, the shippers generating the demand for transportation of various types of containers, together with their requirements and expectations in terms of cost and service quality. The last one considers the fares, services and schedule the carrier is setting up to satisfy this demand and address these requirements over a medium-term, tactical planning horizon. The challenges and aims related to the representation of RM activities into the scheduled service network design with resource management formulation (detailed in Section III.4) are discussed at the second and third dimension, respectively.

Physical network and resources. A barge intermodal transportation system is defined over a *physical network* of rivers and canals plus, eventually, coastal and short-sea-shipping navigation corridors. A number of physical characteristics often constrain navigation on this network, e.g., the maximum draft of fully loaded vessels sailing on a given part of a river or canal, and the number of vessels that may simultaneously navigate, in both directions, the same part of a river or canal during a given period of time.

A number of ports with *container terminals* are located along these rivers and canals or on the sea shore. The layout and physical organization of a terminal, together with the equipment available and the operation policies (as well as the conventions stating the working rules for the personnel) constrain the activities that may be performed within and influence the associated costs and performance measures. Prominent among these limits and measures for the problem at hand are the maximum draft of fully loaded vessels berthing at the terminal, the number of vessels and associated length that may simultaneously berth, the number of containers that may be stored within the terminal for a given period of time, and the rate of vessel loading and unloading operations in terms of containers per period of time. Costs are associated to terminal activities and are charged to carriers using the port. Given the problem addressed in this chapter, we target particularly the cost of calling at the port, which varies by vessel type and the duration of the presence in the port, as well as the container loading/unloading (per container) and holding (per container and time period) costs.

The carrier operates a number of vessels to transport the containers shipped by its customers. *Containers* come in several types. They differ in terms of dimensions, 20 and 40-foot long being the standard dimension for maritime and river navigation, while longer boxes are used within land-based intermodal transportation systems, such as the 53-feet ones found in North America. Containers also differ in scope and requirements, e.g., insulated, refrigerated, bulk, tank, open top, high cube, and so on and so forth. For tactical planning purposes, the standard twenty-feet equivalent unit (TEU) measure is generally used, where 20-foot containers measure 1 TEU, while 40-foot ones account for 2 TEUs. *Vessels* also come in several types defined by their characteristics in terms of dimensions, draft, maximum number of TEUs carried, speed, etc., A limited number of vessels of each type is available for the next season (vessels may be owned or rented, but we will treat them in a similar way in this chapter). Operating a vessel incurs costs. Other than the port-related costs mentioned above, we consider in this chapter the travel costs between particular pairs of ports, as well as the cost (maintenance, depreciation, etc.) associated with not using a vessel for the considered schedule length.

Customer demand. Customers ship loaded and empty containers of given types among particular pairs of terminals in the network. Shippers have quality and price requirements for each demand for transportation of a certain number of TEUs. “Quality” may involve the type of vehicle and handling equipment required for the particular type of containers involved. It always involves, however, requirements in terms of travel time and delivery date. In this chapter, we represent the quality requirements as the *due date* associated to the demand, that is, the latest date containers have to be delivered at destination. The price expectations of shippers are related to the value of the cargo and the urgency of delivery. Obviously, they desire the lowest fare possible.

In traditional settings, including navigation-based intermodal transportation, a single service type (in terms of delivery time between two terminals in the network) is offered to shippers, the fare being determined mainly by the distance involved, and the cargo characteristics such as volume, weight, cargo type and handling requirements (e.g., dangerous goods require special treatment), etc. On these bases, the final price paid by a given shipper then results from the negotiations it and the carrier engage into, the existence of long-term contracts or understandings with regular and trustworthy customers strongly influencing the proceedings.

Following this commercial model, most service network design cases and models in the literature consider a single category of customers, making up what is generally identified as *regular demand*. One generally finds in this category customers, or groups of customers in particular zones, that are strongly believed to bring business on a regular basis for the coming season. This forecast (formal forecasting methods may or may not be involved) is based on a combination of signed long-term contracts, informal understanding with long-standing, trustful customers, and market estimation by sales and customer-relation personnel. Regular demand is expected to make up a good part (a 80% figure is often mentioned) of what is serviced during any “normal” period.

When revenue management mechanisms are in place, or contemplated, the situation is different. At a strategic level, one establishes a service and tariff policy, e.g., segmenting the potential customers and defining a number of traffic/tariff classes and service levels to attract the targeted customers and volume of demand. One also negotiates long-term contracts or understandings with important customers to ensure a good level of regular business, which translates into regular levels of demand and traffic. During actual operations, the revenue management mechanisms are used to determine the acceptance and tariff of each request for transportation and, thus, to adjust the actual demand to the offer of services with fixed capacities, regular schedules, and so on, which was planned based on demand forecasts. The questions then are, how to represent such mechanisms within tactical planning models, and what is the benefit of using RM-based information and knowledge when building the transportation plan.

Services and schedules. Each potential *service* is defined by an origin terminal and associated departure time within the schedule length, a destination terminal, a route through the physical network, a sequence of intermediary calls at ports along this route (the sequence is empty for direct services), and a schedule indicating the arrival and, for the intermediate stops, the departure times at ports. Without loss of generality, and because it reflects actual practice for the problem setting we examine, we assume the longest service duration to be less than the schedule length. A vessel of particular characteristics is associated to each service. Each service is thus characterized by the attributes of its designated type of vessel, as well as by the costs to set up and operate on the links of its route.

Symmetrically, a vessel is assigned to a set of services during the schedule length. Without loss of generality, we assume vessels return to their home port. Consequently, each operated vessel supports a circular sequence of services starting and ending at the same port. These cycling vessel routes, that we call *service cycles* in the following, ensure that there are no empty-repositioning movements in the system we study.

The set of services selected by the carrier to efficiently and profitably satisfy the estimated demand, makes up the transportation plan and defines its *service network* and *operating schedule*. Each customer demand is moved over this service network by one of the possible itineraries for the particular demand. Remark that the same physical customer may have several shipments over the schedule length, and that these shipments may differ in volume, characteristics, and requested service level. We represent such cases as different customer demands. Remark also that, while demand estimations may be made individually for major and regular customers, most demands represent an aggregation of regular and potential customers within a given zone and with similar transportation requests.

A demand *itinerary* is then defined by the origin terminal of the shipment and its availability period (i.e., the time it is supposed to arrive at the origin terminal), the sequence of services until the associated destination terminal, and the number and type of containers moved. The sequence of services thus yields the schedule of the itinerary, i.e., the arrival and departure moments at each port terminal, together with the time spent in the terminal to 1) unload the cargo from the incoming service, 2) wait in the terminal for the next service, and 3) load on that next service. We assume unloading operations take place immediately after the arrival of the service at the terminal, followed by loading operations taking place before leaving the terminal.

The SSND-RRM problem. As indicated earlier, the carrier aims to meet demand and the shipper requirements in the most resource- and cost-efficient way, through planned operations that maximize its net profit. The aim is thus to 1) select the services, out of a set of potential feasible ones, and, through their departure times, the schedule to operate, 2) determine the circular asset routes, the service cycles, supporting the selected services, and 3) identify the demand itineraries. The combination of these three objectives also yields the loads of vessels during their movements from one stop of the corresponding service to the next, and the amount of work to be performed on vessels and containers at each port of call in the network.

The integration of revenue management considerations to tactical planning is performed through two major modifications to the traditional problem setting and modeling approach.

First, we take the different view of explicitly considering several categories of customers, tariff and operation classes. The first category is the regular demand as discussed above. Two other categories correspond to demand that is potentially there and that the carrier could accept or not, given the estimated revenue and the capacity it plans to deploy. Such demand is usually explicitly accounted for in fleet [Crainic et al., 1993, Powell, W.B. and Topaloglu, H., 2005] and revenue management [Bilegan et al., 2015], but is not normally included into tactical-planning formulations. The challenge of integrating it into an SSND-RRM formulation comes from the required qualitative and quantitative translation of the business relationship the carrier holds with its customers into a compact representation adequate for the aggregated tactical level. This translation is logically performed in terms of demand characterization, starting with customer behavior (segmentation) considerations, but also including service-level (delivery delays) requirements.

Second, contrary to service network design literature, the goal here is the maximization of the net revenue. The net revenue is computed as the difference between the estimated profit of servicing the regular and the accepted potential demand and the cost of performing the planned service. The cost accounts both for setting up the services and for operating vessels and transporting containers. It is also generalized, accounting simultaneously for operations and the cost of time for resources and cargo, given the latter's service and tariff class (remark that service differentiation was considered in a number of earlier contributions, e.g., [Crainic et al., 1984, Crainic and Rousseau, 1986, Crainic and

Roy, 1988], without being contrasted to the revenues of the carrier).

The resulting SSND-RRM model may therefore be used both to plan the operations for the next season and as a tool to evaluate RM policies. It aims, in particular, to provide the means to answer questions, e.g., is it profitable to increase the level of service in terms of service frequencies or capacities, resulting in higher fixed and variable costs, in order to attract more, higher-priced, demand? Are the current or contemplated differentiated customer categories, and fare classes with their associated values adequate? Is the contemplated contract or business relationship for regular demand actually profitable? Which and how much of the potential demand should/could be serviced within a predefined schedule length, while optimally using the available resources?

We describe in the next section the methodology used to address these issues and formulate the planning problem at the tactical level.

III.4 The SSND-RRM Formulation

We present the formulation of the scheduled service network design with resource and revenue management (SSND-RRM) model for the tactical planning of intermodal barge transportation in three steps. We first discuss the representation of the revenue management considerations in terms of customer service and fare differentiation (Section III.4.1). We then introduce the time-space representation of operations, the demand, and the services one has to select in order to satisfy it (Section III.4.2). The formulation is presented next (Section III.4.3).

III.4.1 Revenue Management Modeling for the SSND-RRM

Let $\mathcal{D}$ represent the set of regular and potential customer demands, and the notation $d \in \mathcal{D}$ will denote a particular demand. We model customer service and fare differentiation through a two-dimensional mechanism: *business relationship* and *service requirement*.

Business relationship addresses principally the contractual profile of customers, that is, the commitment to work with the carrier: regular customers with long-term contracts or understandings, and customers present on the spot market that we may service or not. The latter correspond to a pool of irregular potential customers, who may arrive to the system as "short-notice" requests. Individually, these customers could be "small" in terms of volume and, even, not regularly present but, taken collectively, they form a significant and consistent demand in terms of total volume per origin-to-destination pair; Identified within a given geographical zone - around a port that is the origin of their requests for transportation - the decision to service them is to be made according to their particular requirements and the available planned capacity on the transportation network.

We define three categories of business relationships (and customers), partitioning the customer set, $\mathcal{D} = \mathcal{D}^{\mathrm{R}} \cup \mathcal{D}^{\mathrm{P}} \cup \mathcal{D}^{\mathrm{F}}$, as follows:

- *Regular* customer demands, grouped within set $\mathcal{D}^{\mathrm{R}}$, representing customers with long-term contracts or understandings; This class corresponds to the regular demand in classical SSND formulations and must be always satisfied;
- *Proportional-punctual* customer demands, set $\mathcal{D}^{\mathrm{P}}$, that may be fragmented and only partly satisfied, which means a fraction of it could be integrated in the demand to be serviced by the planned services, the rest not being served at all by the carrier; We model this decision further down in this section through continuous decision variables yielding the percentage of the demand that is going to be serviced;
- *Full-punctual* demands, set $\mathcal{D}^{\mathrm{F}}$, consisting of demands that may be either entirely accepted and serviced or not accepted at all; Binary selection variables are introduced in the formulation to represent these decisions.

Two service types are defined with respect to the service requirement dimension of the proposed mechanism, *slow/normal* and *fast* delivery reflecting the due times at destination requested by customers. Fares normally reflect service differentiation, e.g., fast delivery requests would be priced higher than slow delivery ones. We consequently introduce two *fare classes*:

- $class(d)$: Fare class for demand $d \in \mathcal{D}$, related to the type of delivery, *slow/normal* or *fast* requested;
- $f(d)$: Unit fare value for demand $d \in \mathcal{D}$ with fare class $class(d)$.

III.4.2 Network Modeling

Let the oriented graph $\mathcal{G}^{\mathrm{ph}} = (\mathcal{N}^{\mathrm{ph}}, \mathcal{A}^{\mathrm{ph}})$ represent the *physical network* supporting the operations of the carrier. The set $\mathcal{N}^{\mathrm{ph}}$ represents intermodal terminals. Each terminal $i \in \mathcal{N}^{\mathrm{ph}}$ is characterized by a berthing capacity Q_i in number of vessels per time period, and a container holding capacity H_i in number of TEUs per time period. The former is defined with respect to the average length of the vessels used on the network, which is reasonable given the rather limited range of vessels used in such systems.

The set $\mathcal{A}^{\text{ph}}$ groups the physical arcs of the network, each representing a possible navigation movement between two "consecutive" ports, that is, no intermediary port exists between the initial and final nodes of the arc. To simplify the presentation, but without loss of generality, we assume uncapacitated physical arcs.

Let the schedule length be discretized into T periods of equal length by $T+1$ time instants $t \in 0, ..., T$. The period length is generally defined according to the particular operational context of the application, e.g., average travel time along links or stopping time at ports, and the schedule length. For a week-long schedule on a river/coastal navigation network, a period length of a couple of hours appears appropriate. By convention, activities, e.g., demand arrival at terminals and vessel arrivals and departures at and from ports, occur at the beginning of a period.

Let Γ be the set of container types, and the notation $\gamma \in \Gamma$ will denote a particular container type. Then, as discussed above, each demand $d \in \mathcal{D} = \mathcal{D}^{\text{R}} \cup \mathcal{D}^{\text{P}} \cup \mathcal{D}^{\text{F}}$ is characterized by:

- $vol(d)$: Volume in number of TEUs;
- $\gamma(d)$: Container type, $\gamma(d) \in \Gamma$;
- $orig(d)$: Origin node, $orig(d) \in \mathcal{N}^{\text{ph}}$;
- $in(d)$: Period the demand d becomes available for transportation at $orig(d)$;
- $dest(d)$: Destination node, $dest(d) \in \mathcal{N}^{\text{ph}}$;
- $out(d)$: Due date at destination, that is, the latest period the cargo may arrive at the destination terminal;
- $cat(d)$: Category of customer demand (R or P or F), according to whether $d \in \mathcal{D}^{\text{R}}$ or $\mathcal{D}^{\text{P}}$ or $\mathcal{D}^{\text{F}}$;
- $class(d)$: Fare class, *slow/normal* or *fast*;
- $f(d)$: Unit fare value.

The carrier operates vessels of various types, that it owns or rents for the season, according to the scheduled set of services. The set of vessel types is noted $\mathcal{L}$, each vessel type $l \in \mathcal{L}$ being characterized by:

- $cap(l)$: Capacity in TEUs;
- $speed(l)$: Speed of vessel of type $l \in \mathcal{L}$ in normal operations, yielding $\delta_{ij}(l)$, the normal travel time of an l type vessel over arc $(i,j) \in \mathcal{A}^{\text{ph}}$;
- B_l: Maximum number of vessels of type $l \in \mathcal{L}$ available.

The formulation is defined on a circular time-space network capturing the time-dependency and repetitiveness of the demand and schedule (services and resource utilization), taking the form of an oriented graph $\mathcal{G} = (\mathcal{N}, \mathcal{A})$, with node and arc sets $\mathcal{N}$ and $\mathcal{A}$, respectively. The network (and the the transportation plan and schedule) is circular over the schedule length, which means that any arc in $\mathcal{A}$ of length (duration) δ that starts at time t, arrives at destination at time $(t + \delta) \bmod T$.

The node set $\mathcal{N}$ is obtained by duplicating all physical nodes at all periods in the schedule length, so that node $it \in \mathcal{N}$ corresponds to the physical node $i \in \mathcal{N}^{ph}$ at time instant t, $t = 0, \ldots, (T-1)$. The set of arcs $\mathcal{A}$ is the union of the set of holding arcs at terminals, and the set of possible movements performed by services. A *holding* arc $(it, i(t+1))$ captures a one time period waiting at terminal i at time t for vessels, cargo and services. Movements in the time-space network are performed by services traveling physical paths between two consecutive stops on their respective routes. We call such movements *service legs* and these define the *moving* arcs of $\mathcal{A}$.

A service $s \in \mathcal{S}$ is thus defined in the time-space network $\mathcal{G}$ by a number of physical and time-related attributes, illustrated in Figures III.1 and III.2, and described as follows:

- $orig(s)$: Physical origin terminal, $orig(s) \in \mathcal{N}^{ph}$;
- $dest(s)$: Physical destination terminal, $dest(s) \in \mathcal{N}^{ph}$;
- $\eta(s) = \{i_k(s) \in \mathcal{N}^{\text{ph}}, k = 0, \ldots, (K-1)\}$: Ordered set of consecutive stops of the service, where $K = |\eta(s)|$ and k indicates the k^{th} stop of the service;
- $a_k(s) = (i_k(s), i_{k+1}(s))$: k^{th} leg of the service, $k = 0, \ldots, (K-2)$;
- $r(a_k(s)) \subseteq \mathcal{A}^{\text{ph}}$: Path of $a_k(s)$ in the physical network;
- $\delta_k(s)$: Travel time of leg $a_k(s)$;
- $w_k(s)$: Stopping time at terminal $i_k(s)$;
- $\alpha_k(s)$: Arrival time of the service at its terminal $i_k(s)$; By convention:

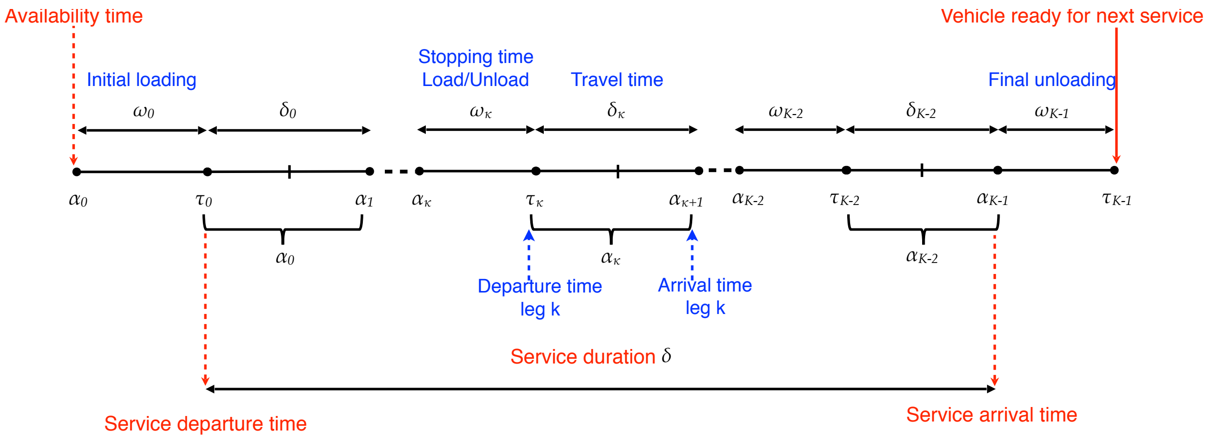

Figure III.1: Time-related attributes of service s

$\alpha_0(s)$: Availability time of service s to load at the origin terminal, i.e., $w_0(s) = \tau_0(s) - \alpha_0(s)$;

$\alpha_{K-1}(s)$: Arrival time at destination;

- $\tau_k(s)$: Departure time of the service from its terminal $i_k(s)$

$$\tau_k(s) = \tau_0(s) + \sum_{j=0}^{k-1}(\delta_j(s) + w_{j+1}(s)) \quad k = 1, \dots, (K-1); \tag{III.1}$$

$\tau_{K-1}(s)$: Time at destination when the vessel is completely unloaded and ready for the next service, i.e, $w_{K-1}(s) = \tau_{K-1}(s) - \alpha_{K-1}(s)$ (by convention);

- $\delta(s) = \alpha_{K-1}(s) - \tau_0(s)$: Total duration of service s;
- $l(s)$: Vessel type of service s, $l \in \mathcal{L}$;
- $cap(l(s))$: Capacity of service s, in TEUs;
- $\phi(s)$: Fixed cost of setting up and operating the service.

Figure III.1 illustrates the time-related attributes of a multi-leg service. Figure III.2 illustrates a time-space network with 9 time periods and four terminals. Horizontal dashed arcs are the holding arcs at terminals, while the plain arrows stand for service legs. Two services are displayed. The first one s_0 is a three-leg service that originates at Terminal A and ends up at Terminal D. The two intermediate stops are one and two periods long, respectively. The second service s_1 travels from Terminal D to Terminal A with an intermediary stop of one period at Terminal C. The availability times of both services are indicated as well.

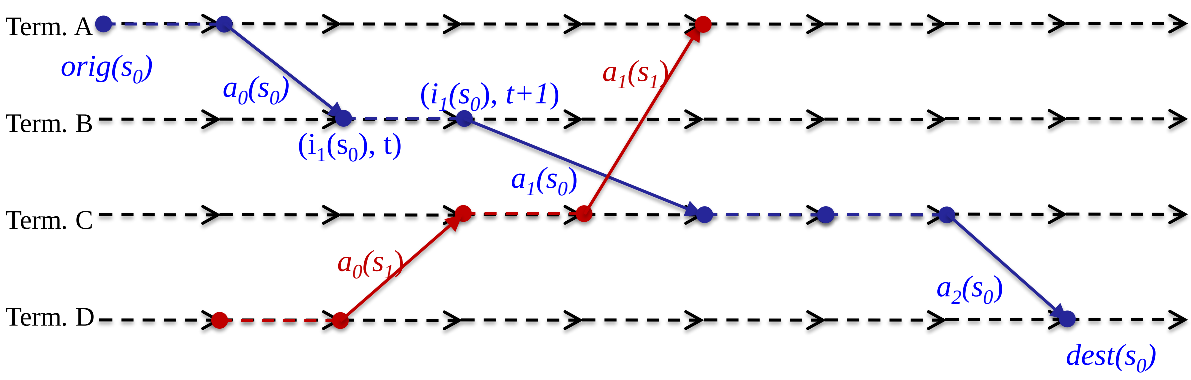

Figure III.2: Time-space representation of the service network with two services

The following unit costs are defined:

- $c_k(\gamma(d), l(s))$: Transportation of a container of type $\gamma(d)$, by a vessel of type $l(s)$, on the k^{th} leg of service s;
- $c(i, \gamma(d))$: Holding a container of type $\gamma(d)$ at terminal i for one period;
- $\kappa(i, \gamma(d))$: Loading/unloading a container of type $\gamma(d)$ at terminal i;
- $h(i, l)$: Holding cost for a vessel of type l at terminal i for one time period;
- $\rho(l)$: Penalty for a vessel of type l that is not used in the optimal plan.

III.4.3 SSND-RRM Model Formulation

We define the following decision variables:

- $y(s) = 1$ if service s is selected, 0 otherwise;
- $\xi(d) \in [0, 1]$ = Percentage of the volume of demand (number of containers) $d \in \mathcal{D}^{\mathrm{P}}$ that is selected and will be serviced;
- $\zeta(d) \in \{0, 1\} = 1$ if the demand $d \in \mathcal{D}^{\mathrm{F}}$ is selected to be serviced, 0, otherwise;
- $z(l, i, t)$ = Number of temporarily idle vessels of type l at terminal i, waiting the period $(t, t+1)$ out for the departure of the next service it supports;
- $v(l)$: Total number of vessels of type l used by the service plan; Due to the circular nature of the schedule, $v(l)$ is the same for all time periods (although, at any given period, vessels may be moving or be idle in ports);

- $x(d,s,k)$ = Volume of demand $d \in \mathcal{D}$ transported by service s on its leg k;

- $x^{out}(d,s,k)$ = Volume of demand $d \in \mathcal{D}$ to be unloaded at terminal i_{k+1} when arriving at time $\alpha_{k+1}(s)$ on leg k of service s;

- $x^{in}(d,s,k)$ = Volume of demand $d \in \mathcal{D}$ to be loaded on leg k of service s before leaving terminal i_k at time $\tau_k(s)$;

- $x^{hold}(d,i,t)$ = Volume of demand $d \in \mathcal{D}$ on hold at terminal i during time period $(t,t+1)$;

The SSND-RRM model formulation then becomes:

$$\begin{aligned} \max \sum_{d\in\mathcal{D}^{\mathrm{R}}} f(d)vol(d) + \sum_{d\in\mathcal{D}^{\mathrm{P}}} f(d)\xi(d)vol(d) + \sum_{d\in\mathcal{D}^{\mathrm{F}}} f(d)\zeta(d)vol(d) \\ - \sum_{l\in\mathcal{L}} \rho(l)(B_l - v(l)) - \sum_{s\in\mathcal{S}} \phi(s)y(s) - \sum_{t\in 0,\dots,(T-1)} \sum_{i\in\mathcal{N}^{\mathrm{ph}}} h(i,l)z(l,i,t) \\ - \sum_{s\in\mathcal{S}} \sum_{k\in\eta(s)} \sum_{d\in D} c_k(\gamma(d),l(s))x(d,s,k) - \sum_{t\in 0,\dots,(T-1)} \sum_{i\in\mathcal{N}^{\mathrm{ph}}} \sum_{d\in\mathcal{D}} c(i,\gamma(d))x^{hold}(d,i,t) \\ - \sum_{s\in\mathcal{S}} \sum_{k\in\eta(s)} \sum_{d\in D} \kappa(i,\gamma(d))(x^{in}(d,s,k) + x^{out}(d,s,k)) \end{aligned} \tag{III.2}$$

Subject to

$$x^{hold}(d,orig(d),in(d)) + \sum_{s\in S: i_k(s)=orig(d), \tau_k(s)=in(d)} x^{in}(d,s,k) = \begin{cases} vol(d), & \forall d \in \mathcal{D}^{\mathrm{R}} \\ \xi(d)vol(d), & \forall d \in \mathcal{D}^{\mathrm{P}} \\ \zeta(d)vol(d), & \forall d \in \mathcal{D}^{\mathrm{F}} \end{cases} \tag{III.3}$$

$$\sum_{in(d)<t\leq out(d)} \sum_{s\in S: i_{k+1}(s)=dest(d), \alpha_{k+1}(s)=t} x^{out}(d,s,k) = \begin{cases} vol(d), & \forall d \in \mathcal{D}^{\mathrm{R}} \\ \xi(d)vol(d), & \forall d \in \mathcal{D}^{\mathrm{P}} \\ \zeta(d)vol(d), & \forall d \in \mathcal{D}^{\mathrm{F}} \end{cases} \tag{III.4}$$

$$\begin{aligned} x^{hold}(d,i,t-1) + \sum_{s\in S: i_{k+1}(s)=i, \alpha_{k+1}(s)=t} x^{out}(d,s,k) \\ -x^{hold}(d,i,t) - \sum_{s\in S: i_k(s)=i, \tau_k(s)=t} x^{in}(d,s,k) = 0, \\ \forall (i,t) \neq (orig(d),in(d)), \forall i \neq dest(d), \forall d \in \mathcal{D} \end{aligned} \tag{III.5}$$

$$x^{in}(d,s,k) - x(d,s,k) = 0, \forall s \in \mathcal{S},\ i_k(s) = orig(d),\ d \in \mathcal{D} \tag{III.6}$$

$$x(d,s,k-1) - x^{out}(d,s,k-1) = 0, \forall s \in \mathcal{S},\ i_k(s) = dest(s),\ d \in \mathcal{D} \tag{III.7}$$

$$\begin{aligned} x(d,s,k-1) - x^{out}(d,s,k-1) + x^{in}(d,s,k) - x(d,s,k) = 0, \\ \forall s \in \mathcal{S},\ i_k(s) \neq orig(s), i_k(s) \neq dest(d),\ d \in \mathcal{D} \end{aligned} \tag{III.8}$$

$$\sum_{d \in \mathcal{D}} x(d,s,k) \leq cap(l(s))y(s), \quad \forall s \in \mathcal{S}, k = 0, \ldots, (K-2) \tag{III.9}$$

$$v(l) = \sum_{i \in \mathcal{N}^{\mathrm{ph}}} z(l,i,0) + \sum_{s \in \Lambda_{0l}} y(s), \quad \forall l \in \mathcal{L} \tag{III.10}$$

$$v(l) \leq B_l, \quad \forall l \in \mathcal{L} \tag{III.11}$$

$$\sum_{s \in S^-_{itl}} y_s + z(l,i,t-1) = \sum_{s \in S^+_{itl}} y_s + z(l,i,t), \quad \forall l \in \mathcal{L},\ it \in \mathcal{N} \tag{III.12}$$

$$\sum_{l \in \mathcal{L}} z(l,i,t) + \sum_{l \in \mathcal{L}} \sum_{s \in S: i_k(s)=i, l(s)=l, \alpha_k(s) \leq t < \tau_k(s)} y(s) \leq Q_i, \quad \forall it \in \mathcal{N} \tag{III.13}$$

$$y(s) \in \{0,1\}, \quad \forall s \in \mathcal{S} \tag{III.14}$$
$$\xi(d) \in [0,1], \quad \forall d \in \mathcal{D}^{\mathrm{P}} \tag{III.15}$$
$$\zeta(d) \in \{0,1\}, \; \forall d \in \mathcal{D}^{\mathrm{F}} \tag{III.16}$$
$$z(l,i,t) \geq 0, \quad \forall l \in \mathcal{L}, \quad it \in \mathcal{N} \tag{III.17}$$
$$v(l) \geq 0, \quad \forall l \in \mathcal{L} \tag{III.18}$$
$$x(d,s,k) \geq 0, \quad \forall d \in \mathcal{D}, \; s \in \mathcal{S}, \; k = 0 \ldots (K-2) \tag{III.19}$$
$$x^{out}(d,s,k) \geq 0, \quad \forall d \in \mathcal{D}, \; s \in \mathcal{S}, \; k = 0 \ldots (K-2) \tag{III.20}$$
$$x^{in}(d,s,k) \geq 0, \quad \forall d \in \mathcal{D}, \; s \in \mathcal{S}, \; k = 0 \ldots (K-2) \tag{III.21}$$
$$x^{hold}(d,i,t) \geq 0, \quad \forall d \in \mathcal{D}, \; it \in \mathcal{N}. \tag{III.22}$$

The objective function (III.2) maximizes the net profit, where the first three terms correspond to the revenue obtained by servicing the complete demand of regular customers, the selected proportion of demand of the proportional-punctual customers, and the complete demand of the selected and full-punctual customers respectively. Remark that, for a given set of demands, the first term (revenue obtained by servicing the complete demand of regular customers) is a constant. It is kept to make the objective function homogeneous. The following terms stand for the activity and time-related costs of operating the selected service network and resource routes, that is, the penalty cost of having but not using vessels (never assigned to a service during the entire schedule length), the fixed cost of setting up and operating services, the cost of the vessels idling at a port waiting for their next service departure, the cost of transporting containers on services, and the cost of holding and handling containers in terminals.

Equations (III.3), (III.4) and (III.5) are flow-conservation constraints for containers of all customer types, at their particular origins, destinations, and intermediary nodes, respectively. Similarly, Equations (III.6), (III.7) and (III.8) enforce the conservation of container flows, for all customer types, on each service at its origin, destination and intermediary stops, respectively. Constraints (III.9) enforce the service capacity on each leg.

Equation (III.10) computes the number of vessels used in the plan as the sum of vessels idling in ports or moving between them performing services. Due to the resource management concerns and the resulting circular vessel routs, $v(l)$ is the same at all periods, only the relative proportion of idle versus active vessels being different at different time periods. We therefore compute this number for the first period, i.e., $t = 0$, the set $\Lambda_{0l} = \{s \in S, l(s) = l | (\alpha_{K-1}(s) \quad mod \quad T) < \tau_0(s) \quad \text{and} \quad \tau_0(s) \geq 0\} \subseteq \mathcal{S}$ containing all services, of the appropriate vessel type, that operate one of its legs during the first period.

Constraints (III.11) enforce the fleet size for each vessel type, while Equations (III.12) are the so-called design-balance constraints, enforcing the vehicle-flow conservation at terminals (the number of services and vessels entering a node equals the number exiting the node), where sets S^-_{itl} and S^+_{itl}

$$S^-_{itl} = \{s \in S \mid dest(s) = i, \tau_{K-1}(s) = t, l(s) = l\} \quad \text{(III.23)}$$
$$S^+_{itl} = \{s \in S \mid orig(s) = i, \alpha_0(s) = t, l(s) = l\} \quad \text{(III.24)}$$

group the services of type l that arrive at their destination or depart from their origin i at time t, respectively. Finally, Constraints (III.13) enforce the terminal berthing capacity at each time period, while decision-variable domains are defined by Constraints (III.14) - (III.22).

III.5 Simulation and Numerical Results

In this section, we design and conduct a set of experiments to validate the proposed Scheduled Service Network Design with consideration of Resource and Revenue Management (SSND-RRM) model. Two research questions are discussed: first, the benefits of differentiating products for decision making at tactical level; and second, the impacts of customer classification and fare differentiation on the scheduled service plan and the flow distribution. The rest of this section is organized as follows. We first describe the procedure of test instance generations in Subsection III.5.1. Subsection III.5.2 briefly introduces the experiment plan. We then present and analyze the experiment results, with respect to each research question, in Subsection III.5.3 and III.5.4, respectively. A brief analysis relative to the computational times can be found in Subsection III.5.5.

III.5.1 Test Instances Generation

In this subsection, we present the procedure of test instance generation. Remark that, as one of the objectives of this chapter is to provide a proof-of-concept, we deliberately choose small test instances to better understand how the introduction of revenue management can affect the service network design. Without loss of generality, however, three different topologies, i.e., *Linear 4 (n4)*: linear network of 4 terminals, *Star 6 (n6)*: hub-and-spoke network of 6 terminals and *General 7 (n7)*: general network (combination of linear and hub-and-spoke) of 7 terminals, as illustrated in Figure III.3, are studied to represent the reality of different physical networks.

For a given network, 14 time units (stands for one week) are considered as the schedule length. Two types of vessels (large and small) are considered. The capacity of a large vessel is considered to be 2.5 times greater than that of a small one, while the fixed cost of a large vessel is just 2 times more expensive. Potential services consist of all possible itineraries in the network, using both types of vessels.

As test instances are generated following the same rules for all the tested topologies, we describe the generation of test instances with an example of the physical network *Linear 4*.

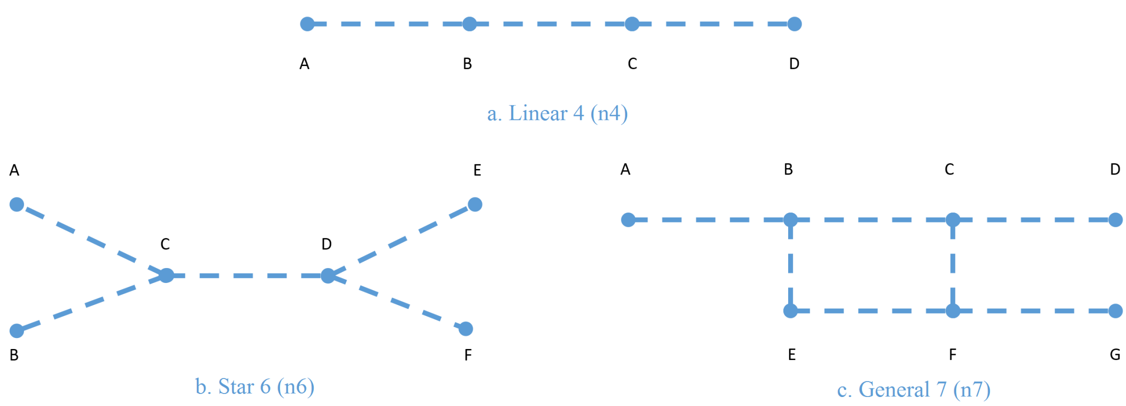

Figure III.3: Three physical network topologies considered for the SSND-RRM model validation

For one instance, in order to generate a well-balanced combination of demands requiring *slow* and *fast* delivery, we first generate a set of demands corresponding to only regular (R) customers. In the instance, we assume that each possible origin-destination (OD) pair in the network should appear at least twice, and no specific delivery type is fixed for the moment. The volume of each individual demand is randomly generated, according to the uniform distribution, with an upper bound of half of the capacity of a large vessel. Note that the volume of a demand might exceed the capacity of a small vessel. However, this is not restrictive since demand splitting is allowed. Thus, we fix the total volume of demands of that instance. Then, the volume of demands requiring *fast* delivery is specified by a percentage (p) out of the total volume of demands. We may thus generate instances with a fixed total volume of demands but with varied proportions of demands requiring *fast* and *slow* delivery. Note that, the different delivery types and thus the different types of demands are associated with different fare classes. A *low fare* corresponds to a *slow* delivery demand type, and a *high fare* is associated with a *fast* delivery demand type.

When demands from other categories of customers (P or F) are also considered, we simply “duplicate” the demands from R customers and change their customer category to P or F. Therefore, the total volume of a test instance considering R and P (or R and F) customers is twice that of its corresponding test instance considering only R customers. Furthermore, we assume that all demands from P customers require *slow* delivery, whereas all demands from F customers require fast delivery. For each given total volume, each specified percentage p and each particular customer category mix, 20 test instances are randomly generated based on this procedure.

We solve all the optimization problems with the help of a commercial MILP solver (IBM CPLEX 12.5) on a multi-processor server running under Linux 64-bit with Inter Xeon X5675, 3GHz and 30 GB of RAM.

III.5.2 Experiment Plan

In this subsection, we introduce the experiment plan. Two groups of experiments are set up to study: first, the influences of having different delivery requirements (*slow* and *fast*) from customers on the decisions made at tactical level; and second, the benefits of considering the customer classification and fare differentiation for the selection of services and the flow distribution, respectively.

The characteristics of the two groups of experiments are briefly displayed in Table III.1. In the first group, to eliminate the influences of other parameters, only regular (R) customer demands are considered. Fare differentiation is not applied, even if *fast* and *slow* delivery types are considered. *Fast* demands are considered to be distributed over the set of O-Ds in two different fashions: first, customers requiring *fast* delivery are distributed evenly, and second, *fast* delivery is required by customers concentrating at a single main terminal (the one with the highest throughput), which is either the origin or destination of a *fast* demand. The ratio of *fast*/*slow* demands (considered as Parameter 1) is varying in the first group.

Table III.1: Characteristics of the two groups of experiments

	Demand categories	Fare differentiation	Request for fast delivery	Varied parameters
Group 1	only R	no	spread over the network or concentrated at a single terminal	1
Group 2	R+P or R+F	yes	spread over the network	2+3

In the second group of experiments, partially spot (P) customer demands and fully spot (F) customer demands are considered together with R. The total volume of P (or F) is equal to the volume of R in each test instance. In addition, fare differentiation is also applied, and transport requests for *fast* delivery appear all over the network.

In this second group of experiments, an important parameter (considered as Parameter 2) is used: the degree of freedom of service selection. Three different cases are explored: *fix all services*, *fix open services* and *fix no service*. The difference among the three cases is the restriction on the service selection once the initial optimization problem is solved for R customers only. In the first two cases, we first solve the optimization problem considering only R demands and obtain a scheduled service plan. In the case of *fix all services*, we then fix all services (fix decision variables $y(s) = 0$ or $y(s) = 1$) according to the obtained assignment (for only R) and solve again the optimization problem considering all demands (R, P and F). In the case of *fix open services*, we fix only the open services (fix decision variables $y(s) = 1$) according to the obtained assignment, and solve again the optimization problem. Thus, more services might be open, considering all demands (R, P and F). The most flexible case is *fix no service*, in which no additional constraint is applied and the optimization model has the right to choose the best set of services, considering all demands from the beginning (no second solving is needed).

Another important parameter (Parameter 3) refers to the mix of customer categories within the same test instance, with or without fare differentiation. Four different cases are compared in the second group of experiments:

- Case *only R*: only R demands with no fare differentiation;
- Case *R+P*: R and P demands with no fare differentiation;
- Case *R+F no price*: R and F demands with no fare differentiation;
- Case *R+F with price*: R and F demands with fare differentiation.

All R demands are identical in all four cases. The total volume of spot (P or F) demands is equal to the volume of R demands. Note that, throughout this whole group of experiments, all R and P demands ask for *slow* delivery, while all F demands ask for *fast* delivery. Fare differentiation is applied only according to the delivery type, and the price ratio of *slow* delivery to *fast* delivery is 1:1.5.

Performance indicators (PIs) used to analyze the solutions for both groups of experiments are:

- **Total cost**: Sum of all costs, i.e., fixed cost (opening services) and variable costs (holding barges, holding non-used barges, holding containers, transportation and handling containers);

- **Opening services cost**: Fixed cost alone corresponds to the maximum transportation capacity made available in the optimal solution on the whole service network;

- **# of open services (small)**: Number of open services with small vessel;

- **# of open services (large)**: Number of open services with large vessel;

- **Distance*Capacity usage**: Indicator represents the degree of resource utilization; it is calculated as the ratio of used service distance*capacity over the maximum possible service distance*capacity according to a given optimal solution; as shown in equation (III.25), used service distance*capacity is the sum of all service legs' used capacity multiplied by their corresponding transport distance, while maximum possible service distance*capacity is the sum of all service legs' capacity multiplied by their corresponding transport distance, for all open services;

$$Distance * Capacityusage = \frac{\sum\limits_{s}\sum\limits_{k}\sum\limits_{d} dis(k) * x(d,s,k)}{\sum\limits_{s}\sum\limits_{k} dis(k) * cap(s)} \tag{III.25}$$

- **Waiting at origin**: Sum of waiting time of all regular demands at their origins, weighted by their volumes, which is an indicator of the flow congestion level on the network;

- **Transshipment**: Sum of waiting time of all regular demands at their intermediate stops, weighted by their volumes, which is another indicator of the flow congestion level on the network;

- **Slow splitting**: When distributing the flow, some demands have to be split to fit in the residual capacity of services and to derive the optimal flow distribution; this indicator is the ratio of split R demands (in TEUs) over all R demands, which may also give an idea about the flow congestion level on the network;

- **Relative yield**: Computed as the net profit divided by the total cost and used as an indicator of the profitability for accepted demands;

- **Additional TEUs accepted**: Total volume of P or F demands accepted by the model.

III.5.3 Experiment Results and Analysis: First Group

As described in the previous subsection, the first group of experiments is dedicated to the study of the influences of having different delivery requirements (*slow* and *fast*) from customers on the decisions made at tactical level. TableIII.2 illustrates the results of the first group of experiments, when customers are requiring *fast* delivery all over the network of *Linear 4*. In Table III.2, the *no fast* column indicates that all customers are asking for *slow* delivery, while the percentages 25%, 50%, 75% and 100% in the following columns indicate the ratio of total *fast* demands to all demands (distance*volume). Table III.3 presents the results of the first group of experiments, when customers are requiring *fast* delivery concentrated at only one terminal. In Table III.3, the *no fast* column also indicates that all customers are asking for *slow* delivery. The following columns indicate that in turn, 25%, 50%, 75% and 100% of *fast* demands concentrate at the highest throughput terminal. Just to recall, all the values presented here are calculated as the average according to 20 test instances.

Table III.2: Topology *n4*: Fast demands spread uniformly over the network, no fare differentiation

	no fast	25% fast	50% fast	75% fast	100% fast
Total cost	9175.37	9459.17	9946.92	10364.02	10996.47
Opening services cost	4567.5	5040	5557.5	6198.75	6997.5
# of open services (small)	5.7	13.2	17.1	22.15	24.5
# of open services (large)	7.3	4.6	3.8	2.7	3.3
Distance*Capacity usage (%)	70.17	69.34	64.46	59.32	52.62
Waiting at origin	469.05	377.25	347.6	216.25	115.45
Transshipment time	1.60	6.95	3.7	2.45	0
Splitting of slow(%)	27.82	43.46	48.92	56.68	NA

Table III.3: Topology *n4*: Fast demands concentrate at one port, no fare differentiation

	no fast	25% fast	50% fast	75% fast	100% fast
Total cost	9175.37	9426.67	9619.72	9886.52	10204.87
Opening services cost	4567.5	4927.5	5175	5535	5940
# of open services (small)	5.7	11.7	15.6	19.4	21.6
# of open services (large)	7.3	5.1	3.7	2.6	2.4
Distance*Capacity usage (%)	70.17	69.59	68.27	65.37	61.97
Waiting at origin	469.05	431.4	388.9	335	282.85
Transshipment time	1.60	4.15	3.4	0.7	0.7
Splitting of slow(%)	27.82	38.02	47.06	48.00	48.83

Note that, as the total volume of all test instances, in either Table III.2 or Table

III.3, is identical, and only R demands are considered with no fare differentiation, the indicators related to profit make no difference when analyzing the solutions. Therefore, no performance indicator related to profit is used in these two tables.

As shown in Table III.2, the columns *No fast* and *100% fast* provide the lower and upper bounds, in terms of total cost, respectively. When the volume of fast demands increases, the *total cost* is getting higher. Furthermore, to satisfy more fast demands (even with the same total volume of demands), more services are needed, which results in higher cost of opening services. According to the solutions, when we increase the ratio of fast demands, more small vessels are needed with direct services. As direct services, which have no intermediate stops, are open to satisfy the restrictive time constraints of those urgent demands, the remaining capacity of these services can not be used, if not loaded at their origins. As more transport capacity is open and the total volume of all demands remains the same, the utilization of resources drops from 70.17% to 52.62% ($distance * capacity\ usage$). Therefore, the profitability of transport capacity per unit is getting lower without fare differentiation. When looking at the values of PI *splitting of slow demands*, we remark that the more fast demands are satisfied, the more slow demands are fragmented to match the remaining capacity, after satisfying the fast. In order to satisfy the urgent delivery time of fast demands, some demands are kept at terminals for several time periods instead of being immediately and directly transported to their destinations. Most of the waiting (or container holding) take place at demands' origins to avoid further handling cost, while very few demands are transshipped and being held at intermediate stops. This phenomenon is due to the fact that 1) given the current service network, demands with loose time constraints have to give the priority to those with tight time constraints; and 2) the cost to open new services is higher than the sum of handling and holding costs for the demands concerned.

Similar trends are also observed in Table III.3, which is a clear indication that some demands do consume more resources, and consequently result in higher total cost for the carriers, than the others in a general case, no matter how the fast demands are encountered in the network. Therefore, we conclude that offering high service level without fare differentiation decreases the profitability, which means, for carriers, it is necessary and promising to charge different fares on different customer services (fast or slow delivery). Note that, in Table III.3, as fast demands are concentrated at one port, some of these fast demands are able to be transported together and benefit from consolidation. Accordingly, compared to Table III.2, less services with small vessel are open, and higher capacity usage and less total cost are also observed. Therefore, even the fast demands do consume more resources, these demands can still benefit from consolidation, if we organize and transport them properly, and the proposed SSND-RRM model is able to help the carriers to achieve that.

The same type of experiments are also conducted on the other two physical networks (i.e., *Star n6* and *General n7*). Table III.4 and Table III.5 illustrate the results of the first group of experiments for physical network *Star n6*, and results of the first groups of experiments for physical network *General n7* are shown in Table III.6 and Table III.7. For both *Star n6* and *General n7*, as bigger physical networks are considered, compared to *Linear n4*, more demands (or higher total volume of demands) are included in each test instance. This explains the higher total cost and more consumed resources observed in Table III.4-III.7. However, with respect to each tested physical network, the same trends are observed as those for *Linear n4* and result in the same type of conclusions.

Table III.4: Topology *n6*: Fast demands spread uniformly over the network, no fare differentiation

	no fast	25% fast	50% fast	75% fast	100% fast
Total cost	20594.80	21469.37	22727.00	24180.60	25889.55
Opening services cost	10811.25	11418.75	12510.00	14175.00	15975.00
# of open services (small)	20.65	26.95	33.70	37.50	39.60
# of open services (large)	13.70	11.90	10.95	12.75	15.70
Distance*Capacity usage (%)	83.09	80.83	74.72	66.53	58.37
Waiting at origin	110.7	81	68.1	27.8	2.15
Transshipment	187.75	170.22	109.35	48.35	3.35
Splitting of slow(%)	33.49	39.79	44.22	45.49	NA

Table III.5: Topology *n6*: All fast demands concentrate at one port, no fare differentiation

	no fast	25% fast	50% fast	75% fast	100% fast
Total cost	20594.80	20958.70	21510.75	22076.65	22783.55
Opening services cost	10811.25	11002.50	11463.75	11936.25	12757.50
# of open services (small)	20.65	23.40	25.85	26.75	30.60
# of open services (large)	13.70	12.75	12.55	13.15	13.05
Distance*Capacity usage (%)	83.09	82.25	80.32	77.20	73.35
Waiting at origin	110.7	108.9	84.1	75.45	65.8
Transshipment	187.75	191.85	180.8	173.05	126.7
Splitting of slow(%)	33.49	38.38	37.39	37.35	40.26

Table III.6: Topology *n7*: Fast demands spread uniformly over the network, no fare differentiation

	no fast	25% fast	50% fast	75% fast	100% fast
Total cost	22134.75	23129.78	23939.00	24967.10	26461.80
Opening services cost	10552.50	11643.75	12521.25	13995.00	15873.75
# of open services (small)	13.20	30.65	39.65	47.1	53.25
# of open services (large)	16.85	10.55	8	7.55	8.65
Distance*Capacity usage (%)	77.91	76.43	73.11	66.62	58.83
Waiting at origin	64.1	59.5	58	32.51	5.85
Transshipment	209.9	153.5	144.8	67	9.95
Splitting of slow(%)	33.36	48.91	56.5	59.33	NA

Table III.7: Topology *n7*: All fast demands concentrate at one port, no fare differentiation

	no fast	25% fast	50% fast	75% fast	100% fast
Total cost	22134.75	22596.10	23018.00	23394.95	23879.40
Opening services cost	10552.50	11002.50	11418.75	11857.50	12465.00
# of open services (small)	13.20	21.1	24.25	30.2	34.9
# of open services (large)	16.85	13.9	13.25	11.25	10.25
Distance*Capacity usage (%)	77.91	76.97	75.84	74.31	71.64
Waiting at origin	64.1	71.35	84.75	88.45	64.35
Transshipment	209.9	192.65	187.25	137.4	138.65
Splitting of slow(%)	33.36	40.14	40.92	44.94	43.31

III.5.4 Experiment Results and Analysis: Second Group

As described in the experiment plan (Subsection III.5.2), in this subsection, we study the impacts of considering customer classification and fare differentiation for the selection of services and the flow distribution. Parameter 2 (freedom of service selection) and parameter 3 (mix of customer categories within the same test instance, with or without fare differentiation) are discussed within this group of experiments. Table III.8 presents the results of second group of experiments for physical network *Linear n4*.

As shown in Table III.8, interesting observations, with respect to *mix of customer categories within the same test instance, with or without fare differentiation*, are as follows:

- When comparing *R+P* with *only R*, higher relative yield is obtained by serving the additional demands with services' residual capacity (same total fixed cost with different revenue);
- When comparing *R+P* with *R+F without fare differentiation*, as P demands may

Table III.8: Topology *n4*: Experiment group 2

		only R	R+P	R+F no price	R+F with price
Relative Yield	fix all services	0.13	0.24	0.22	0.33
	fix open services	0.13	0.25	0.23	0.46
	fix no service	0.13	0.29	0.26	0.51
# of open services (small)	fix all services	5.7	5.7	5.7	5.7
	fix open services	5.7	7.2	9.5	11.7
	fix no service	5.7	0.8	2.1	3.8
# of open services (large)	fix all services	7.3	7.3	7.3	7.3
	fix open services	7.3	12.9	11.6	14.5
	fix no service	7.3	15.6	15.3	17.5
Additional TEUs accepted	fix all services	0	173.65	135.35	151
	fix open services	0	488.4	446.75	576.1
	fix no service	0	503.25	480.75	577.55

be fragmented, but F demands cannot (in terms of acceptance), *R+P* always results in higher relative yield with more accepted additional TEUs;

- When comparing *R+P* with *R+F with fare differentiation*, even if P demands may be split, better relative yield is still observed in *R+F with fare differentiation*; Note that, for the case of *fix all services*, *R+F with fare differentiation* generates even better relative yield with less additional TEUs accepted;

- As expected, when comparing the two cases of R+F, because of the higher price charged for the *fast* delivery, better relative yield is obtained by *R+F with fare differentiation*, which shows that fare differentiation makes a difference.

Note that, when we fix all services, even with higher price, less F demands are served than P demands with the same price, because P demands fit easily (even if not entirely) into the residual capacity while F demands do not.

With respect to *freedom of service selection*, in the case *fix open services* and *fix no services*, when resources are relatively abundant, more F demands (with higher price) are accepted compared to P demands. Based on this observation, we may conclude that customer classification has more impacts on additional demand acceptance when resources are limited, while fare differentiation influences more the selection of additional (spot) demands when there is more flexibility in opening services. It also indicates that a good understanding of the behavior of different customers (especially when resources are scarce) and charging different fares on different products, at the tactical level, result in a better resource utilization and extra profits for the transport companies. Nevertheless, in practice, higher price may drive the customers away because of the very competitive environment of the market. Therefore, pricing should be done based on a deep analysis of customers behavior, which is not the focus of this chapter.

The relative yield obtained from the second group of experiments is also illustrated in Figure III.4, where the vertical axis stands for the relative yield. As shown in the figure, it is obvious that the consideration of a mix of regular and spot demands (R+P and R+F) results in better relative yield, compared with considering only the regular demands. Relative yield also grows when fare differentiation is introduced into the model. From the perspective of the freedom of service selection, it becomes clear that, in order to achieve a better relative yield, no additional constraints should be taken into account and the SSND-RRM model should take the full responsibility for the decisions, in terms of service selection. Therefore, we conclude that it is profitable to include revenue management consideration into tactical SSND plan.

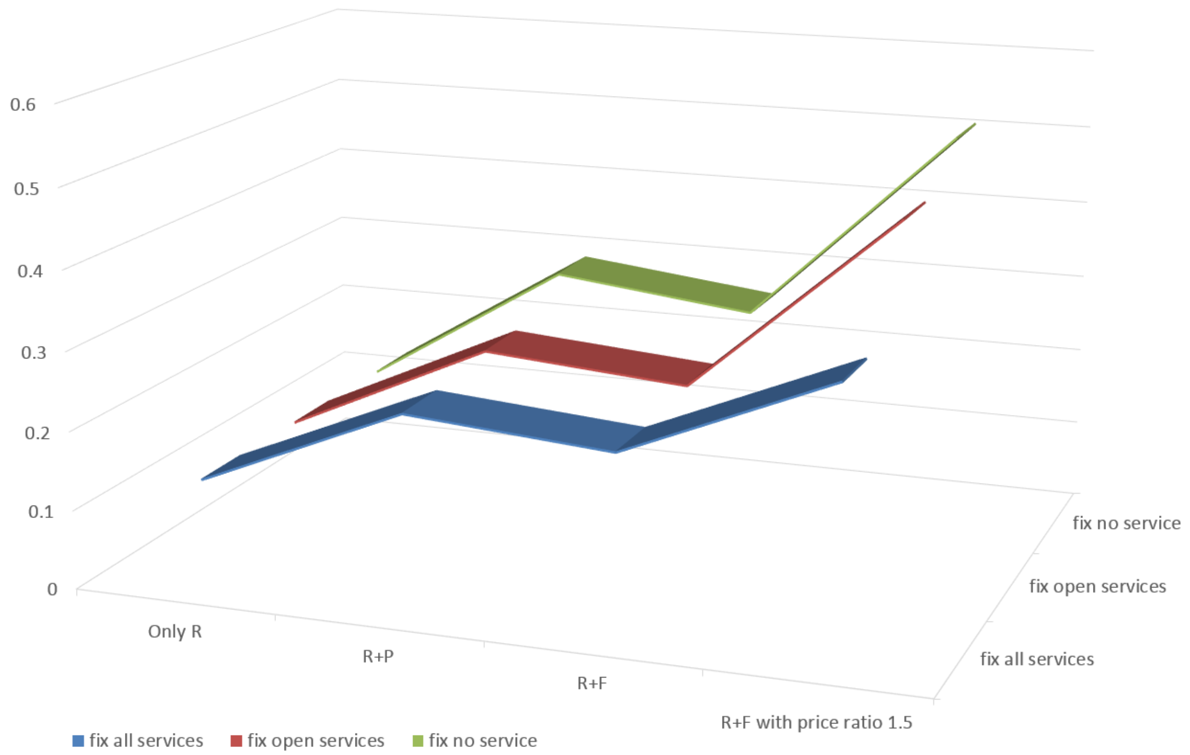

Figure III.4: Relative yield obtained in the second experiment group

As the experiments conducted on the other physical network topologies show the same trends and consequently result in the same type of conclusions, numerical results for the other physical networks are presented in Table III.9 for *Star n6* and Table III.10 for *General n7*, respectively, without further analysis.

Table III.9: Topology *n6*: Experiment group 2

		only R	R+P	R+F no price	R+F with price
Relative Yield	fix all services	0.14	0.25	0.22	0.31
	fix open services	0.14	0.26	0.23	0.46
	fix no service	0.14	0.30	0.27	0.52
# of open services (small)	fix all services	20.65	20.65	20.65	20.65
	fix open services	20.65	25.10	29.15	38.95
	fix no service	20.65	9.9	14.55	20.10
# of open services (large)	fix all services	13.70	13.70	13.70	13.70
	fix open services	13.70	25.80	23.55	27.00
	fix no service	13.70	32.45	31.30	34.05
Additional TEUs accepted	fix all services	0	310.25	233.35	246.65
	fix open services	0	1033.05	933.75	1191.1
	fix no service	0	1063.2	1034.7	1210.7

Table III.10: Topology *n7*: Experiment group 2

		only R	R+P	R+F no price	R+F with price
Relative Yield	fix all services	0.29	0.40	0.38	0.49
	fix open services	0.29	0.39	0.37	0.64
	fix no service	0.29	0.42	0.39	0.68
# of open services (small)	fix all services	13.20	13.20	13.20	13.20
	fix open services	13.20	15.50	21.25	31.90
	fix no service	13.20	1.9	8.70	13.10
# of open services (large)	fix all services	16.85	16.85	16.85	16.85
	fix open services	16.85	34.55	31.45	32.65
	fix no service	16.85	39.55	37.6	40.2
Additional TEUs accepted	fix all services	0	386.6	337	372.45
	fix open services	0	1411.95	1308.75	1487.5
	fix no service	0	1406.45	1346.75	1489.4

III.5.5 Computational Time

As described in Subsection III.5.1, all the MILP optimization problems are solved with the help of a commercial solver (IBM CPLEX 12.5) on a multi-processor server running under Linux 64-bit with an Inter Xeon X5675, 3GHz and 30 GB of RAM. In Table III.11, we present the statistics of the computational time for the 180 test instances in experiment group 1 of topology *n4*. As the size of the tested instances is not too large (4 terminals, 616 potential services and around 60 demands), most of them have a computational time less than 10 minutes to obtain the optimal solution.

Another set of test instances of more realistic scale are designed to test the computational power of the commercial solver. To generate the test instances, we first fix the number of demands for each test instance. Then, all the characteristics of a demand

Table III.11: Statistics of computational time for 180 test instances in group 1 of topology Linear *n4*

Running time (s)	1 - 200	201 - 400	401 - 600	600+
# of test instances	171	7	1	1

are generated randomly according to the uniform distribution. The commercial solver (CPLEX 12.5) is set with a maximum running time of 10 days. The size, the computational time and the corresponding status of optimality of six particular test instances are presented in Table III.12. In the table, $|\mathcal{N}^{ph}|$, $|\mathcal{S}|$, $|\mathcal{D}|$ and $|\mathcal{D}^F|$ indicate number of physical terminals, number of potential services, number of total demands and number of F demands. respectively. Remark that, decisions with respect to service selection and F demand selection are formulated as binary decision variables, from where the computational difficulties come. Numbers of decision variables and constraints generated for each test instance according to the SSND-RRM model are also presented in column *# DVs* and column *# Constraints*, respectively. As shown in Table III.12, computational difficulties are encountered when solving the SSND-RRM problems of realistic scale. For the last three test instances, no optimal solution can be obtained after 10 days with the commercial solver.

Table III.12: Computational time and size of large instances on topologies of Linear *n4*, Star *n6* and General *n7*

Test instance	$\|\mathcal{N}^{ph}\|$	$\|\mathcal{S}\|$	$\|\mathcal{D}\|$	$\|\mathcal{D}^F\|$	# DVs	# Constraints	Time consumption	Optimality
1	4	616	480	180	119858	104703	27.6 minutes	yes
2	4	616	960	307	230238	202045	36.7 minutes	yes
3	6	1848	150	66	77866	66225	26.8 hours	yes
4	6	1848	300	107	144686	122180	10 days	no
5	7	4200	210	79	265354	222719	10 days	no
6	7	4200	420	130	546397	450447	10 days	no

III.6 Conclusions

In this chapter, we proposed what we believe to be the first comprehensive tactical planning model for barge freight carriers that integrates both revenue and resource management considerations (SSND-RRM). In the proposed model, revenue management (RM) policies: customer classification and fare differentiation, are considered. In terms of resource management, design-balance constraints and limits on the quantity of resources are formulated. To synchronize with other transport modes, scheduled services are planned to answer to demands with time-delivery constraints.

We tested the model on various problem settings, in terms of network topologies, fare classes and quality-of-service (e.g., delivery time). According to results, when we increase the ratio of fast demands for a given set of demands, more small vessels are needed with lower capacity usage to satisfy those urgent demands. It also results in some slow traffic to be split. It is obvious that fast demands consume more resources and violate the idea of consolidation-based service, which encourages demands from different customers to be transported together. Therefore, those demands, which result in more costs, should be discriminated by charging different prices. In addition, by classifying customer into different categories and having different treatments accordingly, carriers may benefit from consolidation, obtain a better resource utilization and consequently gain better revenue. Our results indicate that, higher relative yield (or profitability) and better resource utilization for the carriers are always obtained, regardless of the physical network topology, by considering RM policies when designing the network of scheduled services. It is thus promising to classify customers and differentiate fare-products at tactical level.

Further research may be carried out to extend the proposed model. For example, different price policies could be applied. In the current SSND-RRM model, the price policy is only related to the required delivery type. A different price policy can be also considered according to the customer categories. To be more precise, the unit price charged on the regular (R) customers should be lower than that charged on the spot (P and F) customers, with respect to the same delivery type. The lower price here, is applied to encourage the establishment of solid business relationship (or long-term contract) between the carriers and customers. Even though the lower price seemingly decreases the potential revenue of the carriers, it actually reduces the uncertainty of demands, in terms of volume, OD and even delivery time, due to the signed long-term contract. Therefore, it may result in better service plans, in term of resource utilization and relative yield (profitability). Furthermore, within the spot customers, as P customers fit in the residual capacity better, they should be charged with lower price, compared with F customers. Thus, more P customers could be attracted. Another interesting perspective is to formulate the stopping time of each service at each terminal as decisions in the SSND-RRM model. Facing the uncertain demands, in terms of available time, and/or delayed services, better service plans are expected, if the stopping time of a service at each terminal is decided by the model, instead of fixed as a predefined value. Moreover, it is also interesting to explicitly consider the uncertainty of demands, based on their customer categories. For example, demands from regular customers are more predictable, while demands from spot customers are more uncertain, in terms of volume, available time, etc.

As one of the objectives of this chapter is to prove the concept of integration of revenue (and resource) management considerations into tactical planning model, no deep insight is offered with respect to the analysis of customer classification and fare differentiation. Therefore, it is more convincible, especially for the carriers, to validate the SSND-RRM model in case studies with real data and have a discussion on the market segmentation and service qualification. In addition, the computational difficulties encountered when solving the proposed problems of large scale urges that efficient solution approaches should be proposed and developed.

Chapter IV

A Metaheuristic for Scheduled Service Network Design with Resource and Revenue Management for Intermodal Barge Transportation

Contents

Revenue management is seldom considered when planning consolidation-based freight transport services. In the previous chapter, we formalized and addressed the scheduled service network design problems with resource management and revenue management considerations (SSND-RRM). As the proposed SSND-RRM problems are NP-hard, in this chapter, we propose a metaheuristic (MH), which is composed of four phases, to efficiently solve the SSND-RRM problems, especially for the large-scale instances. In the first phase, a constructive heuristic is proposed to obtain initial solutions, which are then iteratively improved in the following phases. Adaptive large neighborhood search (ALNS) and tabu search are combined to guide the iterative search in the second phase. New neighborhood structures are proposed to explore in the search space of service selection, based on service-cycles, producing high-quality solutions quickly. The other two phases considered are intensification and diversification. Given some interesting characteristics of services, small regions of solution space are identified based on the global best solutions and are deeply explored (intensification). Diversification, on the other hand, is called to direct the search towards non-thoroughly-explored regions of solution space.

A previous version of this research work has been presented at CORS/INFORMS International Conference, 2015 with the following reference information:

Wang Y., Crainic T.G., Bilegan I.C., Artiba A. (2015). A Metaheuristic for Service Network Design with Revenue Management for Freight Intermodal Transport. CORS/INFORMS International Conference, Montreal, Canada, June.

Based on the material included in this chapter, a working paper is in preparation for submission to an international journal.

IV.1 Introduction

Service network design (SND) is a core problem and is widely used as a generic model to formulate network design problems faced in the fields of telecommunication, logistics, transportation, etc. In the field of freight transportation, SND models generally consist of selection and scheduling of services, and routing demands with the selected services while minimizing the total cost. [Crainic, 2000, Crainic, 2003] offer an introduction to service network design in freight transport. In addition to selection and scheduling of services, and routing demands, managing limited key resources (or assets), e.g., power units, vehicles, crews or containers, is also integrated within SND problems (e.g., [Pedersen et al., 2009, Andersen et al., 2009b, Andersen et al., 2009a, Crainic et al., 2014]). Due to the increasing competition (e.g., decreasing costs and improving customer satisfaction) on carriers from the market, different polices are taken in the literature to make "better" plans tackling the tactical planning problems. For example, maximizing the net profit (or revenue) instead of minimizing the total costs (e.g., [Agarwal and Ergun, 2008, Teypaz et al., 2010, Gelareh and Pisinger, 2011]), rejecting some demands instead of accepting all demands at tactical level (discrimination on customers/customer classification) (e.g., [Andersen and Christiansen, 2009, Thapalia et al., 2012, Braekers et al., 2013, Stålhane et al., 2014]). Although not explicitly identified, these different polices are Revenue Management (RM) related. RM, which was initially applied to passenger airline transportation, starts to draw attention in research nowadays for freight transportation, as illustrated in the reviews related to air cargo operations [Feng et al., 2015], railway transportation [Armstrong and Meissner, 2010], and container synchromodal services [van Riessen et al., 2015a]. However, the few contributions considering both RM and freight transportation [Bilegan et al., 2015, Wang et al., 2015] focus on the operational level, while the tactical level is rarely envisaged [Crevier et al., 2012].

Therefore, in the previous chapter, we proposed a Scheduled Service Network Design model with consideration of both Resource and Revenue Management (SSND-RRM) to solve the tactical planning problems for freight carriers. To integrate resource management into the SSND-RRM, *design-balance constraints*, which ensure the balance of incoming and outgoing vehicles at each terminal for each time instant, and *limits on the quantity of resource* (vehicles) are formulated. In terms of RM policies, various fare classes according to the required delivery types are modeled. Moreover, customers are classified into three categories, i.e., Regular customers (R), Proportional-punctual customers (P) and Full-punctual customers (F). According to their business relationships with the carriers and their behaviors, demands from different customers are treated differently. To be more precise, demands from R must always be satisfied, while demands from P can be partially accepted and demands from F may be either entirely accepted or not accepted at all.

Therefore, in addition to the selection of scheduled services and routing of demands, decisions related to the selection of demands to transport are also made in the proposed SSND-RRM. Further complexity to the SSND-RRM problems is added because of the competition of different categories of customers for the network capacity with different fares and trade-offs between opening more services with higher revenue and rejecting more demands with lower total costs.

As shown in Chapter III, introducing resource and revenue management considerations into the SND formulations poses great computational challenges. The goal of this chapter is to propose a solution approach to efficiently identify good-quality feasible solutions for the SSND-RRM problems of large scale. The contributions of this paper are threefold: First, we propose a Metaheuristic (MH) that combines adaptive large neighborhood search (ALNS) and Tabu search, and utilizes long and short-term memory structures for addressing the SSND-RRM. Second, new neighborhood structures considering design-balance constraints are introduced to accelerate the search in the space of service selection. Third, we study the efficiency of the proposed solution approach through comprehensive experiments and benchmark against a state-of-the-art commercial solver.

The rest of this chapter is organized as follows. Following a brief literature review in Section IV.2, we recall the statement of the problem and present the model of SSND-RRM in Section IV.3. Section IV.4 is dedicated to introduce the solution approach, while computational results are presented and analyzed in Section IV.5. We conclude with perspectives in Section IV.6.

IV.2 Literature Review

In SND problems, continuous and binary variables are used to represent commodity flows throughout the designed network and the selection of services, respectively. With two of the most common constraints, i.e., network capacity constraints and flow conservation constraints, SND problems are considered as a fixed-charge capacitated multicommodity network design problem (CMND).

Considerable efforts directed towards investigating and developing effective solution techniques, in particular, metaheuristics and hybrid approaches, are proposed for the problems of CMND/SND. [Crainic et al., 2000] propose a hybrid approach for CMND, combining a tabu search method with pivot-like neighborhood moves and column generation. The work is continued by [Ghamlouche et al., 2003] and a more efficient cycle-based neighborhood structure for CMND is proposed. In their study, two paths (sequence of design arcs) connecting the same origin-destination nodes in the network constitute a cycle. As no resource management is considered, a generated cycle is used to redirect flow from one path to another and contribute to the selection of design variables simultaneously. Neighborhood moves proceed by redirecting flow around cycles, and closing and opening design arcs accordingly. [Ghamlouche et al., 2004] later enhance the approach of [Ghamlouche et al., 2003] by combining the cycle-based neighborhood structure and the mechanism of path-relinking, introduced by [Glover, 1997]. Promising attributes of a set of elite solutions (called the reference set) are used to guide the local search (as well as the intensification and diversification).

[Pedersen et al., 2009] study more generic service network design models in which the resource balance constraints are considered. A multi-start metaheuristic, based on tabu search, is developed and tested. With respect to the resource balance constraints, infeasible solutions (with unbalanced resource) are allowed in the exploration phase. Arc-add moves are therefore included to restore the balance of resource and to lead the search towards feasible solutions. [Vu et al., 2013] and [Chouman and Crainic, 2014] in their proposed solution approaches, also allow infeasible solution and have an additional procedure to restore the feasibility with respect to the design-balance constraints. Various mechanisms within a guided local search framework to solve the design-balanced SND problems are investigated by [Bai et al., 2012]. Compared with [Pedersen et al., 2009], the proposed tabu assisted local search approaches obtain solutions of the same quality, with a reduction of 30% in the computational time. [Chouman and Crainic, 2014] propose a matheuristic for the design-balanced SND problems. In the proposed algorithm, a cutting-plane procedure is applied to compute the lower bounds. Memories on characteristics of promising solutions are built when tightening the lower bounds and are used in a variable-fixing heuristic to reduce the size of the problem by fixing a number of design variables. After an extensive computational study, the authors point out that appropriate learning mechanisms and variable-fixing techniques are able to identify high quality solutions rapidly. [Crainic et al., 2014] propose a solution approach that combines column generation, meta-heuristic and exact optimization techniques to their new design-balanced SND model. In the proposed model, the limit on the resources at each terminal is considered.

Exact algorithms can also be found in the literature [Andersen et al., 2011, Meng et al., 2012, Bektaş et al., 2010]. However, as the problems are NP-hard, exact methods reach their limits rather rapidly as the size of the instances grows. It has been proved that solving realistic instances of such planning problems are difficult. For example, [Andersen et al., 2011] study a branch and price method for the design-balance SND problems. Although the proposed algorithm finds solutions of higher quality than the previous methods, the 10-hour computational time required by the algorithm indicates a great challenge for its practical applications. Therefore, the focus of our research in this chapter is not on exact algorithms. For those who are interested in exact algorithms, we refer to [SteadieSeifi et al., 2014] as an overview.

Little effort has been dedicated, however, to solving scheduled service network design problem while simultaneously considering resource management and revenue management. This chapter aims to help fill this gap.

This chapter is organized as follows. In Section IV.3, we recall the statement of the problem and the model of SSND-RRM. Section IV.4 is dedicated to introduce the solution approach, while computational results are presented and analyzed in Section IV.5. We conclude with perspectives in Section IV.6.

IV.3 Problem Statement and Formulation of SSND-RRM

In this section, we first briefly present the tactical planning problem with consideration of resource and revenue management. The formulation of SSND-RRM is then presented.

As described in Chapter III, we first assume the demands $\mathcal{D} = \{d\}$ from customers and services $\mathcal{S} = \{s\}$ offered by carriers follow a repetitive pattern during the middle-term planning horizon (e.g., a season). A scheduled service plan is then built up for a given schedule length (e.g., a week) and then repeatedly operated over the planning horizon to satisfy demands.

We then formulate the SSND-RRM problem on a circular time-space network $\mathcal{G} = (\mathcal{N}, \mathcal{A})$. The node set $\mathcal{N}$ is obtained by duplicating all physical terminals (of rivers, canals, etc.) at all periods in the schedule length T, so that node it corresponds to the physical terminal i at time instant t, $t = 0, \ldots, (T-1)$. The set of arcs $\mathcal{A}$ is composed of two subsets of arcs: holding arcs at terminals and moving arcs performed by services.

Customers are classified, according to their business relationships with the carriers, into three categories, i.e., Regular customers (R), Proportional-punctual customers (P) and Full-punctual customers (F). Accordingly, demands from different customers are treated differently. Demands $\mathcal{D}^R$ requested from regular customers R must always be satisfied, while demands $\mathcal{D}^P$ from P can be partially accepted and demands $\mathcal{D}^F$ from F may either be entirely accepted or not accepted at all. Then, each demand $d \in \mathcal{D} =$

$\mathcal{D}^{\mathrm{R}} \cup \mathcal{D}^{\mathrm{P}} \cup \mathcal{D}^{\mathrm{F}}$ is characterized by: the requested volume $vol(d)$ in TEUs; the origin and destination terminals, $orig(d)$ and $dest(d)$, respectively; the time $in(d)$ it becomes available for transportation at its origin terminal; the last time $out(d)$ it may arrive at its destination terminals; the category $cat(d)$ of customers; the fare class $class(d)$, *slow/normal* or *fast*; and unit fare value $f(d)$.

Vessels $\mathcal{L}$ owned or rented by the carriers are operated for the scheduled services. Each vessel type $l \in \mathcal{L}$ is characterized by: capacity $cap(l)$ in TEUs; and maximum number B_l of vessel type l.

A service $s \in \mathcal{S}$ is thus characterized by: the origin and destination terminals, $orig(s)$ and $dest(s)$, respectively; Ordered set of consecutive stops $\eta(s) = \{i_k(s) \in \mathcal{N}^{\mathrm{ph}}, k = 0, \ldots, (K-1)\}$ of the service, where $K = |\eta(s)|$ and k indicates the k^{th} stop of the service; k^{th} leg $a_k(s) = (i_k(s), i_{k+1}(s))$ of the service; arrival and departure time at and from its terminal $i_k(s)$, $\alpha_k(s)$ and $\tau_k(s)$, respectively; vessel type $l(s)$ of the service; capacity $cap(l(s))$ of the service; and fixed cost $\phi(s)$ of setting up and operating the service.

A set of unit costs are also defined: transportation cost $c_k(\gamma(d), l(s))$ of a container of type $\gamma(d)$, by a vessel of type $l(s)$, on the k^{th} leg of service s; holding cost $c(i, \gamma(d))$ of a container of type $\gamma(d)$ at terminal i for one period; Loading/unloading cost $\kappa(i, \gamma(d))$ of a container of type $\gamma(d)$ at terminal i; Holding cost $h(i, l)$ for a vessel of type l at terminal i for one time period; and penalty $\rho(l)$ for a vessel of type l that is not used in the plan. For an in-depth statement and detailed notation explanation of the problem, we refer to Chapter III.

We now present the formulation of the *scheduled service network design with resource and revenue management* (SSND-RRM) model for the tactical planning of intermodal barge transportation. To avoid repetition, for decision variables defined for the SSND-RRM model and the SSND-RRM model formulation, we refer to Chapter III as well.

IV.4 Solution Approach

To solve the capacitied multicommodity network design (CMND) problems, a conventional methodology adopted in the literature is to consider a CMND problem as two related components: a). determine "optimal" design variables $\overline{\mathcal{Y}}$ (selection of open arcs / services); and then b). for a given feasible design variable vector $\overline{\mathcal{Y}}$, search the optimal flow distribution $\mathcal{X}(\overline{\mathcal{Y}})$. Here, compared to the CMND problems, further complexity is added to the SSND-RRM problem due to, among other factors, the additional decisions on F-demand selection (which are binary decision variables) and resource management (design-balance constraints and limits on the quantity of resource).

As described in Section IV.3, a solution to the SSND-RRM is composed of service selection $y(s)$, vehicle holding $z(l,i,t)$, F-demand selection $\zeta(d)$ and P-demand selection $\xi(d)$, flow distribution vector $\mathcal{X}$, whose components are the decision vectors $x(d,s,k), x^{in}(d,s,k), x^{out}(d,s,k), x^{hold}(d,i,t)$. According to the design-balance constraints (III.10), the decision variables $z(l,i,t)$ are related to $y(s)$ and their values can directly be calculated from the values of $y(s)$. Moreover, the decision variables $\xi(d)$ are continuous and can be determined when the flow distribution problem is solved. Therefore, a SSND-RRM problem can be considered as three components: a). identify promising F-demand selection variables $\overline{\mathcal{F}}$; and then b). for a given vector $\overline{\mathcal{F}}$, search promising design variables $\overline{\mathcal{Y}}$ (service selection); and then c). for given vectors $\overline{\mathcal{F}}$ and $\overline{\mathcal{Y}}$, determine the optimal flow distribution $\mathcal{X}(\overline{\mathcal{F}}, \overline{\mathcal{Y}})$. The motivation of considering SSND-RRM as a sequence of three successive components is that by fixing some parts of the solution, one may work on some other part of the solutions. As the service selection and F-demand selection are formulated as binary decision variables and the flow distribution as continuous variables, one of the most difficult challenges to obtain the optimal solution is to identify promising $\overline{\mathcal{F}}$ and $\overline{\mathcal{Y}}$.

Therefore, we propose a metaheuristic (MH) framework that combines adaptive large neighborhood search (ALNS) and Tabu search, and utilizes long- and short-term memory structures for addressing the SSND-RRM. The intuition of the proposed MH is to improve the solutions by iteratively exploring the search space of F-demand selection, service selection or the combination of both. The mechanism of choosing the search space on which to concentrate is inspired by a modified ALNS strategy. To be more precise, to explore the search space of service selection, a set of *$\mathcal{Y}$-selection heuristics* are introduced. New neighborhood structures considering the design-balance constraints are proposed to accelerate the search. The proposed neighborhood structures are based on a concept of *service cycle*, which is a set of consecutive services using the same type of resource/vehicle, and going back to the same terminal where the first service starts, with or without vehicle holding arcs. Meanwhile, to explore the search space of F-demand selection, a set of *$\mathcal{F}$-selection heuristics* are introduced. Moreover, as the first two components of SSND-RRM are not independent, these two sets of heuristics are also able to be combined to explore the integrated search space of both F-demand selection and service selection. Short-term memory is maintained to record the performance of each heuristic, whereas long-term memory (called trajectory lists in this chapter) is maintained to record the influence of each F demand and service on the solutions. Short-term memory tabu lists are also maintained to prevent repeatedly visiting a particular set of solutions.

The overview of the proposed MH is illustrated in Algorithm 1. The number next to each step indicates the corresponding section where the step is discussed. As shown, the proposed MH consists of two main phases. We first obtain an initial solution by applying a constructive heuristic, and then improve the obtained solutions by iteratively exploring the search space of service selection, F-demand selection or the combination of both. Phases of intensification and diversification are also included.

1 **Phase 1: Initialization** ▷ Section IV.4.1
2   Solve the relaxed SSND-RRM with all F demands rejected;
3   Round up the selection of services;
4   Rebalance the resources;
5   Restore the feasibility of limit on the resources;
6   Intensification;
7 **Phase 2: Improvement** ▷ Section IV.4.2
8   **while** *stopping criteria are not met* **do**
9   Choose one $\mathcal{F}$-selection heuristic; ▷ Section IV.4.2.2
10   Choose one $\mathcal{Y}$-selection heuristic; ▷ Section IV.4.2.1
11   Set up the candidate list of neighbors;
12   Identify the best neighbor;
13   **if** *the new solution is better than the global best* **then** ▷ Section IV.4.2.3, IV.4.2.4
14   Update trajectory list and reward chosen heuristics; ▷ Section IV.4.2.5
15   Update global best;
16   Set new solution as incumbent;
17   **else if** *the new solution is better than incumbent or not 10% worse than the global best* **then**
18   Update trajectory list and reward chosen heuristics;
19   Set new solution as incumbent;
20   **end**
21   **if** *conditions are met* **then** ▷ SectionIV.4.2.6, IV.4.2.7
22   Conduct intensification and diversification;
23   **end**
24   **end**

Algorithm 1: Overview of the proposed MH

In the first phase, to facilitate the construction, a subset of $\mathcal{Y}$-*selection heuristics* are applied to build up the design variables. Design-balance constraints and limit on the quantity of resources are guaranteed by the procedures indicated at line 4 and 5, respectively. In the second phase, an attempt is made to improve the solutions by applying the proposed $\mathcal{F}$-*selection heuristics* and $\mathcal{Y}$-*selection heuristics* according to tabu search and a modified Adaptive Large Neighborhood Search (ALNS) strategy inspired by [Ropke and Pisinger, 2006]. Short-term memory tabu lists are maintained to prevent repeatedly visiting a particular set of solutions (see Section IV.4.2.8), and the modified ALNS strategy (see Section IV.4.2.3 and IV.4.2.4) is used to guide the search in different directions with different neighborhoods. In each iteration, we first choose one $\mathcal{F}$*-selection heuristic*, and then one $\mathcal{Y}$*-selection heuristic*. As the neighborhoods applied in this chapter are very large, a list of promising neighbors, called *candidate list of neighbors*, are generated to accelerate the search. The iterative exploration continues until the global stopping criteria are met. As no infeasible solution is allowed in the second phase, to escape from a local optimal, moves that worsen the solutions are also accepted. A procedure is applied to diversify the incumbent solution when predefined number of consecutive no-feasible-neighbors situation is met (see Section IV.4.2.6). When predefined number of no-global-improvement situation is encountered, another procedure is applied to intensify the current global best solution by addressing the corresponding reduced-size problems with a commercial MILP solver (see Section IV.4.2.7). Long-term memory, i.e., *trajectory F list* and *trajectory service list* (explained in Section IV.4.2.5), is maintained to record the influence of each F demand and service on the solutions, respectively

IV.4.1 Initialization

As the proposed SSND-RRM is NP-hard, we first propose an *initialization phase* to efficiently obtain an initial feasible solution *sol*, which will be used to start the *improvement phase*.

To obtain *sol*, the first step is to solve the *relaxed SSND-RRM* with all F demands rejected. The reason to reject all F demands is that as $\zeta(d)$ are binary variables, fixing the values of all $\zeta(d)$ can reduce the dimension of the optimization problem. According to the solution to the *relaxed SSND-RRM*, in the second step, we round up the selection of services. More precisely, if no flow is found on any leg of a service s, we set $y(s)$ to 0; otherwise, it is set to 1. In the third step, the indegree $\sum\limits_{s \in S^-_{itl}} y(s) + z(l, i, t-1)$ and outdegree $\sum\limits_{s \in S^+_{itl}} y(s) + z(l, i, t)$ of each node (i, t) in the time-space network for each type of vehicle are calculated to verify the balance of resources. If unbalance is found, we first eliminate the unbalanced nodes among the same terminals by adding vehicle holding arcs. If there are still some unbalanced nodes from different terminals, we then open extra services to connect the unbalanced nodes until all nodes are balanced. Note that, after the second and third steps, constraints III.11 may be violated, which indicates that the limit on the quantity of resources may be exceeded. In such a case, a specific step, is conducted to restore the feasibility of the resource limit, as illustrated in Algorithm 2. Only three basic $\mathcal{Y}$*-selection heuristics*, i.e., *drop one service cycle*, *replace large with small service cycle* and *replace small with large service cycle*, are applied in this algorithm. The first heuristic is chosen to reduce the number of planned resources, while the last two are chosen

while *constraints III.11 are still violated* **do**
  Randomly choose one $\mathcal{Y}$-*selection heuristic*;
  Modify $\overline{\mathcal{Y}}$ accordingly;
  Fix $\overline{\mathcal{Y}}$ and $\overline{\mathcal{F}^0}$ (all $\zeta(d) = 0$);
  Solve the flow distribution problem without constraint III.11;
end

Algorithm 2: Restore the feasibility of the limit on resources

to balance the numbers of different kinds of resources and contribute to diversifying the solution. The three heuristics are selected, from the proposed eight $\mathcal{Y}$-*selection heuristics*, for this step in the interest of simple and fast reduction of the number of open design variables. In addition, all the three heuristics have the same probabilities to be chosen in Algorithm 2. The detailed explanation of the three heuristics, among others, are introduced in Section IV.4.2. A valid selection of design variables $\overline{\mathcal{Y}}$ for the SSND-RRM is supposed to be obtained after this step.

IV.4.2 Improvement

Given an initial solution, in this phase, we try to iteratively improve the solutions by exploring in the search space of service selection, F-demand selection and the combination of both, according to tabu search and a modified Adaptive Large Neighborhood Search (ALNS) strategy. To explore the search space of F-demand selection and service selection, seven $\mathcal{F}$-*selection heuristics* and eight $\mathcal{Y}$-*selection heuristics* are introduced, respectively. The iterative exploration continues until the global stopping criteria are met. In each iteration, we first choose one $\mathcal{F}$-*selection heuristic*. One $\mathcal{Y}$-*selection heuristic* is then chosen from a predefined associated set of $\mathcal{Y}$-*selection heuristics*. To be more precise, the proposed $\mathcal{F}$-*selection heuristics* can be briefly classified into two categories: *reject accepted F demands* and *accept extra F demands*. As the intuitions of *reject accepted F demands* and *accept extra F demands* are not the same, not all $\mathcal{Y}$-*selection heuristics* are of equal interest according to a given $\mathcal{F}$-*selection heuristic*. The set of $\mathcal{Y}$-*selection heuristics* associated to each $\mathcal{F}$-*selection heuristic* is discussed later in this section and presented in Table IV.3. According to the selected heuristics, if changes have to be made on both $\overline{\mathcal{F}}$ and $\overline{\mathcal{Y}}$, we explore the integrated search space of both F-demand selection and service selection. Otherwise, if the chosen $\mathcal{F}$-*selection heuristic* is "*change no* $\overline{\mathcal{F}}$", we explore the search space of service selection; or if the chosen $\mathcal{Y}$-*selection heuristic* is "*change no* $\overline{\mathcal{Y}}$", we explore the search space of F-demand selection. The selection among all heuristics is guided by a modified ALNS strategy depending on the historical performance of each heuristic.

As the applied neighborhoods are very large and not all neighbors are of equal interest, according to the chosen $\mathcal{Y}$*-selection heuristic*, we generate a candidate list of neighbors by limiting the number of service cycles generated. Each neighbor in the list is then evaluated by solving the corresponding flow distribution problem with fixed $\overline{\mathcal{F}}$ and $\overline{\mathcal{Y}}$, and the "best" neighbor is chosen as the new solution. In each iteration, if the new solution is better than the global best, update the global best and set it as the incumbent; if the new solution is not better than the global best, but better than the incumbent or not 10% worse than the global best, set it as the incumbent solution, then continue. Note that, it is possible that all neighbors in the list have no feasible solution during the procedure. When this happens, we keep the incumbent solution and proceed to the next iteration. As no infeasible solution is allowed in the this phase, to escape from a local optimal, moves that worsen the solutions are also accepted and diversification is applied when necessary (see Section IV.4.2.6). Learning mechanisms are embedded to guide the search by identifying good characteristics/attributes of solutions, i.e., promising service and F-demand selection. Intensification is also included by addressing the corresponding reduced-size problems with a commercial MILP solver (see Ssection IV.4.2.7).

In the following of Section IV.4.2, we first introduce the proposed $\mathcal{F}$*-selection heuristics* and $\mathcal{Y}$*-selection heuristics*. Consequently, the modified ALNS is discussed, following with learning mechanism. The diversification and intensification are then introduced.

IV.4.2.1 $\mathcal{Y}$*-selection Heuristics*

The set of proposed $\mathcal{Y}$*-selection heuristics* is composed of eight competing heuristics. Without considering the $\mathcal{F}$*-selection heuristics*, all the $\mathcal{Y}$*-selection heuristics* explore the search space of service selection. One basic neighborhood move to search the space of design variables of CMND problems is defined by changing one, or sometimes two decision variables at a time. However, [Ghamlouche et al., 2003], in their study, point out that this conventional neighborhood move is not efficient to solve the CMND problems. They justify that changing one arc in the network at a time has limited impact and generally results in equivalent solutions. Therefore, they propose cycle-based neighborhoods, in which a set of design variables are changed at a time to accelerate the search. However, design-balance constrains are not considered in their study and the cycle-based neighborhoods are proposed from the perspective of redirecting the flow, not resource management. [Pedersen et al., 2009], in their study, consider resource management by introducing the design-balance constraints, and propose a tabu search metaheuristic framework for the arc-based formulation. The proposed metaheuristic first explores the search space of design variables by dropping or adding arcs. Infeasible solutions, with respect to design-

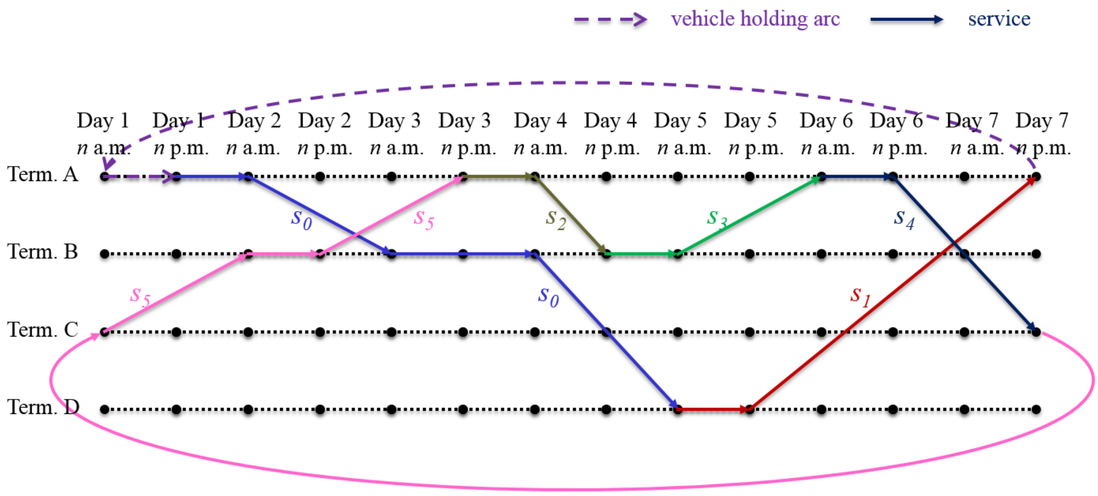

Figure IV.1: An example of service cycles

balance constraints, are allowed in the exploration phase. A post-phase is then conducted to reconstruct a feasible solution from by rebalancing the resources. [Vu et al., 2013] in their proposed three-phase matheuristic also apply an additional phase to restore feasibility, with respect to the design-balance constraints. Indeed, allowing infeasible solutions helps to diversify the search and to escape from local optimal. Conducting an additional phase to rebalance the resources, however, is time consuming and sometimes degenerates the solutions, in terms of objective-function values.

Therefore, in this chapter, we propose a new neighborhood structure in which the design-balance constraints are considered. As to our knowledge, no such neighborhood structure exists in the literature. The proposed neighborhood structure is based on a "new" concept of *service cycles*. A *service cycle* is a set of consecutive services using the same type of resource/vehicle, and going back to the same terminal where the first service starts, with or without vehicle holding arcs. Figure IV.1 illustrate a valid design of services with resource management. Two service cycles can be identified in Figure IV.1. The first one is composed of s_0, s_1 and two holding arcs (presented as dashed arcs), and the second one is composed of four services (from s_2 to s_5) without holding arcs. Note that, all nodes in the time-space network related to a given service cycle are resource balanced. Therefore, moves based on service cycles always ensure the design-balance constraints. The basic idea of add/drop/swap is the intuitive scheme to define moves around service cycles. Consequently, service cycles could be added, dropped, replaced or improved by swapping a subset of services in the cycles. The motivation of exploring around service cycles is twofold: First, to ensure the design-balance constraints; Second, to explore the search space more efficiently by changing one set of services at a time.

To search in *service-cycle-based* neighborhoods, the first step is to identify service cycles. However, a solution to a problem of realistic size may involve a huge number of service cycles. The enumeration of all possible service cycles and the exhaustive exploration are not practical for most situations. Moreover, not all service cycles are of equal interest for different purposes. For example, in order to decrease the total transport capacity by dropping a service cycle, there is a higher possibility to find a better solution by dropping a service cycle with the lowest capacity usage than dropping the cycle featuring the highest capacity usage. Thus the specific way, a candidate list of promising neighbors is determined, will be presented later in this section.

Before describing the eight $\mathcal{Y}$*-selection heuristics*, we first introduce how *service cycles* are identified.

IV.4.2.1.1 Identify service cycles To identify a service cycle, we apply an adapted labeling algorithm (shortest-path like). Let $\mathcal{G} = (\mathcal{N}, \mathcal{A})$ be a graph where N is the set of all nodes and $\mathcal{A}$ is the set of all arcs in $\mathcal{G}$. Here, $\mathfrak{n} \in \mathcal{N}$ represents a node, while $(\mathfrak{i}, \mathfrak{j}) \in \mathcal{A}$ represents an arc when $\mathfrak{i}, \mathfrak{j} \in \mathcal{N}$, and $dis\_a(\mathfrak{i}, \mathfrak{j})$ is the length of arc $(\mathfrak{i}, \mathfrak{j})$. Let $path(\mathfrak{i}, \mathfrak{j})$ represent the set of arcs leading the path from node $\mathfrak{i}$ to node $\mathfrak{j}$, and the length of path from node $\mathfrak{i}$ to node $\mathfrak{j}$ is denoted by $Dis\_n(\mathfrak{i}, \mathfrak{j})$. Given a start node and an end node $\mathfrak{o}, \mathfrak{d} \in \mathcal{N}$, the labeling algorithm used to generate the shortest path from $\mathfrak{o}$ to $\mathfrak{d}$ is presented in Algorithm 3.

Set $\mathfrak{o}$ as the current node $\mathfrak{n}_\mathfrak{c}$;
for *each node* $\mathfrak{n} \in \mathcal{N}$ **do**
    Set $Dis\_n(\mathfrak{n}_\mathfrak{c}, \mathfrak{n}) = +\infty$;
end
marker:
for *each arc* $(\mathfrak{n}_\mathfrak{c}, \mathfrak{i}), \mathfrak{i} \in \mathcal{N}$ *and* $(\mathfrak{n}_\mathfrak{c}, \mathfrak{i}) \notin path(\mathfrak{o}, \mathfrak{n}_\mathfrak{c})$ **do**
    if $Dis\_n(\mathfrak{o}, \mathfrak{n}_\mathfrak{c}) + dis\_a(\mathfrak{n}_\mathfrak{c}, \mathfrak{i}) < Dis\_n(\mathfrak{o}, \mathfrak{i})$ **then**
        $Dis\_n(\mathfrak{o}, \mathfrak{i}) = Dis\_n(\mathfrak{o}, \mathfrak{n}_\mathfrak{c}) + dis\_a(\mathfrak{n}_\mathfrak{c}, \mathfrak{i})$;
        Update $path(\mathfrak{o}, \mathfrak{i})$;
    end
end
Find the current smallest $Dis\_n(\mathfrak{o}, \mathfrak{j})$;
if $\mathfrak{j} == \mathfrak{d}$ **then**
    The "shortest" path from $\mathfrak{o}$ to $\mathfrak{d}$ is found;
else
    Set $\mathfrak{j}$ as the current $\mathfrak{n}_\mathfrak{c}$;
    Goto marker;
end

Algorithm 3: Adapted labeling algorithm

In our problem setting, $\mathcal{N}$ is the set of all nodes in the time-space network, and therefore a node $\mathfrak{n}(i, t)$ in the time-space network is presented by its corresponding physical terminal i and time instant t; while $\mathcal{A}$ is composed of services and vehicle holding arcs.

The "length" of each arc (a service or a vehicle holding arc) is defined by its corresponding *estimated contribution*, which is explained later in this section.

To identify a service cycle by applying the adapted labeling algorithm, we follow the procedure illustrated in Algorithm 4. First, we define the "length" of each arc according to the chosen $\mathcal{Y}$*-selection heuristic*. As shown in Table IV.1, *average capacity usage*, *average residual capacity* or *estimated profit* is defined as the "length", or *estimated contribution*, of each arc, according to the category of decrease capacity, increase capacity or other, respectively. *Average capacity usage* of a service s, $cap\_usage(s)$, is calculated according to equation (IV.7). For a vehicle holding arc decision variable $z(l,i,t)$, the average capacity usage is 0, if $z(l,i,t) > 0$ according to the current solution; otherwise, it is 1. Furthermore, the *average residual capacity* $residual\_usage(s)$ is calculated according to equation (IV.1).

$$residual\_usage(s) = 1 - cap\_usage(s); \tag{IV.1}$$

The *estimated profit* of a service s, $profit(s)$, is calculated according to equation (IV.2), in which the first term is the estimated revenue of s and the following three terms are fixed costs, transport costs and handling costs, respectively. Note that, to calculate the estimated revenue of s serving d, the transport volume of d and transport distance are considered. For a vehicle holding arc decision variable $z(l,i,t)$, the *estimated profit* is $-h(i,l)$, if $z(l,i,t) > 0$; otherwise, $(T-1)h(i,l)$. Further explanation can also be found in the description of each neighborhood.

$$\begin{aligned} profit(s) = & \sum_{k\in\eta(s)}\sum_{d\in\mathcal{D}} f(d)x(d,s,k)\frac{dis(k)}{dis(orig(d),dest(d))} \\ & - \phi(s) - \sum_{k\in\eta(s)}\sum_{d\in\mathcal{D}} c_k(\gamma(d),l(s))x(d,s,k) \\ & - \sum_{k\in\eta(s)}\sum_{d\in\mathcal{D}} \kappa(i,\gamma(d))(x^{in}(d,s,k)+x^{out}(d,s,k)) \end{aligned} \tag{IV.2}$$

After defining the length of each arc, we then identify a pair of $\mathfrak{o}$ and $\mathfrak{d}$ in the time-space network. These two nodes are identified by selecting a start arc, i.e., a service s. According to the selected s, the end node $(dest(s),\tau_{K-1}(s))$ and start node $(orig(s),\alpha_0(s))$ of s are set as $\mathfrak{o}$ and $\mathfrak{d}$, respectively. After identifying $\mathfrak{o}$ and $\mathfrak{d}$, we apply Algorithm 3 to identify the shortest path from $\mathfrak{o}$ to $\mathfrak{d}$. The start arc s and all arcs (services and holding arcs) of the shortest $path(\mathfrak{o},\mathfrak{d})$ then constitute the service cycle.

An identified service cycle, consequently, is dropped, replaced or improved by swapping one or a subset of services in the cycle according to different $\mathcal{Y}$*-selection heuristics*. For a given solution, the number of all possible service cycles is large, because the number of services is large and one service can be used to construct different service cycles.

Define the length of each arc (service and vehicle holding arc);
Select a start arc (service s);
Set end node $(dest(s), \tau_{K-1}(s))$ and start node $(orig(s), \alpha_0(s))$ of s as $\mathfrak{o}$ and $\mathfrak{d}$, respectively;
Identify the shortest path from $\mathfrak{o}$ to $\mathfrak{d}$; ▷ Algorithm 3
Construct the service cycle;

Algorithm 4: Identify a service cycle in time-space network

Table IV.1: Definition of estimated contribution of arcs to each $\mathcal{Y}$-*selection heuristic*

Section	Category	$\mathcal{Y}$-*selection heuristic*	Estimated contribution
IV.4.2.1.2	Decrease capacity	Drop a service cycle	Average capacity usage
IV.4.2.1.3		Replace large with small service cycle	
IV.4.2.1.6		Integrate two service cycles	
IV.4.2.1.4	Increase capacity	Replace small with large service cycle	Average residual capacity
IV.4.2.1.7		Split one service cycle	
IV.4.2.1.5	Other	Improve one service cycle	Estimated profit
IV.4.2.1.8		Add service cycles	
IV.4.2.1.9	Fake	Change no $\overline{\mathcal{Y}}$	NA

Moreover, not all service cycles are of equal interest. Therefore, for each $\mathcal{Y}$-*selection heuristic*, only a set of promising service cycles are generated to limit the search. We identify the promising service cycles by specifying a set of start arcs (services), which have interesting characteristics. Each start arc are then used to generate only one service cycle by applying Algorithm 3. Selected start arcs with interesting characteristics for each $\mathcal{Y}$-*selection heuristic* are presented in Table IV.2. To be more precise, for those $\mathcal{Y}$-*selection heuristics* belonging to the category "decrease capacity", lowest capacity usage is an interesting characteristic for selecting service. On the contrary, for those $\mathcal{Y}$-*selection heuristics* belonging to the category "increase capacity", highest capacity usage is an interesting characteristic. For heuristic *improve one service cycle*, least estimated profit is an interesting characteristic. Moreover, least estimated profit and lowest influence are the interesting characteristics for all $\mathcal{Y}$-*selection heuristics* mentioned. Note that, in addition to start arcs with interesting characteristics, randomly selected start arcs are also applied for all $\mathcal{Y}$-*selection heuristic* to enrich and diversify the search. In Table IV.2, two $\mathcal{Y}$-*selection heuristics*, i.e., *Change no* $\overline{\mathcal{Y}}$ and *add service cycles* are not included. The first one is not presented in the Table, because it is a fake heuristic and nothing needs to be done. The second one is not presented, because different start arcs are applied. Details of the start arcs to *add service cycles* are discussed in its corresponding section.

To set up the candidate list of promising neighbors, we follow the procedure illustrated in Algorithm 5. After generating the set of promising service cycles, a set of neighbors is defined for each identified service cycle. Even with limited number of service cycles,

Table IV.2: Start arcs with interesting characteristics to each $\mathcal{Y}$*-selection heuristic*

Section	$\mathcal{Y}$*-selection heuristic*	Start arcs
IV.4.2.1.2	Drop a service cycle	Service with lowest capacity usage (small & large)
IV.4.2.1.3	Replace large with small service cycle	Service with lowest capacity usage (large vehicle)
IV.4.2.1.4	Replace small with large service cycle	Service with highest capacity usage (small vehicle)
IV.4.2.1.5	Improve one service cycle	Service with least estimated profit
IV.4.2.1.6	Integrate two service cycles	Service with lowest capacity usage
IV.4.2.1.7	Split one service cycle	Service with highest capacity usage
All above	All above	Service with least estimated profit Service with lowest *influence* in the trajectory list Service chosen randomly

the complete evaluation of all possible neighbors rapidly becomes computationally demanding, as the number of neighbors is still huge. To simplify and accelerate the search, for each service cycle, we keep evaluating its neighbors until the very first neighbor with improvement is identified. This neighbor is considered as the candidate proposed by the corresponding service cycle. Therefore, the candidate list of promising neighbors are determined for a given $\mathcal{Y}$*-selection heuristic*.

```
for each specified start arc do
    Generate a service cycle;                                  ▷ Algorithm 4
end
A set of promising service cycle are identified;
for each identified promising service cycle S^c do
    Identify a set of neighbors;                ▷ see each Y-selection heuristic
    for each neighbor do
        Evaluate this neighbor;
        if improvement is found on the incumbent then
            Update the local best neighbor;
            Break;
        else
            Update the local best neighbor;
        end
    end
    if a local best neighbor is found then
        Set this neighbor as the promising neighbor for S^c;
    else
        No promising neighbor is identified for S^c;
    end
end
A candidate list of promising neighbors are determined;
```

Algorithm 5: Set up the candidate list of promising neighbors

In the following of Section IV.4.2.1, we introduce the proposed eight $\mathcal{Y}$*-selection heuristics*.

IV.4.2.1.2 Drop one service cycle The move of this heuristic is defined by dropping a service cycle from the incumbent solution. It attempts to improve the solution by reducing the total transport capacity. If dropping a service cycle could improve the solutions, it implies that the total transport capacity is sufficient, or even more than necessary. Therefore, the low-capacity-usage service cycles are more interesting than others. As illustrated in Table IV.1, the estimated contribution of each arc is consequently defined as the average capacity usage. Promising service cycles are generated with specified start arcs, which are presented in Table IV.2. According to the definition of the neighborhood move, there is only one neighbor for each identified service cycle.

IV.4.2.1.3 Replace large with small service cycle The move of this heuristic is defined by replacing a large-vehicle service cycle $\mathcal{S}'$ with a small-vehicle service cycle $\overline{\mathcal{S}}$. In addition to reducing the total transport capacity, this heuristic also contributes to diversifying the search. According to Algorithm 5 (line 6), for a given large-vehicle service cycle $\mathcal{S}'$, we identify a set of neighbors following the procedure illustrated in Algorithm 6. To be more precise, for each service s' in $\mathcal{S}'$, a corresponding alternative list $\mathcal{S}^*$ is generated. A related s^* of s' is characterized from three aspects: first, s^* is a service using small vehicle; second, s^* has the same start and end terminal as s'; last, both start time and end time of s^* are no more than ± 1 time period away from those of s'. By choosing one service for each $s' \in S'$ from its corresponding alternative list, we obtain a possible $\overline{\mathcal{S}}$. Therefore, all the possible $\overline{\mathcal{S}}$ are generated by the enumeration of all service-selecting combinations from the alternative lists. These possible $\overline{\mathcal{S}}$ are then sorted decreasingly according to the sum of *influence* of each $s^* \in \overline{\mathcal{S}}$, according to the *trajectory service list*. To evaluate an $\overline{\mathcal{S}}$, we calculate the estimated revenue of it by restoring the flow of $\mathcal{D}'$,

for *each* $s' \in \mathcal{S}'$ **do**
    for *each* <u>*related* s^*</u> *of* s' **do**
        if $s^* \neq 1$ *in* $\overline{\mathcal{Y}}$ **then**
            s^* is considered as a possible alternative of s';
        end
    end
end
Enumerate all the possible $\overline{\mathcal{S}}$ by choosing one service for each $s' \in \mathcal{S}'$ from its corresponding alternative list;

Algorithm 6: Identify a set of neighbors for a given $\mathcal{S}'$ (Replace large with small)

which is transported by S' in the current solution. A basic greedy algorithm is applied to calculate the estimated revenue of $\overline{\mathcal{S}}$: sort all $d \in \mathcal{D}'$ decreasingly according to their revenue; for each $d \in \mathcal{D}'$, if $\overline{\mathcal{S}}$ and the residual capacity of the network without S' is able to serve it, update the flow distribution plan accordingly and the estimated revenue of $\overline{\mathcal{S}}$.

After evaluating all possible $\overline{\mathcal{S}}$, if no $\overline{\mathcal{S}}$ is able to restore the whole flow of $\mathcal{D}'$, the small-vehicle service cycle with the highest estimated revenue is chosen to define the promising neighbor for S'. During the evaluation of all possible $\overline{\mathcal{S}}$, if one small-vehicle service cycle is identified to be able to restore the whole flow of $\mathcal{D}'$, stop the evaluation procedure and use this small-vehicle service cycle to define the promising neighbor for S'.

IV.4.2.1.4 Replace small with large service cycle The move of this heuristic is defined by replacing a small-vehicle service cycle $\mathcal{S}'$ with a large-vehicle service cycle $\overline{\mathcal{S}}$. The motivations behind this move are threefold: first, it increases the total transport capacity, therefore, the profitable demands which are denied in the current solution can be accepted to increase the total profit; second, it offers more possibilities for the selection of Fs and Ps, and the flow distribution as well; third, it also contributes to diversifying the search. As illustrated in Table IV.1, the estimated contribution of each arc is defined as the average capacity usage, which means we are identifying small-vehicle service cycles with highest capacity usage and then replace them with large-vehicle service cycles. Note that, the presented heuristic proceeds as the previous one except for two things: first, the choice of vehicle types is the opposite, which means replace a small-vehicle service cycle with large one; second, when calculate the estimated revenue of each possible $\overline{\mathcal{S}}$, a set of extra F demands selected by *$\mathcal{F}$-selection heuristics*, if necessary, should also be considered.

IV.4.2.1.5 Improve one service cycle The move of this heuristic is defined to improve a service cycle S' by swapping one service in S'. It has the potential to improve the flow distribution and the selection of F and P demands. With respect to the adapted labeling algorithm for identifying interesting service cycles, the estimated contribution of each arc is the estimated profit. Therefore, the neighborhood move can be interpreted as identifying a service cycle with the lowest total estimated profit and improving the solution by changing one service in the cycle. For a given service cycle $\mathcal{S}^c$, to identify a set of neighbors and evaluate these neighbors, we follow the procedure illustrated in Algorithm 7. For a given service cycle $\mathcal{S}'$, we first sort all services increasingly in the cycle with respect to the estimated profit. For each $s' \in \mathcal{S}'$, an alternative list $\mathcal{S}^*$ of s' is then identified, following the same rules described in the previous Section IV.4.2.1.3, but with the same type of vehicle. Before choosing the next s' and generate the corresponding alternative list, we calculate the estimated revenue of each $s^* \in \mathcal{S}^*$ earned by restoring the flow of $\mathcal{D}'$ transported by s' and extra F demands, if necessary. Only s^* with the highest estimated revenue is evaluated by solving the flow distribution problem. If a better solution than the incumbent one is found, stop exploring around $\mathcal{S}'$; otherwise, continue.

Sort all $s' \in \mathcal{S}'$;
for *each* $s' \in \mathcal{S}'$ **do**
    Identify an alternative list $\mathcal{S}^*$ of s';
    for *each* $s^* \in \mathcal{S}^*$ **do**
        Calculate the estimated revenue of s^*;
    end
    Evaluate only the s^* with the highest estimated revenue;
    if *improvement is found on the solution* **then**
        promising neighbor of $\mathcal{S}'$ is identified;
        break;
    end
end

Algorithm 7: Identify and evaluate neighbors (improve one service cycle)

IV.4.2.1.6 Integrate two service cycles The move of this heuristic is defined by integrating two service cycles into one. The intuition of this searching direction is to get rid of the redundant services, to improve the selection of F and P demands, and the flow distribution. Let us consider a physical network of three terminals A, B and C, and 4 services transporting from A to B, from B to A, from B to C and from C to B, respectively. The first two services constitute a service cycle and the last two constitute another service cycle. To integrate those two service cycles into one, for instance, the services transporting from C to B and from B to A could be replaced by a service transporting from C to A, with or without B as an intermediate stop. Therefore, integrating two services cycles into one is able to be considered as integrating two services into one. Consequently, the move of this heuristic is interpreted as integrating two services in a service cycle into one service. With respect to the labeling algorithm, the estimated contribution of each arc in this neighborhood is defined as the average capacity usage. Given an identified service cycle composed of s_1, s_2 and s_3, instead of generating the alternative list for each service, we generate alternative lists for $s_1 + s_2$, $s_2 + s_3$ and $s_3 + s_1$, respectively. An alternative s^* for particular two services, e.g., $s_1 + s_2$, must use the same type of vehicle as s_1 and s_2, and is selected according to the start node of s_1 and the end node of s_2. Moreover, if s_1 is the start arc when the service cycle is identified, the order to explore the alternative lists is first $s_1 + s_2$, then $s_2 + s_3$ and last $s_3 + s_1$. The same procedure as Algorithm 7 is applied.

IV.4.2.1.7 Split one service cycle The move of this heuristic is defined by splitting one service cycle into two. It can be considered as the opposite move of the previous heuristic. The validity of this neighborhood move indicates the total transport capacity may not be enough. However, it also has the potential to improve the selection of F and P demands, and the flow distribution. With respect to the labeling algorithm, the average residual capacity is defined as the estimated contribution of each arc. Without repeating all the similarities, in this heuristic, the differences come from how to generate the alternative list and how to identify the candidate for each service cycle. Given a service cycle, we first sort all the services increasingly with respect to the *influence* in trajectory list. The exploration of alternative lists follows that increasing order. For each service in the cycle, to generate the alternative list, two types of replacement could happen: ABC replaced by AB+BC (opposite case of previous heuristic) or AB replaced by AC+CB with extra F demands related to C.

IV.4.2.1.8 Add service cycles The heuristic is defined by adding cycles. It is called after only "profitable acceptance" and "random acceptance" $\mathcal{F}$-selection heuristic. One service cycle, which is made of closed services according to the current $\overline{\mathcal{Y}}$, is generated to transport the new accepted F demands by those two $\mathcal{F}$-selection heuristics. Keep generating service cycles until all new accepted F demands are satisfied. Note that, without serving more new demands, this heuristic is going to degenerate the quality of the solution, in terms of objective value, and that is why this heuristic is only triggered by the *$\mathcal{F}$-selection heuristics* of *profitable acceptance* and *random acceptance*.

IV.4.2.1.9 Change no $\overline{\mathcal{Y}}$ This is a fake *$\mathcal{Y}$-selection heuristic*. When it is chosen, no change is applied on the service selection. In other words, we only explore the search space of F-demand selection. Note that, this fake heuristic is not in the associated set of *change no $\overline{\mathcal{F}}$* heuristic.

IV.4.2.2 *$\mathcal{F}$-selection Heuristics*

The proposed *$\mathcal{F}$-selection heuristics* can be briefly classified into two categories: *reject accepted F demands* and *accept extra F demands*. In addition, a "fake" heuristic, *change no $\overline{\mathcal{F}}$*, is also considered separately. In each iteration, if the *change no $\overline{\mathcal{F}}$* heuristic is chosen, we fix $\overline{\mathcal{F}}$ and explore only in the search space of service selection.

To reject a set of accepted F demands, three heuristics are applied, i.e., *random rejection*, *minimal profit rejection* and *worst record rejection*. All three reject heuristics need an integer $p \in [1, MAX]$ as input, where p indicates the number of accepted F demands to be rejected and MAX stands for the total number of accepted F demands according to the current $\overline{\mathcal{F}}$.

Random rejection: The *random rejection* heuristic simply selects p accepted F demands at random and change their value from 1 to 0 in the current $\overline{\mathcal{F}}$.

Minimal profit rejection: Given a feasible solution to the SSND-RRM, we calculate the estimated profit of each accepted demand $d \in \mathcal{D}^{\mathrm{F}}$ as follows:

$$profit(d) = revenue(d) - cost(d) \tag{IV.3}$$

where $revenue(d)$ is the revenue of accepting whole d, and $cost(d)$ is the estimated total cost of d:

$$revenue(d) = f(d)vol(d) \tag{IV.4}$$

Calculated by equation (IV.5), $cost(d)$ is the sum of transport costs, holding costs, handling costs and total estimated fixed costs, i.e., $estimate(\phi(d))$, of d:

$$\begin{aligned} cost(d) = & \sum_{s\in\mathcal{S}} \sum_{k\in\eta(s)} c_k(\gamma(d), l(s))x(d,s,k) + \sum_{t\in T} \sum_{i\in\mathcal{N}^{\mathrm{ph}}} c(i,\gamma(d))x^{hold}(d,i,t) \\ & + \sum_{s\in\mathcal{S}} \sum_{k\in\eta(s)} \kappa(i,\gamma(d))(x^{in}(d,s,k) + x^{out}(d,s,k)) + estimate(\phi(d)) \end{aligned} \tag{IV.5}$$

where $estimate(\phi(d)) = \sum_{s\in\mathcal{S}} estimate(\phi(s(d)))$ is the total estimated fixed cost that d is supposed to pay for all the services used for the routing of d. To calculate the estimated fixed cost that d is supposed to pay for s, i.e., $estimate(\phi(s(d)))$, we take into account two factors: a). for the used service s, the lower the *capacity usage* of s, the more d should share the fixed cost; b). the more capacity of s used for transporting d, the more d should share the fixed cost. Therefore, $estimate(\phi(s(d)))$ is calculated according:

$$estimate(\phi(s(d))) = \frac{\phi(s)}{cap\_usage(s)} * \frac{\sum\limits_{k\in\eta(s)} x(d,s,k)}{\sum\limits_{k\in\eta(s)} cap(l(s))} \tag{IV.6}$$

where capacity usage $cap\_usage(s)$ of s is calculated as the ratio of *used distance capacity* over the *maximum possible distance capacity* according to the current solution, illustrated in equation (IV.7). *Used distance capacity* is the sum of all legs' used capacity multiplied by their corresponding transport distance $dis(k)$, while *maximum possible distance capacity* is the sum of all legs' capacity multiplied by their corresponding transport distance.

$$cap\_usage(s) = \frac{\sum\limits_{s\in\mathcal{S}} \sum\limits_{k\in\eta(s)} \sum\limits_{d\in\mathcal{D}} dis(k)x(d,s,k)}{\sum\limits_{s\in\mathcal{S}} \sum\limits_{k\in\eta(s)} dis(k)cap(l(s))} \tag{IV.7}$$

All accepted F demands are then sorted in ascending order according to their estimated profit. The first p demands in the list are then rejected and their corresponding values in the $\overline{\mathcal{F}}$ are changed.

Wost-record rejection: As learning mechanism is embedded: the influence of each F demand on the solutions is recorded in a *trajectory F list*. In the *trajectory F list*, each F demand is associated with an *influence*, which is calculated according to the historical performance of that F demand. Details about the *trajectory F list* are discussed in Section IV.4.2.5. Each time, p accepted F demands have to be rejected, all accepted F demands are sorted in an ascending order according to their *influence* in the trajectory list. The first p demands in the list are then rejected and their corresponding values in the $\overline{\mathcal{F}}$ are changed.

Moreover, to accept extra F demands, three heuristics are applied, i.e., *basic greedy acceptance*, *profitable acceptance* and *random acceptance*. For the last one, an integer q is needed to indicate the number of extra accepted F demands. For the first two, however, no such input is required. We now introduce the three accept extra F demands heuristics.

Basic greedy acceptance: The *basic greedy acceptance* heuristic accepts extra F demands according to the residual capacity of the current solution. The selection of extra F demands to be accepted follows the basic greedy algorithm described in Algorithm 8:

```
Sort all non-accepted F demands in descending order, according to their revenue;
for each F demand do
    if residual capacity is able to serve it then
        Accept this F demand;
        Update residual capacity;
    end
end
```

Algorithm 8: Basic greedy algorithm to select accepted F demands

Note that, as the selection of extra accepted F demands depends on the residual capacity of current $\overline{\mathcal{Y}}$, no additional services are needed.

Profitable acceptance: To apply the profitable acceptance heuristic, we first fix $\overline{\mathcal{Y}}$, accept all accepted F demands, and relax the binary decision variables $\zeta(d)$ of all rejected F demands, according to the current solution. An LP solver is then called to solve the "modified" flow distribution problem and obtain a new solution sol'. For each rejected F demand according to $\overline{\mathcal{F}}$, if it has a positive value of $\zeta(d)$ in sol', we change its corresponding value in $\overline{\mathcal{F}}$. Additional services may be needed to satisfy the extra accepted F demands.

Random acceptance: Given the current solution, we are able to identify the port i that has the highest transport requests of all rejected F demands, and the number, M, of total number of rejected F demands around port i. We then give an integer $q \in [1, M]$, randomly select q rejected demands around port i, and change their corresponding values in $\overline{\mathcal{F}}$. Additional services may be needed to satisfy the extra accepted F demands.

In the current implementation of the proposed MH, both p and q are generated randomly. As the intuitions of *reject accepted F demands* and *accept extra F demands* are not the same, not all $\mathcal{Y}$*-selection heuristics* are of equal interest according to a given $\mathcal{F}$*-selection heuristic*. For example, after rejecting p accepted demands, we know that the total transport capacity is sufficient for all the accepted demands. In this case, $\mathcal{Y}$*-selection heuristics*, which intend to increase the total transport capacity, should not be selected and vice versa. Moreover, even $\mathcal{F}$*-selection heuristics* in the same category (rejection or acceptance) are not serving the same purposes. Therefore, for each $\mathcal{F}$*-selection heuristic*, we define an associated set of $\mathcal{Y}$*-selection heuristics*. Each time a $\mathcal{F}$*-selection heuristic* is chosen, only $\mathcal{Y}$*-selection heuristics* in its associated set can be chosen. The association table of $\mathcal{F}$*-selection heuristics* with $\mathcal{Y}$*-selection heuristics* is illustrated as Table IV.3. In the column of "Associated $\mathcal{Y}$-selection heuristics", the number indicates the section, where we present the associated $\mathcal{Y}$-selection heuristics.

Table IV.3: Association table of each $\mathcal{F}$*-selection heuristic* with $\mathcal{Y}$*-selection heuristics*

No.	Category	$\mathcal{F}$-selection heuristic	Associated $\mathcal{Y}$-selection heuristics
1		Random	
2	Reject	Minimal profit	IV.4.2.1.2; IV.4.2.1.3; IV.4.2.1.5; IV.4.2.1.6; IV.4.2.1.9
3		Worst record	
4		Basic greedy	IV.4.2.1.4; IV.4.2.1.5; IV.4.2.1.7; IV.4.2.1.9
5	Accept	Profitable	IV.4.2.1.4; IV.4.2.1.5; IV.4.2.1.7; IV.4.2.1.8
6		Random	IV.4.2.1.4; IV.4.2.1.5; IV.4.2.1.7; IV.4.2.1.8
7	Fake	Change no $\overline{\mathcal{F}}$	all except IV.4.2.1.8 and IV.4.2.1.9

IV.4.2.3 Choosing one $\mathcal{F}$*-selection heuristic* and one $\mathcal{Y}$*-selection heuristic*

The proposed metaheuristic is composed of a number of competing heuristics for both $\mathcal{F}$*-selection* and $\mathcal{Y}$*-selection*. The heuristics are selected by a roulette wheel mechanism based on their historic performance. Each heuristic is associated with a *weight*. Heuristics that have successfully found new improving solutions have a higher weight and therefore a higher probability to be chosen again. Note that, in each iteration, one $\mathcal{F}$*-selection heuristic* and one $\mathcal{Y}$*-selection heuristic* are selected. Both of these two heuristics are rewarded the same, because we do not know whether it is the $\mathcal{F}$*-selection heuristic* or $\mathcal{Y}$*-selection heuristic* that results in the improvement. But the probability of each heuristic to be chosen is calculated in group separately. For each group, either $\mathcal{F}$*-selection* or

$\mathcal{Y}$*-selection*, the probability of a heuristic to be chosen is calculated as follows:

$$p_i = \frac{w_i}{\sum\limits_n w_n} \tag{IV.8}$$

In equation (IV.8), i indicates the selected heuristic and n indicates the total number of heuristics in the given group.

IV.4.2.4 Adaptive weight and score adjustment

The probabilities of all heuristics to be chosen are the same in the beginning. Furthermore, the probabilities are recalculated after each m iterations according to the *weight* of each heuristic, as illustrated in equation (IV.9).

$$w_i = w_i(1-r) + r\frac{score_i}{counter_i} \tag{IV.9}$$

In equation (IV.9) [Ropke and Pisinger, 2006], $score_i$ is the score of each heuristic and $counter_i$ is the number of times that the heuristic i is selected during the last m iterations, and r is a number between 0 and 1. If $r = 0$, we do not change the weight of i; if $r = 1$ the weight of i totally depends on its performance during the last m iterations. Otherwise, the weight of i depends on both its performance during the last m iterations and the performance before.

The initial *score* for each heuristic is 0. Each time we get a new feasible solution, the *score* of the heuristic that results in the new feasible solution is updated as shown in Algorithm 9, in which $objs(opt)$, $objs(incum)$ and $objs(new)$ denotes the objective value of the global best, the incumbent and the new feasible solution, respectively. Note that, each time after recalculating the weight of each heuristic, the score of each heuristic $score_i$ is reset as 0.

if $objs(new) > objs(opt)$ **then**
    $score_i = score_i + 2 * objs(new) - objs(incum) - objs(opt)$;
else if $objs(new) > objs(incum)$ **then**
    $score_i = score_i + objs(new) - objs(incum)$;
end

Algorithm 9: Score the chosen heuristics

IV.4.2.5 Trajectory service list and F list

Trajectory service list and *trajectory F list* are the long-term memory learning mechanism for evaluating the influence of each service or each F demand on the quality of the solutions, respectively. To be more precise, when a new solution sol is found better than then current global best solution sol', we reward each open service and each accepted F demand in sol as

$$reward_{i,j} = \frac{diff(objs)}{card(sol)} \tag{IV.10}$$

where i is the index number of a service or an F demand accordingly, and j indicates the index number of an improvement found on current global best, $diff(objs)$ is the difference between the two objective values, namely $sol - sol'$, and $card(sol)$ is the number of open services for the service list and number of accepted F demands for the F list in sol, respectively. Besides that, the closed services and rejected F demands are rewarded with 0. The influence of a service or an F demand, is then calculated as

$$influence_i = \sum_{j=J-c}^{J} reward_{i,j} \frac{counter_i}{c} \tag{IV.11}$$

where i is the index number of a service or an F demand; j is the index number of an improvement found on the current global best, and J is the total number of improvement; $counter_i$ is the number of i^{th} service/F demand that appear in the last c times of current global best. The influence of i^{th} service/F demand is the sum of its rewards in the last c times multiplied by the ratio of it that appears in the current global best in the last c times. Note that, a reward of a service/F demand is calculated and updated each time an improvement is found on the global best solution.

IV.4.2.6 Diversification

When a predefined number g of consecutive no-feasible-neighbor situation is met, a procedure is conducted to diversify the incumbent solution. The basic idea of diversification is to identify a set of closed "umpromising" services and force them to be open in the new solution, aiming to escape from the current searching area. Based on the current $\overline{\mathcal{Y}}$, among all $y(s) = 0$, we choose the service with the lowest *influence* according to the *trajectory service list*. The chosen service is then used as the start arc of the adapted labeling algorithm to identify a service cycle to add in the incumbent solution. The estimated contribution (or length) of each arc to identify the shortest path is its corresponding *influence* in the *trajectory service list*. After identifying the service cycle, we fix $y(x)$ and $\zeta(d)$, then solve the flow distribution problem and set the new solution as the incumbent for the search procedure.

IV.4.2.7 Intensification

As the exploration in the search space of $\mathcal{Y}$ is around service cycles, a set of services are modified in one move so that the optimal solution maybe missed. In addition, the pace of exploration in the search space of $\mathcal{F}$ is also big. Therefore, it is quite necessary to have this intensification phase in the proposed MH. The goal of this phase is to find better solutions by intensifying the search in regions of the solution space, where interesting characteristics of services are identified.

Given a feasible solution $(\overline{\mathcal{F}}, \overline{\mathcal{Y}}, \mathcal{X}(\overline{\mathcal{F}}, \overline{\mathcal{Y}}))$, two types of intensification are applied in this proposed solution approach. The first type of intensification calls the MILP solver to solve a reduced SSND-RRM problem, in which only open services in $\overline{\mathcal{Y}}$ can be chosen to serve all demands. This type of intensification is called right after the Initialization phase in order to feed the improvement phase with a promising start point. The second type of intensification first identifies a promising service cycle from the closed services according to $\overline{\mathcal{Y}}$ of current global best solution. *Influence* of closed services in the *trajectory service list* is considered to aid identifying the promising service cycle. The MILP solver is then called to choose the best design variables among the open services and the identified service cycle, serving all demands. This type of intensification is called each time a consecutive b times of no-global-improvement situation is encountered. The solution obtained by the intensification is then set as the incumbent for the search procedure.

IV.4.2.8 Tabu Lists

Three short-term memory tabu lists are maintained to record generated service cycles for different purposes. The first one is used for the $\mathcal{Y}$*-selection heuristics*, to avoid the same service cycle to be dropped or replaced. The second one and the third one, is used for diversification and intensification to avoid adding back the same service cycle, respectively. The size of all three tabu lists are set as 30 for now.

IV.5 Computational Results and Analysis

The purpose of this section is to study the effectiveness of the proposed solution approach. After introducing the procedure of test instance generation in Subsection IV.5.1, we calibrate all the parameters applied in the proposed MH in Subsection IV.5.2. Then the performance of the proposed MH is benchmarked, in Subsection IV.5.3, against a commercial MILP solver. Finally, we analyze the solution approach on extensive experiments in order to identify the effectiveness of each algorithmic component in Subsection IV.5.4.

The only considered parameter is r, which indicates how the weight of a heuristic depends on its historical performance, is calibrated based on just one test instance with one repetition. A complete calibration based on a set of test instances with a large number of repetitions for each is under way. In Subsection IV.5.3, we present a preliminary result of only six test instances with one repetition. More test instances, with respect to different physical networks, number of potential services, number of demands, etc., are currently under study. As there are many random elements, each instance will be tested a large number of times with the proposed MH. A more comprehensive analysis will be presented in further work based on the extensive study.

IV.5.1 Test Instance Generation

In this subsection, we present the procedure of test instance generation. Three different topologies, i.e., Linear 4, Star 6 and General 7 as illustrated in Figure IV.2, are studied. From the perspective of supply for the freight transportation system, two types of vehicles (large and small) are considered. Moreover, all possible itineraries in the network are covered by the potential services, using both types of vehicles.

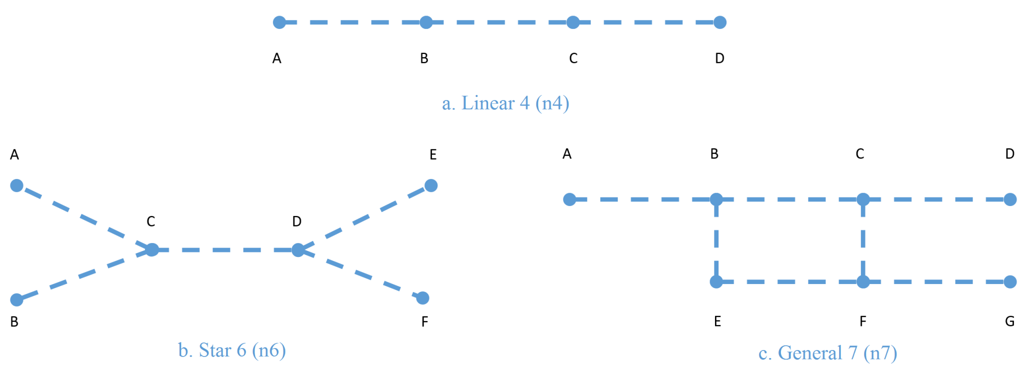

Figure IV.2: Three considered physical network topologies

In terms of demand, all three customer categories are considered (R, P and F). For a given physical network, we indicate the number of demands generated for each possible OD pair in one test instance with f. In addition, the volume of each individual demand is randomly generated, according to uniform distribution, with an upper bound of half of the capacity of a large vehicle. All the other characteristics of a demand are randomly generated according to uniform distribution.

All experiments are performed on a multi-processor server running under Linux 64-bit with an Inter Xeon X5675, 3GHz and 30 GB of RAM. In addition, CPLEX 12.5 is the commercial solver that we used for solving LP and reduced MILP in the proposed MH.

IV.5.2 Calibration

Before launching the extensive computational study to evaluate the proposed MH, we first conduct a small set of experiments to calibrate the parameters used in the proposed solution approach. Test instances used for this set of experiments are generated following the procedure introduced in [Wang et al., 2014] on a physical network of four terminals with a schedule length of 14 Time Units (TUs). Just to recall, all the parameters required to be decided are as follows:

- r: is a number between 0 and 1. It indicates how the weight of a heuristic depends on its historical performance;
- m: indicates the number of iterations, after which the probability of each heuristic to be chosen is recalculated;
- g: indicates the condition for triggering diversification. In the improvement phase, after g consecutive no-feasible-neighbors, we conduct diversification;
- b: indicates the condition for triggering intensification. In the improvement phase, after b consecutive no-global-improvement, we conduct intensification;
- c: indicates the memory length for the trajectory lists, i.e., how many times of performance of a given service (or F demand) should be considered to evaluate its influence on the solution

Four values of r are tested: $r = 0$, 0.1, 0.5 and 1. As described in IV.4.2.4: $r = 0$ indicates that the weight of a given heuristic for calculating the chosen probability is not changed; $r = 1$ indicates that the weight of a given heuristic totally depends on its performance during the last m iterations; $r = 0.5$ is a moderate consideration of both its performance and the current weight; $r = 0.1$ is a value recommended by [Ropke and Pisinger, 2006]. As shown in Figure IV.3, given the same number of iterations, $r = 0.5$ results in the best solution, in terms of the objective value.

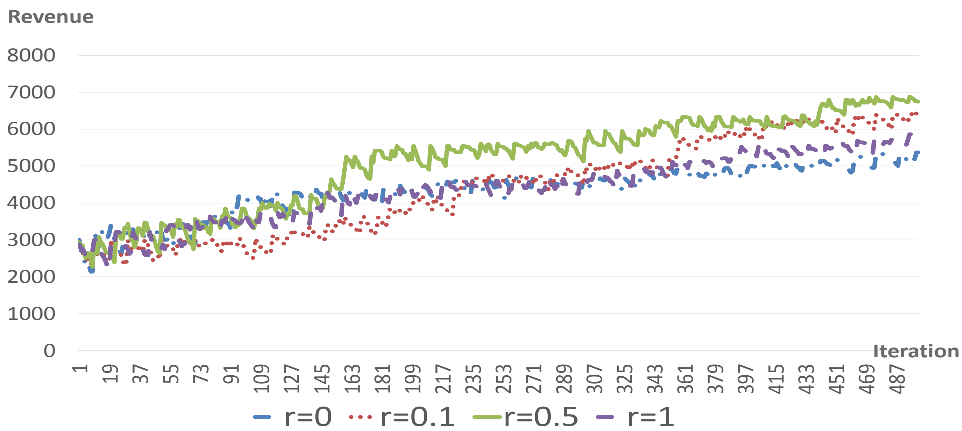

Figure IV.3: Calibration of parameter r

The complete calibration results in the following parameter vector $(r, m, g, b, c) = (0.5, 30, 5, 10, 50)$. We then conduct further computational study with this parameter vector.

IV.5.3 Benchmarking against an MILP Solver

To determine the effectiveness of the proposed MH, experiments of six test instances are conducted. Each test instance is labeled as nfv, where n is the number of terminals, f indicates the quantity of demands, and v is the number of considered vehicle types. To be more precise, three different physical network topologies are tested, i.e., Linear 4, Star 6, and General 7, as shown in Figure IV.2. Given a physical network, we use f to indicate how many demands are generated for each possible OD pair. In our experiments, the number of potential services are 616, 1848 and 4200 for topology of Linear 4, Start 6 and General 7, respectively. Two types of vehicles (large and small) are considered when assigned to services.

As no other solution approach to the SSND-RRM problems exists in the literature, we benchmark the performance of our MH against a commercial MILP solver (CPLEX 12.5) on all test instances. Table IV.4 presents the details of the solutions to all test instances obtained by CPLEX with a maximum computational time of 24 hours. As shown, only the two test instances with four terminals reach optimality within 24 hours. For the other four test instances with bigger physical network and problem size, the optimality of the obtained feasible solutions is not proved. The corresponding values in column *Gap* indicate the quality of the obtained best feasible solutions compared to the upper bounds given by CPLEX (as the objective is to maximize the net revenue). We then run the proposed MH to solve the same set of test instances with time limits of one hour and ten

Table IV.4: Details of the solutions to all test instances obtained by CPLEX after one day

Test instance	Optimal solution obtained or not	Gap
n4f40v2	yes	0%
n4f80v2	yes	0%
n6f5v2	no	0.48%
n6f10v2	no	116.04%
n7f5v2	no	67.56%
n7f10v2	no	50.13%

Table IV.5: Numerical results obtained by the proposed MH with CPLEX as comparison

Test instance	MH 1h/CPLEX 1h (%)	MH 1h/CPLEX 10h (%)	MH 10h/CPLEX 10h (%)
n4f40v2	6.4	6.4	6.4
n4f80v2	7.31	7.31	4.69
n6f5v2	-4.9	4.8	1.8
n6f10v2	-39.5	-0.01	-161.7
n7f5v2	-571.5	15.56	-27.42
n7f10v2	-7.6	14.4	-22.9

hours, respectively. The numerical results obtained by the proposed MH are presented in Table IV.5, with CPLEX as comparison. As shown, we compare solutions obtained by MH in 1 hour with those obtained by CPLEX in 1 hour, solutions obtained by MH in 1 hour with those obtained by CPLEX in 10 hours, and solutions obtained by MH in 10 hours with those obtained by CPLEX in 10 hours. The figures illustrated in the table are calculated as solutions obtained by CPLEX subtract solutions obtained by MH, and then divide by the absolute value of solutions obtained by CPLEX, for each given computational time limit. Therefore, positive numbers indicate that CPLEX obtains better solutions than MH, while negative values indicate that MH performs better.

As shown in Table IV.5, the proposed MH does not reach the optimality as its competitor when tackling problems of relative small size. Nevertheless, the proposed solution approach yields solutions with small gaps (less than 8%) compared to CPLEX. When facing problem of more realistic size, however, the proposed MH is superior to CPLEX. Within the same time limits, i.e., column *MH 1h/CPLEX 1h* and *MH 10h/CPLEX 10h*, better solutions are always obtained by MH. The only exception happens when we compare solutions to test instance $n6f5v2$ obtained by MH and CPLEX in 10 hours, but with a very small gap (1.8%). For test instance $n6f10v2$, MH, in one hour, even obtains a solution better than that obtained by CPLEX in ten hours. In addition, for all other test instances, our solution approach, in one hour, also obtains solutions which have almost the same quality as those obtained by CPLEX in ten hours.

IV.5.4 Analysis of the Impact of Each Algorithmic Component

The promising performance of the proposed MH comes from the new service-cycle-based neighborhood structures, especially when the size of the problem is large. As a set of services are changed in each iteration, searches are prevented from being stuck in a restricted neighborhood. Long-term learning mechanisms (i.e., *trajectory service list* and *trajectory F list*) are applied to identify interesting characteristics of solution components (open services and accepted F demands). When combining this with a phase of intensification, solutions of good quality are then identified efficiently in the reduced region of solution space. During the exploration around the service-cycle-based neighborhoods, short-term memory tabu lists are maintained to prevent searching in restricted neighborhoods. Moreover, given the fact that the SSND-RRM model takes into account the resource management, a separate phase aiming to repair the design-balance constraints is no more necessary benefiting from the service-cycle-based moves.

Note that, as one of the objective of this chapter is to offer the proof-of-concept for the new service-cycle-based neighborhood structure, only low-level heuristics are used to explore the search space of service selection and F-demand selection. In the future, more advanced heuristics and learning mechanism could be adopted to improve the performance of the MH.

Further experiments should also be designed and tested to fine tune all the parameters and precisely identify the influence of each algorithmic component, on the behaviors, trajectories and the overall performance of the proposed MH.

IV.6 Conclusions and Future Work

In this chapter, we propose a new solution approach for the scheduled service network design with resource management and revenue management problem. The proposed solution approach is composed of four phases. In the first phase, a constructive heuristic is proposed to obtain initial solutions to the SSND-RRM. Once an initial solution is obtained from the first phase, we then try to improve the solutions in the second phase by iteratively exploring the search space of service selection, F-demand selection and the combination of both. The selection of search space is based on a modified adaptive large neighborhood search (ALNS) inspired by [Ropke and Pisinger, 2006]. To explore the search space of service selection, eight $\mathcal{Y}$-selection heuristics are proposed based on a service-cycle related neighborhood structure. This service cycle based neighborhood structure allows the changes of a set of services in each iteration and guarantees the design-balance constraints simultaneously. Short-term memory tabu lists are maintained to avoid searching in the same restricted neighborhoods. To explore the search space of F-demand selection, seven F-selection heuristics are proposed and different strategies are considered to accept or reject F demands. Long-term memories are maintained to record the influence of each service and each F demand on the solution, and are then used to identify interesting characteristics of the components of the solutions.

The performance of the metaheuristic is compared with a state-of-the-art solver by solving a set of generated test instances. According to the numerical results, the proposed metaheuristic does not guarantee to find global optimal solutions, however, it can often find good solutions with less computational effort than its competitor, especially when facing problems of realistic scale.

However, research related to this chapter is still in progress. In our future research, a complete calibration of all the parameters will be done. Extensive experiments, in terms of different physical networks, number of potential services, number of demands, etc., are going to be conducted. We shall also examine why the MH does not reach optimality when applied on small problems and how to improve it. One of our guesses is the existence of the symmetric structures in the solution, for example, different services or accepted demands which result in the same objective values. To address this challenge, the concept of column generation could be introduced.

Chapter V

Performance Indicators for Planning Intermodal Barge Transportation Systems

Contents

Various indicators are used to qualify the performance of intermodal transportation systems. Some of these are found in public documents, e.g., annual company reports, usually providing global measures such as total flow volumes, profits, and share values. While of great interest, such measures are not sufficient to support a fine analysis of different operation strategies, commercial policies, and planning methods. A number of additional measures are therefore used in the scientific literature to address these issues. In this chapter, our first goal is to review the performance indicators (PIs) found in public sources and scientific literature, and to qualify them with respect to tactical planning of intermodal barge transportation systems. We extend this analysis to include revenue management policies, e.g., market segmentation and differential pricing, a topic generally neglected in freight transportation. A first classification of these different PIs is proposed and adequate PIs for analyzing the proposed R-DSS are identified for each category. We also discuss procedures to generate problem instances that provide the means to analyze planning methods and system behavior based on these PIs. The proposed R-DSS methodology is then assessed in an integrated simulation framework with the help of a set of PIs.

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V.1 Introduction

Intermodal freight transportation is generally defined as moving cargo loaded into some type of boxes, the well-known containers, by a series of at least two transportation modes or carriers, without handling the cargo, containers being moved from one mode (vehicle) to the next in intermodal terminals, e.g., ports and rail yards [Bektaş and Crainic, 2008, Crainic and Kim, 2007]. It is a core economic activity supporting for a large part national and international trade. As such, it is a well-known and intensely investigated application field in operations research and transportation science. Planning and management of activities at the strategic (e.g., market development, and location and dimensioning of facilities), tactical (e.g., service and capacity planning) and operational (e.g., dispatching and resource management) are both essential to the economic and operation efficiency of intermodal transportation systems and stakeholders, and complex processes in their own right. This resulted into a rather rich collection of models and methods aiming to optimize operations, service and resource utilization for intermodal freight transportation carriers. Not all components of the industry received equal treatment, however. We are thus particularly interested in such a less-studied branch of the field, namely barge intermodal freight transportation systems (river/in-land vessel transportation), which is gaining in interest as a component of environment-friendly modal shifts.

The study we undergo, and the results presented here, focus on the tactical level decision-making problems and concern, in particular, the scheduled service network design (SSND) with asset management considerations. There are very few service network design models and methods proposed for barge transportation yet, but one observes raising interest for the topic, including within freight forwarders and carriers, mainly due to modal-shift public policies and increasing concerns in the public and shippers alike with respect to the environmental impact of other modes of freight transportation. This translates for barge carriers into a new motivation and willingness to have a higher level of competitiveness, to devise a different way of designing their services, and to explore new customer-service strategies offered by the revenue-management concepts.

Many studies assess existing decision-support tools, policies and practice or proposed SND models and solution techniques, generally through comparison of optimization or numerical simulation results. The transportation system is generally modeled through network-based formulations with assumptions regarding the underlying physical network and infrastructure, characteristics of available assets (fleets of vehicles, terminal resources, capacities, etc.), and future demands (demand forecasts). Test instances are then generated, hopefully with reference to actual practice, the corresponding SSND formulations are solved, and solutions and characteristics of the corresponding operation plans are analyzed and performances are evaluated. Performance indicators thus play an important role in the analysis of models, methods, results, and corresponding policies.

Performance indicators are broadly used, in practice and research, to characterize the performance of a given transportation system under current (e.g., the annual activity and financial reports of carriers) or proposed (e.g., optimization and simulation studies) operating conditions. They are, of course, also widely used to validate and evaluate models and solution methods, as well as the corresponding results and strategies. Many such indicators are found in official documents and the scientific literature, as shown in the following. Yet, there is no general framework for analyzing the interest of particular performance indicators in the context of specific problem settings, generating appropriate problem instances, and choosing the most representative indicators. Nevertheless, it is commonly accepted that, some indicators give more insights than others when evaluating the performances of a transportation system or methodology, and some critical ones may be singled out. In the same time, the performance indicators can only be computed if specific information and data are collected for this purpose. Our goal is to contribute toward addressing this issue.

One of the contributions of the research presented here therefore is to propose a classification and analysis of the performance indicators generally used to evaluate tactical planning solutions in freight transportation, aiming to identify adequate ones for SSND with revenue management considerations. The performance indicators analyzed herein may be applied to assess performances of different modes (maritime, rail, etc.) supporting container transportation systems; we illustrate our study with an inland navigation system. We also give some insights in the way the necessary test instances are generated for a general network barge transportation system.

Another contribution of this chapter is the assessment of the proposed R-DSS methodology. The two proposed Revenue Management (RM) model, i.e., DCA-RM (in Chapter II) and SSND-RRM (in Chapter III), are examined in an integrated simulation framework to study the influence of the introduction of RM policies in the intermodal freight transportation.

The structure of the chapter is as follows. We give a brief description of the general SSND problem in Section V.2, together with corresponding literature and specific issues related to the introduction of revenue management considerations in the tactical planning problem. Section V.3 gives the first steps toward a general classification of performance indicators and identifies a number of particular ones related to the problem studied here. The description of a general procedure to generate problem instances for SSND models of general barge transportation networks is the focus of Section V.4, followed by Section

V.5 where numerical results and an analysis of the different performance indicators are presented. In Section V.6, we assess the proposed R-DSS with the help of a set of PIs. The chapter ends with conclusions about the presented study.

V.2 Problem Characterization

Service network design formulations [Crainic, 2000] are extensively used to address planning issues within many application fields, in particular for the tactical planning of operations of consolidation-based modal and multimodal carriers (e.g., [Bektaş and Crainic, 2008,Christiansen et al., 2007,Cordeau et al., 1998,Crainic, 2003,Crainic and Kim, 2007]). Building such a plan involves principally selecting the services to operate and their schedules or frequencies, and routing the demand through the selected service network. Most service network design models proposed in the literature consider the resources required to perform the services (vehicles, power units, drivers, etc.) and the different types of customers only indirectly, however, which is increasingly inadequate to reflect the operation strategies of a broad range of transportation systems.

One observes a recent trend in the field aiming to introduce more explicit resource-management considerations into tactical planning models (e.g., [Andersen et al., 2009b, Andersen et al., 2009a, Crainic et al., 2014, Agarwal and Ergun, 2008, Lai, M.F. and Lo, H.K., 2004, Pedersen et al., 2009, Sharypova et al., 2012, Smilowitz et al., 2003]). These so-called scheduled service network design with resource (or asset) management take the form of mixed-integer formulations defined on time-space networks (except [Sharypova et al., 2012], working with continuous time). The schedule length (e.g., a week), which will be repeated during the planning horizon (e.g., the season), is divided into periods (e.g., the day), and the terminals are duplicated to have a time-labeled copy within each such period. The set of time-labeled terminals makes up the set of nodes of the graph. In the basic problem setting, demand is then defined in terms of commodities, that is, given quantity of freight available at an origin node at a given period to be moved to a given destination node within some duration restrictions. Potential services (mode, speed, etc., may further characterize the service) from a terminal at a given period (departure time) to a different terminal and time period are making up the set of design arcs of the model. Holding arcs, for freight and resources waiting at a given terminal for one period, are included between two consecutive copies of the same terminal. Service arcs are generally characterized by a capacity limiting the total quantity of flow transported (sometimes, commodity-specific capacities are also included), as well as by a fixed cost to be paid if the service is included in the final design (i.e., it will operate) and a unit commodity cost.

Only the latter characterizes holding arcs. Resources, vehicles of a single or a low number of types, support the operations of the services. In the current state-of-the-art, a unit of resource is required to operate each selected service, and it may operate at most a service at each time period. Resources are allocated to terminals out of which they operate and where they return according to various rules and restrictions (e.g., the number of periods they may be out of their home terminal).

The scheduled service network design (SSND) with resource management formulation then includes three sets of variables representing decisions on service selection (arc, binary), demand transportation (arc-based continuous commodity-specific flows), and resource-to-service assignment (binary; path/cycle formulations have also been proposed, e.g., [Andersen et al., 2009a, Crainic, 2003, Pedersen et al., 2009]). The objective function generally minimizes the total cost of the system made up of the total fixed cost of selecting services, the total cost of flowing the demand, the total fixed cost of the used resources, and their respective operating costs. Other than the application-specific restrictions (e.g., number of resources by terminal), the constraints making up the formulation are enforcing the conservation of flow and the balance of services (number of services/resources incoming at a node equal the number departing the node) at nodes, the linking (and capacity) relations between flows and services, the assignment of a single resource to a service and of at most a service to each resource, the time limits on the route of a resource and the transportation of demand.

To perform our experiments in the present study, we use the SSND-RRM model proposed in Chapter III. The model follows this general framework but also includes a representation of the revenue management strategy used by the firm. Revenue management is a well-known set of concepts, strategies, and methods aiming to determine the most appropriate fare for each customer at the moment the reservation is made [Talluri and van Ryzin, 2004]. Used broadly for passenger transportation and in the tourism industry, its utilization within freight transportation is still in its infancy [Bilegan et al., 2015]. Consequently, there is little expertise on how to include such concepts into the tactical-planning methodology. In Chapter III, we propose to proceed by including several types of customers (on the demand side) and several levels of delivery service (on the provider side). Each level of delivery service (e.g., fast or slow delivery) is associated with a specific fare for each origin-destination pair of terminals in the system. The overall objective of the SSND model proposed is to maximize the net profit.

Therefore, two types of customers, and consequently two types of demand are considered in the present study, regular – corresponding to the regular traffic on the network (following long-term contracts or advance bookings with customers); this demand has to be always satisfied –, and punctual or "spot" demand. We stress here that the main difference between the two types of customers lays in the degree of confidence associated to each. We consider the former, the regular customers, to be quite sure (this is the classical assumption of most traditional SSND models); we consider the latter, the punctual or "spot" customers, to be associated to a higher degree of uncertainty (the values used could come from the aggregation of several small and sporadic customers using the transportation capacity of the network in place). Consequently, the solution of the model will never deny regular demands but, in addition, will allow for part of the "spot" customers to be integrated at the tactical level, to offer more flexibility to the proposed solutions. Two types of "spot" demands are considered depending whether a punctual demand must be served in its entirety when accepted (full punctual demand) or whether only a fraction of the punctual demand could be accepted (partial punctual demand). The relative ratios of punctual to regular demand volumes, as well as the ratio of the fares (e.g., fast delivery fare with respect to the slow delivery fare), are normally determining factors for the profitability of the firm and they are addressed when analyzing numerical results in Section V.5.

V.3 A First Step towards a Taxonomy of Performance Indicators

In this section, we present an analysis of some of the performance indicators generally used for validating and evaluating service network design models, and the corresponding results and strategies. In order to keep the presentation short, only a few recent scientific papers are cited. We select those with a high relevance to the present study, in particular those developing models for intermodal barge transportation at the tactical level. We consider them to be quite representative of the existing literature in this field, although we do not claim having performed an exhaustive search in this direction.

[Andersen and Christiansen, 2009] use a set of performance indicators to qualify rail freight services. The authors compute the number of contracts served and the number of vehicles used. The total profit is also given, computed as total costs subtracted from the total revenue obtained from the served contracts. [Andersen et al., 2009b] also use the number of vehicles in use, as well as the number of service departures per week and the duration (number of hours or time periods) of service operations, repositioning moves, and holding vehicles at nodes. [Braekers et al., 2013] focused on the average cost reduction and vessel capacity utilization, as well as on weekly profit and cost, the weekly number of transported containers, and the percentage of empty containers transported. It is worth noticing that, in addition, they use a particular indicator giving the percentage of volume transported by barge out of the total volume of demand, since some of the demands could be transported by road in their setting. In [Caris et al., 2011], average and maximum waiting times, and average turnaround time at the port of Antwerp are used as indicators. The authors also compute the average and maximum capacity utilization at the port of Antwerp in terms of berthing capacity of the port. [Sharypova et al., 2012] calculate the ratio between the number of vehicles used and the total number of vehicles in the fleet, the percentage of containers transshipped between vehicles with respect to the total number of containers transported in the system, and the percentage of direct services out of the total number of services chosen as optimal solution of the SSND model. [Lai, M.F. and Lo, H.K., 2004] develop a two-phase stochastic program formulation for ferry service network design with stochastic demand for passenger transportation. They use the notion of service reliability to differentiate demands and introduce uncertainty into the mathematical model. Total cost is used in comparing their new formulation with the conventional one. They also decompose it by different secondary indicators: ad hoc cost (cost of ad-hoc services added only when needed, subcontracted or outsourced to a third party), waiting cost (passenger waiting time penalties), and regular services operation costs.

We propose a first classification of these different performance indicators based on their relevance and meaning from the service providers' perspective, as well as from the customers' perspective. Thus, we consider that the first and most important category is the one grouping indicators directly giving information about the economic impact of the tactical planning decisions (e.g., costs, profits). The second one includes resource-utilization performance indicators, giving information particularly useful to service providers and other stakeholders directly involved in transportation and handling activities. Last but not least, a third important category, especially from the customers' point of view, is the one concerning quality-of-service performance indicators. Inspired by the set of performance indicators cited above, we present a classification based on these three main criteria in Table V.1. The performance indicators collected in the preliminary analysis are to be found in the upper part of the table, while the lower part displays additional indicators responding to the need of evaluating SSND models with revenue management considerations, as explained in more detail hereafter.

When differentiating types of customers and fares, we need to understand how the system behaves when different values of some key parameters are used (e.g., different ratios of Regular/Punctual customers, different ratios of slow/fast delivery type, etc.). This type of analysis also provides a better understanding of what are the most suitable circumstances under which revenue management policies should be applied to obtain the best results. This is why, when introducing revenue management concepts in service net-

Table V.1: A first classification of performance indicators used for tactical planning of intermodal barge transportation systems

Economic impact	Resource utilization	Quality-of-service
Total profit	Number of vehicles in use	Number of contracts served
Total cost	Number of open services	Waiting time in intermodal terminals
Average cost reduction	Operating hours of services	Waiting time at other terminals
Ad hoc services cost	Operating hours for repositioning	Average turnaround time
Waiting time cost	Duration of holding vehicles at nodes	Time on intermodal services
Regular services cost	Number of vehicles used/fleet size	Handling in intermodal terminals
	Vessel capacity utilization	Waiting time at borders
	Berthing capacity utilization	Containers transported by barge
	Number of direct services/total services	Empty containers transported
	Ratio of transshipped containers	
Net profit increase	Number of less-used vehicles	Volume of rejected partial punctual demands
	Number of empty vehicles	Volume of rejected full punctual demands

work design models, new performance indicators are needed, in particular for evaluating their absolute/relative economic performance, the resource utilization and the improvement of the quality-of-service offered (e.g., the ratio of accepted demand with respect to the total demand, etc.). Moreover, in order to develop more insights into the behavior of the system, several different indicators can be calculated with the purpose of understanding where the effectiveness of the solution comes from, how resources are distributed and used, how freight consolidation is performed, etc.

When analyzing the way resources are used, we focus particularly on the number of empty and less-used vehicles. The empty vehicles are the vehicles used in the transportation plan without any cargo (repositioning moves); the less-used vehicles indicate vehicles whose average capacity usage is less than 20% (the value of this parameter may be changed with respect to the service provider requirements). The service suppliers could decide not to open services whose capacity is less used, which would probably lead to a different solution and plan; this could be confirmed by introducing the corresponding constraints in the mathematical model and by comparing the subsequent solutions thus obtained.

Another indicator that has to be introduced is the percentage of accepted/rejected punctual demands (TEUs) out of the total volume of demands (regular and punctual). As we differentiate demand by category of customers, we are looking at how much of the demand, in terms of TEUs, is accepted/rejected in each category of punctual demands (partial and full punctual demands). This indicator is related to the quality-of-service offered by the carrier, and gives an idea of the capability of the system to discriminate between high-profit and low-profit demands.

V.4 Test Instance Generation

We now turn to how the problem instances are set up and how the data characterizing the transportation system are randomly generated. To represent the reality of a general network, we consider a set of ports and the physical links (water navigation infrastructure) between them representing the physical network, like the one represented in Figure V.1. Without loss of generality, we classify ports into two categories, i.e., main ports and secondary ports. The main ports stand for the deep-sea ports (e.g., port A in Figure V.1) and the secondary ports represent the inland ports. An Origin-Destination (OD) pair is called a main OD pair if it is related to at least one main port. It is considered a secondary OD pair otherwise. We make the assumption that all ports have enough berthing capacity to hold vehicles (in operation or not), and sufficient space to store containers. We also assume that the handling machinery at each port is efficient enough and the duration of servicing a vehicle, for loading and/or unloading activities, is equal to one time period. A single type of vehicle is considered with a capacity equal to 100 TEUs. We make the assumption that the transit time from one port to any other consecutive port is one time period (the distance between any consecutive ports in the physical network is considered to be almost the same). The fleet size is assumed big enough to satisfy all demands.

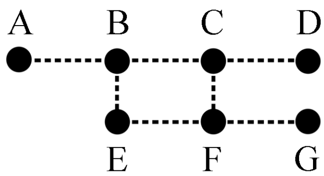

Figure V.1: A general physical network

Every demand is characterized by an OD pair (its origin and destination ports), its availability time at origin (the earliest time the demand is available and ready for transportation), a delivery type (slow or fast) characterizing the maximum delivery time within which the demand has to be transported to its destination (in number of time periods), a volume (in TEUs), and a category differentiating the type of customer or the type of contract (regular or punctual, as explained in Section V.2).

We assume that demands between main OD pairs occur more often than demands between secondary OD pairs. In terms of availability time in port, demands for main OD pairs may arrive at each time instant. To restrict the problem size, demands for the secondary OD pairs may occur at time instants belonging to a specified set (e.g., every two time periods). Moreover, we allow only 10% of the secondary OD pairs to be chosen in a test instance. These 10% are randomly picked up with a uniform distribution from the complete list of possible OD pairs. For each OD pair and availability time in port (randomly generated), two demands, one with fast delivery and the other with slow delivery type, are set. This results in a balanced number of demands requiring fast and slow deliveries within the same test instance.

The volume of each demand is randomly generated between 0 and a maximum value (usually less than the capacity of a vehicle) according to the uniform distribution. In order to generate a well-balanced combination of regular and punctual demands within a test instance, we generate first the set of demands to be used, without specifying their category. Thus, we fix the total volume of demand in the instance. Then, the volume of punctual demands is specified by a proportion (p) over the total volume of demand, the remaining proportion ($1 - p$) corresponding to the total volume of regular demands. We may thus generate instances with a fixed total demand but with varying proportions of main to secondary and regular to punctual ratios.

The maximum delivery time for each demand is computed (in terms of time periods) according to the distance between the origin and destination of the demand and the corresponding delivery type (fast or slow). As a general rule, we assume that a demand associated to a slow delivery would accept to be delivered within a time twice longer than the delivery time required by a fast demand between the same origin and destination. We set the fast delivery time by ensuring feasibility with respect to some of the less time-consuming potential services that could serve that demand. The different delivery types and thus the different types of demands are associated to different fares classes. A low fare corresponds to a slow delivery demand type, and a high fare is associated with a fast delivery demand.

In the following section we give some numerical results obtained when solving the SSND problem for random test instances with data sets generated by this type of procedure.

V.5 Numerical Results and Analysis

We now illustrate how, using a set of problem instances generated as described above, the performance indicators may help analyze the output of an SSND model with asset and revenue management considerations. We compare two mathematical models, a traditional one in which demands are not differentiated, called SSND in the following, and the proposed SSND-RRM in Chapter III, integrating revenue management concerns, namely different categories of customers and different fare classes. The main difference between the two models is that the first one deals with regular demands only (all the demand has to be satisfied), while the second takes into account both regular and punctual demands, which allows potential performance increase by refusing partially or totally some of the less profitable demands. We follow the procedure described in Section V.1. The demands are generated randomly for each test instance, and we run the program and solve the service network design problem for 20 different instances.

The performance indicators used here are a selection of indicators from Table V.1, for each of the three main categories identified: economic impact, resource utilization and quality of service. The main indicators used are the net profit and total cost. For the latter, we also identify and calculate some of its components. In terms of fixed service operating costs, we use the cost of opening a service, called service-start cost. In terms of unit costs we use container-transportation, container-handling, container-holding (holding in the storage yard of a terminal), and in-port vehicle-holding costs. In terms of resource utilization, we compute the number of empty and less-used vehicles, as well as classical indicators such as the number of open services, the number of vehicles used by these services, and the average used capacity of those vehicles. Finally, we add two particular indicators required to study the incorporation of revenue management into the SSND related to the different categories of demands, which can be either partially or fully accepted or denied. The percentage of rejected volume of partial punctual demands and of full punctual demands out of the total volume of demands is denoted p/all and f/all respectively.

The average values (over the 20 instances) are displayed in Table V.2. These relative values of the performance indicators denote an increase or a decrease of the corresponding absolute value of an indicator when the solution of the SSND-RM problem is compared with that of the classical SSND.

The proportion of regular and punctual demands out of the total volume was varied in this set of instances. The five columns of the table correspond to five different ratios for the regular versus punctual demand categories. For example, “R=4P” indicates that the corresponding column displays the values of the performance indicators when in the SSND-RM setting the total volume of regular demands is 4 times as large as punctual demands. In the same way, “R=P” means that the volume of regular demands is almost equal to the volume of punctual demands and, for the last column, “4R=P” means that we have 4 times as large volume for the punctual demands as for the regular ones. Recall that the total volume of demands (regular plus punctual) is maintained equal, and that only the ratio between the two general categories is varied. As shown in the table, the SSND-RRM model always provides a better solution with respect to the performance indicators calculated here. This trend is even more accentuated when we increase the proportion of punctual demands. Figure V.2 shows that the same hierarchy in the value level of the different measures is observed for the five different ratios of regular to punctual demands,

Table V.2: Performance indicators (relative values) with fare ratio (fast delivery/slow delivery) = 1.5 for five regular-punctual ratios

	R=4P	R=2P	R=P	2R=P	4R=P
Total cost decrease (%)	4.00	6.91	10.18	12.85	16.83
Transportation cost decrease (%)	2.79	5.16	7.42	9.14	12.05
Handling cost decrease (%)	3.08	5.37	8.03	9.62	13.15
Holding-containers cost decrease (%)	2.90	-5.19	4.79	6.28	23.36
Holding-barges cost decrease (%)	-33.33	-27.85	-51.90	-39.56	-53.25
Service-start cost decrease (%)	5.60	10.23	14.05	18.28	21.78
Net profit increase (%)	2.68	4.07	6.28	8.42	10.29
Capacity usage increase (%)	3.54	5.00	6.92	9.30	10.87
# Open services decrease (%)	5.60	10.23	14.05	18.28	21.78
# Used vehicles decrease (%)	5.17	9.41	13.44	17.12	20.53
# Empty vehicles decrease (%)	24.66	34.25	55.07	63.24	72.97
# Less-used vehicles decrease (%)	10.83	27.33	36.48	48.67	54.72
Rejected demands volume p/all (%)	1.39	2.30	3.92	4.33	6.36
Rejected demands volume f/all (%)	1.55	2.84	3.66	4.82	5.96

for almost all the performance indicators considered. This is a direct confirmation of the consistency of the system's behavior and of the test instances used when computing the results.

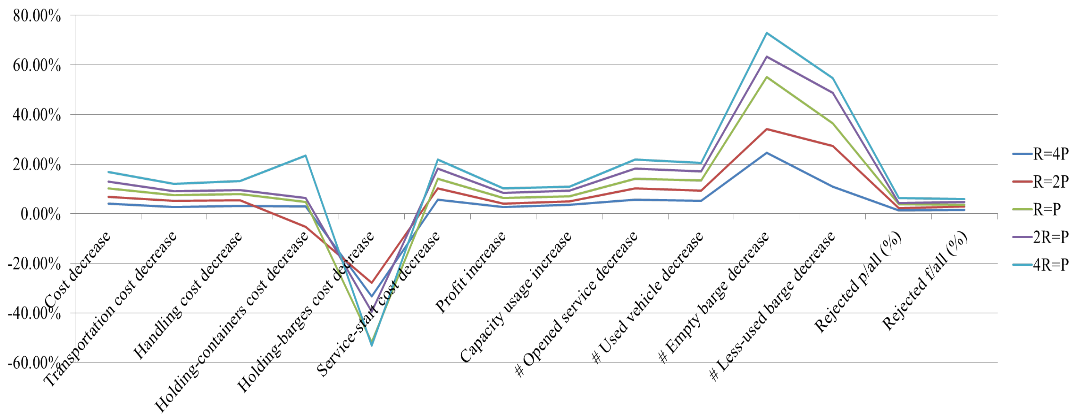

Figure V.2: The value hierarchy of demand category ratios (R/P) for different performance indicators

To be more precise, Figures V.3 and V.4 present trends of relative values of costs and profits. As shown in Figure V.3, the SSND-RRM strategy always offers better solutions, in terms of cost decrease and profit increase. A rising trend appears when we increase the proportion of punctual demands as well. Furthermore, the slope of profit increase is smaller than that of cost decrease. This phenomenon comes from the fact that less money is obtained from the satisfied demands, as more demands are refused when increasing the ratio of punctual demands.

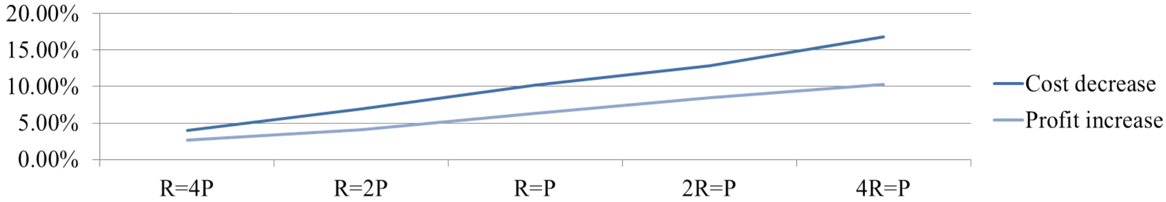

Figure V.3: The trends of total cost decrease and net profit increase when increasing the ratio of punctual demands

We present in Figure V.4 the trends of different cost components when increasing the ratio of punctual demands out of the total volume of demand. One can notice that some of the cost indicators have very similar behavior compared to total cost decrease: service-start cost, transportation cost and handling cost relative value indicators. This implies that the analysis of only one type of indicator (e.g., the total cost decrease) gives reliable and consistent information about the behavior of the system and the related components having the same trend do not necessarily need to be calculated.

A somewhat different behavior is observed for holding-container cost and holding-barge cost decrease, which have irregular trends. For the holding-barge cost decrease, its irregularity can be explained by the fact that, barges are active (in-service) most of the time. Hence, only a small amount of the total cost is spent on holding barges in ports. The relative values of this performance indicator being computed on such small values, the fluctuation is larger compared to other indicators. We can also notice some correlation between the holding-containers cost and holding-barges cost, their trends being in opposite directions.

For the resource utilization, as more demands can be denied, more services and vehicles can be saved. For the same reason, the routing of demands on services is more flexible and

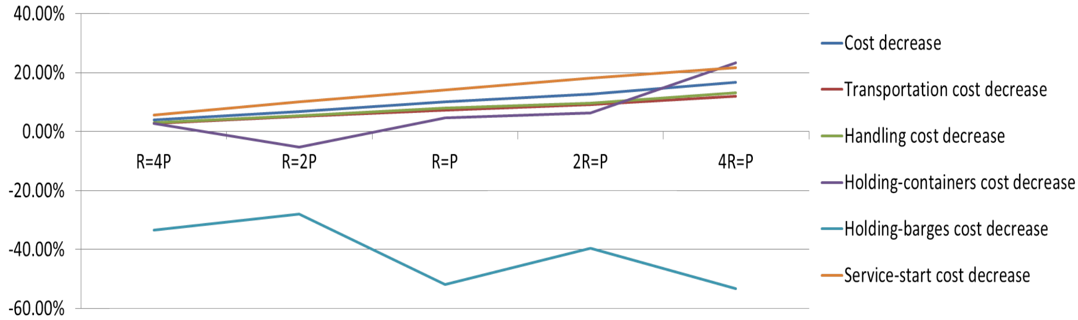

Figure V.4: The trends of different cost component indicators when increasing the ratio of punctual demands

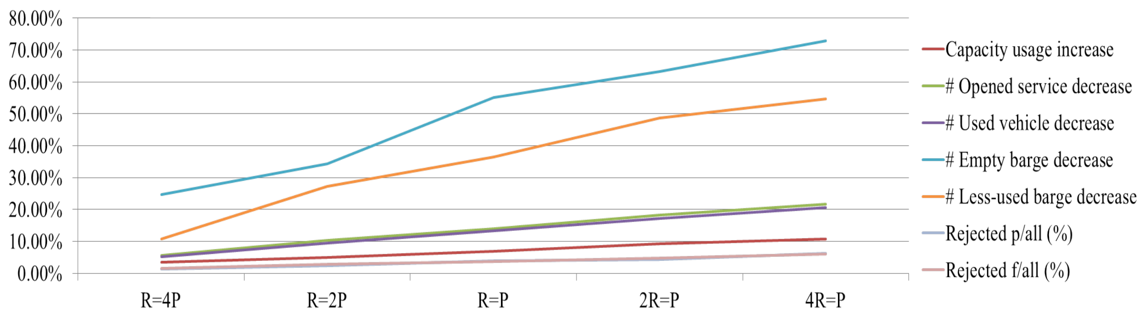

Figure V.5: The trends of resource utilization and quality-of-service indicators when increasing the ratio of punctual demands

efficient. Therefore, the number of empty barges is getting smaller and the capacity usage is increased. All these trends are shown in Figure V.5, where the resource utilization and quality-of-service performance indicator values and trends are displayed. In this figure, we can also observe that more punctual demands (both partial and full punctual demands) are rejected to maximize the revenue associated to the SSND solution.

When comparing the two strategies and models, we evaluate the performances in terms of costs, revenues, resource utilization and quality-of-service. The conclusion is that the introduction of Revenue Management concepts results in better network and asset utilization. Using a large range of performance indicators, a better understanding of the system behavior is obtained. The numerical results presented in this section confirm our intuition that an important increase in net profit results from better resource utilization, and more flexible flow distribution and demand satisfaction, while maintaining a high quality-of-service.

V.6 R-DSS Assessment

In this section, we assess the proposed R-DSS within an integrated simulation framework with the help of a set of PIs. In this framework, scheduled service plans made at tactical level are deployed repeatedly at the operational level. An example is given to illustrate how selected services, i.e., $s1, s2$, from tactical level (Figure V.6a) within a small time-space network are deployed at operational level (Figure V.6b).

To select the scheduled services at tactical level, the proposed SSND-RRM model (Chapter III) and SSND-RM model (without consideration of revenue management) are, in turn, applied. Information about the physical network, potential services and forecasted demands is considered to be available. At the operational level, decisions with respect

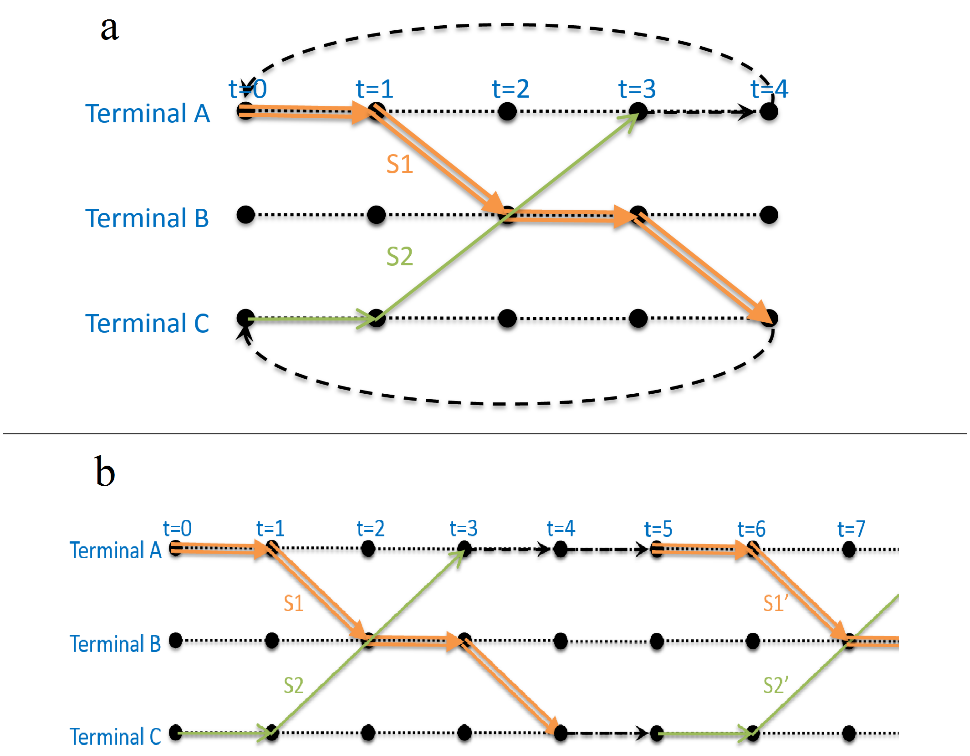

Figure V.6: An example of service deployment from tactical to operational level

to the acceptance/denial of transport requests and the corresponding routing for those accepted are made according to the proposed DCA-RM model (Chapter II). Sequential arrivals of transport requests are simulated at the operational level as an iterative process.

In the rest of this section, we first introduce the procedures to generate test instances for the proposed simulation framework in Subsection V.6.1. Numerical results are then displayed and analyzed in Subsection V.6.2.

V.6.1 Simulation Framework

We now describe the simulation framework and introduce the procedure to generate test instances used for the simulation.

In terms of physical network, four consecutive terminals located along the inland waterway are considered. As a similar topology is also studied in the previous chapters, the same assumptions related to the physical network and terminals as in Chapter II and Chapter III are adopted here.

In terms of services, all possible itineraries with respect to the physical network are considered with two types of vehicles (large and small). The same assumptions related to services and vehicles as in Chapter II and Chapter III are also adopted here.

At tactical level, the schedule length is considered to be 14 time units long (e.g., one week). A test instance (a set of forecasted demands) is supposed to be composed of an equal number of transport requests from each of all the three customer categories (i.e., R, P and F). In addition, each possible Origin-Destination (OD) pair is requested 4 times by each category of customers. With respect to the other characteristics of demand, e.g., volume, delivery type and available time at origin, the values are generated randomly (uniform distribution within predefined limits).

Time is discretized at the operational level into a number of time instants, so that at each time instant there is no more than one transport request. At operational level, when we simulate the sequential arrivals of transport requests, at each time instant, one transport request is generated randomly following the same procedure as that introduced in Chapter II. As analyzed in both Chapter II and Chapter III, the values of price ratio between fare classes have an important impact on the performance of RM models. The higher the price ratio is, the better the RM model performs. Therefore, in this experimentation, we set the values of the price ratios for both delivery type (fast/slow) and booking anticipation (late/early reservation) to 1.5. In practice, better performance of the proposed R-DSS, in terms of the robustness of plans, is expected, when applying higher values of price ratios than 1.5.

V.6.2 Preliminary Assessment

Two groups of experiments are conducted to assess the proposed R-DSS. The first group of experiments is designed to study how the proposed R-DSS reacts, in terms of profit, resource utilization, etc., when facing inconsistent demand forecasts between tactical and operational levels. A second group of experiments are then settled with the assumption that demand forecasts between tactical and operational levels are consistent, to evaluate the performance of the proposed R-DSS with respect to different tactical strategies and accuracy degree of demand forecasts at operational level.

As described previously, at tactical level, both SSND-RRM (with RM consideration) and SSND-RM (without RM consideration) are applied, in turn, to design the service network. When we make decisions to select open services, forecasted demands are required. Obviously, the accuracy of demand forecasts is important. However, it is a hard task to obtain precise demand forecasts. Moreover, according to the business relationships between the carriers and customers (shippers), the behaviors of customers are different.

Accuracies of demand forecasts, with respect to different categories of customers, are thus different. For example, as long-term contracts are signed with the regular customers (R), demands from R are predictable (or the demand forecasts could be considered as accurate). On the contrary, demand forecasts, with respect to the spot customers, could be considered as less accurate. Freight carriers, normally, could make a choice between being *greedy* (to trust demand forecasts with respect to all customers and take the corresponding risks) and being *protective* (to trust only the demand forecasts with respect to regular customers and lose potential market), when making tactical plans. However, by taking into account RM polices, carriers are offered with a different viewpoint, in which customers are classified into different categories (in the decision making process) with different treatments. Carriers, thus, are able to make decisions between being *greedy* and *protective*, and consequently take less risks and win more potential market shares.

Therefore, when the SSND-RM model is applied, two different situations are considered. Given a test instance defined for the SSND-RRM (i.e., considering three different customer categories: R, P and F), either all demands are labeled as “R” (SSND-RM(All R), being *greedy*), or only R demands are kept, the others (P and F) being discarded (SSND-RM(Only R), being *protective*). As stated before, at operational level, only DCA-RM is applied and solved. Selected Performance Indicators (PIs) used to analyze the performance of the R-DSS are described as follows:

- **# of TEUs**: is the total number of containers requested to be transported;
- **# of accepted TEUs**: is the total number of accepted containers;
- **# of open services**: is the number of services selected at tactical level using small or large vehicles;
- **Capacity usage**: is calculated as the ratio of used Distance*Capacity over the maximum possible Distance*Capacity according to the flow distribution plan; it indicates the resource utilization;
- **Revenue**: is the total revenue obtained;
- **Estimated net profit**: is calculated as *Revenue* subtracted by the fixed costs and variable costs.

In Table V.3, we first briefly illustrate the output of the tactical planning in the simulated framework. As shown in the table, SSND-RM(All R) generates a plan with the largest number of open services (26) as all demands have to be satisfied. On the contrary, SSND-RM(Only R) generates the smallest service network (with 8 open services) as only R

Table V.3: Output of the tactical planning with different strategies

	SSND-RRM	**SSND-RM**	
		All R	Only R
# of TEUs	1847	1847	563
# of accepted TEUs	1447	1847	563
# of open services	16 (all large)	26 (2 small, 24 large)	8 (all large)
Capacity usage (%)	91.75	82.38	78.17

demands are considered. Benefiting from the customer classification, SSND-RRM denies some of the demands and consequently obtains a moderate service network with the highest capacity usage. Services selected by those three strategies are applied in turn at the operational level to evaluate the corresponding impact of each of them, when tested in similar operational conditions.

At operational level, in order to better understand the behavior of the proposed R-DSS, simulation was carried out 20 times for each tested demand accuracy and for each tactical planning strategy. The procedure used to generate the sequential arrival of the current transport requests here is the same as we introduced in Chapter II. Average values of the numerical results obtained from the simulation of the first group of experiments are illustrated in Table V.4. *Scale* in the first column of the table indicates the number of potential transport requests received at operational level during one time period of the schedule length (of the tactical level). As shown in Table V.4, when $scale = 80$ and 90, the total volume requested by the customers at operational level is 1655.45 and 1891.05, respectively. These values are within a close range of the total volume estimated at tactical level (1847). Therefore, when the value of *scale* is 80 or 90, we consider that the demand forecast at tactical level is accurate (or the demand forecasts between the two planning levels are consistent). When the value of *scale* is less than 80, the demand forecast at tactical level is considered to be overestimated, and on the contrary, the demand forecast at tactical level is considered to be underestimated ($scale > 90$). Both over- and under-estimation of demands at tactical level implies the inconsistency of demand forecasts between tactical and operational levels. Corresponding values for each PI obtained by applying the three different tactical strategies are displayed in the last three columns.

As opening the largest number of services, SSND-RM(All R) always accepts the highest number of TEUs and consequently generates the highest revenue in all the test instances, compared to the other two planning strategies. However, as the open capacity is too large, even SSND-RM(All R) always accepts the most volume of demands, it still has the lowest capacity usage. In terms of estimated net profit, SSND-RM(All R) even earns the least money, when the number of transport requests at operational level is low ($scale =$ 50 and 60), because of its high fixed cost. Compared to SSND-RM(All R), the SSND-

Table V.4: Assessment of the proposed R-DSS: Group 1

		SSND-RRM	**SSND-RM**	
			All R	Only R
Scale = 50	# of TEUs		1059.3	
	# of accepted TEUs	869.05	978.3	589.7
	Capacity usage (%)	30.60	21.65	41.34
	Revenue	17736.13	19818.43	11137.38
	Estimated net profit	3852.98	1261.03	3100.8
Scale = 60	# of TEUs		1265.3	
	# of accepted TEUs	1060.05	1164.1	658.1
	Capacity usage (%)	36.1	25.67	45.97
	Revenue	21147.65	23742.1	12459.95
	Estimated net profit	6048.2	3806.9	3914.43
Scale = 70	# of TEUs		1456.1	
	# of accepted TEUs	1187.5	1338.25	719.55
	Capacity usage (%)	40.63	29.6	50.23
	Revenue	23379.85	26975.88	13388.2
	Estimated net profit	7317.35	5731.25	4382.28
Scale = 80	# of TEUs		1655.45	
	# of accepted TEUs	1304.85	1521.35	744.35
	Capacity usage (%)	44.81	33.76	52.1
	Revenue	25531.73	30939.18	13900.93
	Estimated net profit	8580.98	8314.65	4703.5
Scale = 90	# of TEUs		1891.05	
	# of accepted TEUs	1396.1	1709.75	787.15
	Capacity usage (%)	47.92	38.04	54.43
	Revenue	26996	34686	14501.88
	Estimated net profit	9365.35	10641.58	5006.75
Scale = 100	# of TEUs		2110.3	
	# of accepted TEUs	1827.21	1993.32	830.55
	Capacity usage (%)	62.02	43.65	56.39
	Revenue	36438.25	41137.88	15098.7
	Estimated net profit	15636.48	15049.58	5316.08

RRM generates more robust plans when facing inaccurate demand forecasts. To be more precise, SSND-RRM always obtains a better capacity usage (around 10% higher) than SSND-RM(All R), when $scale < 100$. When more demands than expected are coming ($scale = 100$), the capacity usage of SSND-RRM is almost 20% better than that obtained by SSND-RM(All R). It is obvious that the idea of discrimination on customers, i.e., different treatments on different customer categories, helps the carriers to have a better resource utilization. In addition, even with less demands served in the simulations, SSND-RRM still generates better estimated net profit than SSND-RM(All R), except when $scale = 90$. However, even for the only exception, SSND-RRM still generates competitive estimated net profit. The better profit performance observed on SSND-RRM, besides customer classification, is also due to the consideration of the profitability of transport requests. By introducing the RM polices at both planning levels, resources of the carriers are better used to satisfy the more profitable demands. Another interesting observation is also found with respect to SSND-RM(Only R). Since it is opening the smallest number of services, SSND-RM(Only R) has the best resource utilization, except when $scale = 100$, in which SSND-RRM has the highest capacity usage. It performs well, in terms of estimated net profit, when there is very few transport requests ($scale < 70$) exist in the market, compared to SSND-RM(All R). However, when the number of transport requests is moderate or high, SSND-RM(Only R) loses in the competition (and may lose its market share in the future). Note that, the capacity usage is quite low at operational level, even when the total volume of TEUs is almost at the same level as the one predicted at tactical level. This phenomenon can be explained, as the generation of demands is random, in terms of OD, available time at origin, delivery type, etc.

In the second group of experiments, to guarantee the consistency of demand forecasts between the two levels, we use test instances ($scale = 90$) at the operational level with a total volume within a close range to the one used for the test instances at the tactical level. When the demands arrival process follows the same probability distribution function as considered in the objective function of the RM model, we say the demand forecast is accurate (Simulate:Estimate = 1.0). Simulate:Estimate = 1.5 indicates that the demands are underestimated by a factor of 0.67, while Simulate:Estimate = 0.5 indicates that the demands are overestimated by a factor of 2. Numerical results with respect to group 2 are presented in Table V.5. As shown in Table V.5, when demands are overestimated, less demands, in terms of TEUs, are accepted by all three strategies as expected, and consequently lower capacity usage and less estimated net profit are obtained. In addition, when demands are underestimated, more accepted demands, in terms of TEUs, are observed also with higher capacity usage and more estimated net profit for all three strategies. Compared to SSND-RM(Only R), SSND-RRM always generates higher estimated net profit, and the difference between these two strategies is getting bigger when more

Table V.5: Assessment of the proposed R-DSS: Group 2

		SSND-RRM	**SSND-RM**	
			All R	Only R
Simulate:Estimate=0.5	# of TEUs	900.5		
	# of accepted TEUs	822.89	867.21	487.73
	Capacity usage (%)	28.25	19.3	33.72
	Estimated net profit	2563.98	-146.28	1732.87
Simulate:Estimate=1.0	# of TEUs	1891.05		
	# of accepted TEUs	1396.1	1709.75	787.15
	Capacity usage (%)	47.92	38.04	54.43
	Estimated net profit	9365.35	10641.58	5006.75
Simulate:Estimate=1.5	# of TEUs	2760.93		
	# of accepted TEUs	2158.7	2521.45	1145.28
	Capacity usage (%)	74.09	56.1	78.19
	Estimated net profit	18413.94	21034.55	8922.57

demands have to be satisfied. Compared to SSND-RM(All R), better resource utilization is always observed by SSND-RRM. In terms of estimated net profit, SSND-RRM earns more than SSND-RM(All R) when demand forecast is overestimated. When demand forecast is considered to accurate or underestimated, SSND-RRM still generates competitive profit, compared to SSND-RM(All R), with almost 400 TEUs less accepted. Note that, even SSND-RM(All R) has the best performance, in terms of net profit, when Simulate:Estimate = 1 and Simulate:Estimate = 1.5, it actually loses money when transport requests are overestimated. Therefore, we conclude that, in the simulated framework, compared to the other two planning strategies, SSND-RRM generates the most robust plans when facing different accuracies of demand forecasts.

V.7 Conclusions

Performance indicators are broadly used to characterize the performance of transportation systems, and to validate and evaluate models and solution methods, corresponding results and strategies. It is also known that some indicators give more insight than others and one would like to single out the critical ones for particular problem settings. This is particularly meaningful when new problem settings are analyzed, as are the emerging needs for tactical planning for container barge transportation with revenue management strategies. Yet, there is no general framework for analyzing the interest of particular performance indicators in the context of specific problem settings, generating appropriate problem instances, and choosing the most representative indicators.

We proposed a first classification and analysis of performance indicators generally used to evaluate tactical planning solutions in freight transportation, and we identified a number of adequate ones for scheduled service network design models with resource and revenue management considerations. We also provided insights into the generation of adequate test instances to study these planning issues in the general context of container barge transportation systems.

The numerical analysis of the results of comparing a classical SSND formulation and a model integrating revenue management strategies has shown the interest of the instance-generation procedure and performance-indicator study in the context of SSND-RM for container barge transportation. The initial insights provided by the study into the behavior of such systems under varying conditions of demand stratification and customer-service strategies (in terms of load acceptance) are a clear indication of this interest. They are also a first step towards more comprehensive studies of such intermodal systems and modeling approaches, studies that we plan to undertake in the near future.

An integrated framework considering both the tactical and operational models is implemented to assess the R-DSS. In this framework, selected services at tactical level are applied at the operational level and no extra-vehicles or rescheduling of services is considered. Simulations at operational level are then conducted to evaluate the decisions made at tactical level, and consequently validate the proposed Reactive Decision Support System (R-DSS). Compared to the decision support systems with no revenue management consideration at tactical level, the proposed R-DSS generates more robust decisions, in terms of net profit and resource utilization. The introduction of Revenue Management strategies at tactical level improves the interaction and information/knowledge exchange between tactical and operational levels of decision making for the intermodal barge transportation system studied.

General Conclusions

Barge transportation, in the recent years, has increasingly received global attention with the intensified emphasis on the relationship between transportation and environmental impact. Compared to the other transport modes, e.g. road and rail, barge transportation is more environment-friendly, in terms of both energy consumption and noise emissions. In addition, it also contributes to relieving the traffic congestion and reducing the number of accidents of the road and rail transport networks. Therefore, in Europe, the adoption of barge transportation (or more generally, river and canal freight navigation) has been encouraged by the [European Commission, 2011] in the context of intermodal freight transportation. However, compared to other transport modes, contributions related to barge, especially in the context of intermodal transportation, are still scarce.

This thesis, therefore, studies the freight intermodal barge transportation from a carrier perspective. A reactive decision support system (R-DSS) covering both middle-term and short-term planning of operations is then proposed to make more robust decisions, in terms of scheduled services plan, resource management, flow distribution, etc. Four related research problems are addressed to achieve the R-DSS: modeling the optimization problems for intermodal barge transportation activities at tactical planning level, at operational planning level, proposing a new solution approach to solve the large scale MILP problems defined at tactical level, and classifying and introducing new performance indicators, together with a methodology to generate test instances for the validation of the proposed R-DSS.

In addition, the fundamental contribution of this thesis is the introduction of Revenue Management (RM) concept and polices into the freight intermodal barge transportation system. To be more precise, for both planning levels (tactical and operational), the best decisions (scheduled services and capacity allocation) are made with respect to the given forecasted demands. However, in a deregulated market, customers have different behaviors, different requires and different willingness to pay. These perspectives of demand uncertainty then challenge those best decisions in practice, and may endanger the benefits of the carriers. Therefore, it is critical and stands for a great challenge to understand the behaviors of customers and take this information into account when making decisions to alleviate the influence of demand uncertainty. RM, which is naturally used in marketing competition, offers us the techniques to tackle this challenge. By integrating the RM polices, e.g., customer classification and fare differentiation, carriers plan and offer different services, and charge different fares according to the behaviors, requires and willingness of customers. As naturally used in practice at operational level for passenger transportation, RM is rather new to the freight transportation and very few contributions exist in the literature. However, according to the numerical results, it is promising to consider RM polices when making decision at each planning level for freight intermodal barge transportation system. Higher revenue and better resource utilization are obtained at each planning level when tested separately. Furthermore, by considering RM polices at both levels, more robust scheduled service plans are made, compared to those made without consideration of RM at tactical level. To be more precise, when demand forecasts are accurate, higher revenue and better resource utilization are observed. In addition, when demand forecasts are inaccurate, the quality of solutions, in terms of income and resource utilization, remains at a high level by considering RM polices, compared to those obtained by the other tested planning strategies.

In the rest of this chapter, we first summarize the results of the thesis for each research problem, and then present future research perspectives.

Summary of the Results

In this subsection, we review the four research problems proposed in Chapter I. The results of each study is summarized accordingly, and an overall summary is also made.

Research topic 1: How to integrate RM policies (which policies) with barge transportation at operational level and dynamically allocate the capacity of transport network facing transport requests sequentially arriving in the system, in the context of intermodal freight transportation.

In Chapter II, we first propose a Revenue Management model (DCA-RM) for dynamically allocating the capacity of the intermodal barge transportation network. To be more precise, according to the business relationship, customers are classified into three categories, whose transport requests are accordingly treated differently. Different fare classes are proposed to customers, in relation with their booking anticipation and requested delivery type (fast or slow), to differentiate the transportation solutions offered by the carrier. In order to validate the DCA-RM model proposed, a set of experiments are conducted. The obtained results show that the DCA-RM model always generates better total revenue, when compared with the first-come first-serve (FCFS) based booking strategy, which has no consideration of profitability. This tendency of the results holds even if demand forecasts are inaccurate (i.e., in case of under- or over-estimation of future demands).

A set of possible negotiation strategies for denied demands coming from regular customers are also studied within the proposed DCA-RM model. By considering the negotiation strategies, better satisfaction from the regular customers is achieved with slightly lower total revenue, which, however, is still higher than the revenue obtained when applying the FCFS strategy.

The proposed DCA-RM model is then extended by integrating the re-routing of some of the accepted demands. Preliminary experiments are conducted to examine the extended DCA-RM model. The obtained results indicate that it is interesting to take into account re-routing of already accepted demands when making the operational plans, as the extended DCA-RM model generates better total revenue, when compared with the basic version.

Research topic 2: How to integrate RM and resource management concepts with barge transportation for service network design problems and how to ensure synchronization with other transport modes, in the context of intermodal freight transportation.

In Chapter III, we propose a scheduled service network design model with consideration of both resource and revenue management (SSND-RRM) for intermodal barge transportation. The same type of RM policies as those applied at the operational RM model (i.e., customer classification and price differentiation) are considered in this model. Note that, at tactical level, as no booking anticipation is considered, the price policy is only related to the required delivery type, e.g., slow or fast delivery. In terms of resource management, design-balance constraints and upper bounds on the quantity of resource are formulated. To synchronize with other transport modes, scheduled services are proposed and time-related characteristics are explicitly associated with demands. Various problem settings, in terms of demand distribution, network topology, fare classes and quality-of-service (e.g., delivery time), are designed and tested to evaluate the proposed SSND-RRM model. According to the results, we conclude that it is promising to consider RM policies at tactical level. By classifying customers and differentiating product-fares, higher net profits and better resource utilization are observed, compared with the conventional SSND-RM model without consideration of revenue management.

Research topic 3: How to efficiently solve the scheduled service network design problems while simultaneously considering resource and revenue management.

In Chapter IV, we propose a metaheuristic (MH) to efficiently solve large scale SSND-RRM problems (introduced in Chapter III). The new solution approach includes four phases. In the first phase, a constructive heuristic is proposed to obtain initial solutions for the SSND-RRM optimisation problem. In the second phase, starting from such an initial solution, the algorithm tries to improve the solutions by iteratively exploring the search space of service selection, F-demand selection or the combination of both. The selection of the search space is based on a modified adaptive large neighborhood search (ALNS). To explore the search space of service selection and F-demand selection, a set of *$\mathcal{Y}$-selection heuristics* and *$\mathcal{F}$-selection heuristics* are designed, respectively. Historical performance of these proposed heuristics is recorded to guide the search. Phases of intensification and diversification are also included. Moreover, the proposed *Y-selection heuristics* are based on *service cycle* related neighborhood structures, in which a *service cycle* is a set of consecutive services using the same type of vehicle back to the terminal where the sequence of services starts. Moves based on the new neighborhood structures guarantee the design-balance constraints and diversify the search simultaneously. Long-term memory is used to record the influence of each service and F demand on the solutions, and to identify promising services and F demands. To avoid exploring repeatedly the same region of search space, short-term memory tabu lists of service cycles are maintained. Compared to a commercial solver (CPLEX), the performance of the proposed MH is superior, in terms of both solution quality and time consumption, when dealing with large scale problems.

Research topic 4: How to validate and evaluate the decision support system of barge transportation, in terms of models, solution methods, corresponding results and strategies; Are there some indicators that give more insights than others.

In Chapter V, we first review the Performance Indicators (PIs) found in public sources and scientific literature, and qualify them with respect to the intermodal barge transportation. The analysis is then extended with RM considerations. Based on their relevance and meaning, these PIs are classified into three categories, i.e., *economic impact*, *resource utilization* and *quality of service*. All these PIs are applied and tested with respect to the tactical planning of intermodal barge transportation system. New PIs considering both resource and revenue management, in the context of freight transportation, are also proposed for the three categories and tested. According to the results, for each category, some PIs do offer more insights than others. These PIs are thus identified to evaluate the proposed R-DSS, and could be used for a more general evaluation of any intermodal freight transportation system.

In addition, we also provide insights into the generation of adequate test instances to study the planning issues in the general context of intermodal barge transportation systems. The proposed R-DSS is then assessed within an integrated simulation framework (both tactical and operational levels are considered) with specified PIs.

Overall, the consideration of RM policies for both middle-term and short-term planning of intermodal barge transportation enhances the interaction and information / knowledge exchange between the two decision levels and consequently generates more consistent and robust decisions. More revenue (net profit) and better resource utilization are observed by applying the proposed R-DSS, compared with its competitors, which have no consideration of RM at tactical level. Carriers, therefore, could benefit from the proposed R-DSS, in terms of net profit, resource utilization, customer satisfaction, etc., and consequently obtain a better market share.

Perspectives

Given the limited time and the scope of the research carried out for this thesis, extensive experiments have not been conducted for all the studies. For some of them, only preliminary results are presented. To thoroughly validate the proposed R-DSS, therefore, more work should and could be done. In this subsection, we discuss future research with respect to each research study conducted in this thesis.

Operational Planning of Intermodal Barge Transportation System (DCA-RM): As discussed in Chapter II, by introducing RM policies into operational planning for freight transportation, carriers are able to obtain better total revenue. Considering both profitability of demands and feasibility with respect to the transportation network, decisions made for the capacity allocation are more robust. In addition, applying different treatments to different categories of customers also contributes to generating robust decisions. However, as the situation faced by carriers in practice is highly dynamic, it is possible (as illustrated in Chapter II) for some of the demands requested by regular customers to be rejected. The rejection of regular (or even spot) customers may result in the decrease of customer satisfaction and consequently loss of market share. Therefore, it is interesting, and also stands for a great challenge, to consider the uncertainty of demands. In the research study in Chapter II, we have already shown that it is possible and promising to have a negotiation phase combined with the proposed DCA-RM model. A future research path could be the integration of different negotiation strategies into the proposed DCA-RM model to better satisfy the regular (or even the spot) customers. Moreover, proposing more comprehensive models to implicitly reduce the degree of uncertainty of demands is also a promising research topic. Two perspectives are then possible to achieve that: robustness and flexibility. In terms of robustness, no further resource is available. Better plans need to be made within the given transport capacity. As shown in the preliminary experiments on the extended DCA-RM model, re-routing some of the accepted demands does result in better solutions, in terms of total revenue. Flow distribution is continuously improved by making decisions based on regularly updated forecasts. In terms of flexibility, outsourcing, paying penalty (could also be interpreted as outsourcing) or re-routing of services should be considered for these denied transport requests of all categories of customers. It would also be interesting to consider the uncertainty of demands directly into the DCA-RM model, for example, flexible available time at origin or due time at destination, or even a stochastic model to formulate all the situations mentioned above. As this thesis attempts to make contributions to the freight transportation on the Northern France inland waterway, a real case study should be more convincible to validate the proposed new DCA-RM model with real carriers in practice. With real data, in terms of unit costs, price, handling time, berthing capacity, etc., we could also better analyze the performance of the proposed DCA-RM model and help carriers to win a better market share.

Tactical Planning of Intermodal Barge Transportation System (SSND-RRM): Extensive experiments have already been conducted in Chapter III. With respect to the numerical results, better solutions, in terms of net profit, resource utilization, etc., are obtained by applying the SSND-RRM model at tactical level. Further studies are also carried out in Chapter V to validate the service plan (made at tactical level) within an integrated framework for the proposed R-DSS. According to the results of simulations at operational level, more robust decisions are observed when applying SSND-RRM model at tactical level. It is promising that without the explicit consideration of uncertainty of demands (demands at tactical level are considered to be known), robust decisions are made by introducing RM policies. The aggregation of customer behavior (customer classification) does improve the information/knowledge flow from operational level to tactical level. Meanwhile, it also reveals another set of research questions: what if we consider the RM policies for demand forecasting at tactical levels, what are the characteristics of demands to be considered with respect to the RM policies applied, etc. It would be also interesting to formulate the stopping time of each service at each terminal as decision variables in the SSND-RRM model. Better service plans are expected, in terms of flexibility and robustness, if the stopping time of a service at each terminal is decided by the model, instead of fixed as a predefined value. Those better plans are also expected to result in higher net profit, when facing the uncertain demands, in terms of available time. By making decisions on the stopping time of each service at each terminal, the delay of services could also be formulated in the SSND-RRM model, which is another practice and interesting perspective. In addition, the research questions we had at operational level could also apply at tactical level.

Metaheuristics for the SSND-RRM Problems: As the research studies related to this chapter are still in progress, several tasks should be conducted as follows:

- A complete calibration on all the parameters applied in the MH should be done, and an analysis of the impacts of each parameter on performance of the MH should be made;
- Further experiments should be designed and tested to identify the influences of each algorithmic component;
- Extensive experiments should be conducted to study the performance of the MH. Test instances, with respect to different physical networks, number of potential services, number of demands, etc., are going to be examined;
- Further experiments can be designed to analyze the performance of the proposed MH, especially when solving problems of small scale. Improvement should be made on the MH, so that the proposed solution approach could achieve the optimality faster. By now, one of our guesses for not obtaining the optimal solutions is the existence of the symmetric structures in the solution. For example, different open services or accepted demands which result in the same objective values. To address this challenge, the concept of column generation could be introduced;
- A more sophisticated algorithm should be designed to tune the values of all the parameters applied for the modified adaptive large neighborhood search (ALNS). A very first attempt could be simulated annealing;

In addition, how the proposed MH could be modified and applied as a general algorithm solving other related SSND problems also arises as a great challenge. As a set of services are changed in each iteration, the balance between continuously searching in different neighborhoods (not “close” to each other) and exploring for optimal solutions within a given neighborhood is hard to be measured. A more intelligent algorithm should make the choices by considering the interesting characteristics of solution components and historical performance of all algorithmic components.

Performance Indicators (PIs): With respect to this research study, more comprehensive studies of PIs for general intermodal freight transportation systems are going to be undertaken. Another important and interesting category of PIs, i.e., *Environment impact*, should also be considered. CO_2 *emission*, *energy consumption* and other indicators should be classified into this category. Inspired by *Environment impact*, PIs belonging to this category, e.g., CO_2 *emission*, could be considered and formulated as one type of costs when we are making decisions for the scheduled service network and capacity allocation.

According to the numerical results, the consideration of RM policies in the intermodal freight transportation systems is able to make robust plans for the carriers, in terms of scheduled service plan, resource utilization, flow distribution, etc., even when encountering inaccurate demand forecasts. So far, the reactive decision support system is composed of two optimization models for tactical and operational level, respectively. It is an interesting topic to propose a stochastic model at tactical level facing uncertain demands with the help of RM policy considerations, and the concept of outsourcing. More flexible and robust decisions, in terms of total revenue, resource utilization, etc. are expected. We could then study the importance of flexibility and robustness for barge transportation in different cases, in terms of physical network topologies, accuracy of demand forecasts, competitions from other carriers, and different pricing policies.

Bibliography

[Agarwal and Ergun, 2008] Agarwal, R. and Ergun, O. (2008). Ship scheduling and network design for cargo routing in linear shipping. *Transportation Science*, 42(2):175–196.

[Andersen and Christiansen, 2009] Andersen, J. and Christiansen, M. (2009). Designing new European rail freight services. *Journal of the Operational Research Society*, 60(March):348–360.

[Andersen et al., 2011] Andersen, J., Christiansen, M., Crainic, T., and Grønhaug, R. (2011). Branch-and-price for service network design with asset management constraints. *Transportation Science*, 46(1):33–49.

[Andersen et al., 2009a] Andersen, J., Crainic, T.G., and Christiansen, M. (2009a). Service network design with asset management: Formulations and comparative analyzes. *Transportation Research Part C: New Technologies*, 17(2):397–207.

[Andersen et al., 2009b] Andersen, J., Crainic, T.G., and Christiansen, M. (2009b). Service network design with management and coordination of multiple fleets. *European Journal of Operational Research*, 193(2):377–389.

[Armacost et al., 2002] Armacost, A.P., Barnhart, C., and Ware, K.A. (2002). Composite variable formulations for express shipment service network design. *Transportation Science*, 36(1):1–20.

[Armstrong and Meissner, 2010] Armstrong, A. and Meissner, J. (2010). Railway revenue management: Overview and models. Technical report, The Department of Management Science, Lancaster University.

[Bai et al., 2012] Bai, R., Kendall, G., Qu, R., and Atkin, J. (2012). Tabu assisted guided local search approaches for freight service network design. *Information Sciences*, 189:266–281.

[Bektaş and Crainic, 2008] Bektaş, T. and Crainic, T.G. (2008). A brief overview of intermodal transportation. In Taylor, G.D., editor, *Logistics Engineering Handbook*, chapter 28, pages 1–16. Taylor and Francis Group, Boca Raton, FL, USA.

[Bektaş et al., 2010] Bektaş, T., Chouman, M., and Crainic, T.G. (2010). Lagrangean-based decomposition algorithms for multicommodity network design problems with penalized constraints. *Networks*, 55(3):171–180.

[Bilegan et al., 2015] Bilegan, I.C., Brotcorne, L., Feillet, D., and Hayel, Y. (2015). Revenue management for rail container transportation. *EURO Journal on Transportation and Logistics*, 4(2):261–283.

[Bilegan and Crainic, 2012] Bilegan, I.C. and Crainic, T.G. (2012). A decision support system for intermodal barge transportation operations. VeRoLog 2012, First meeting of the EURO working group on Vehicle Routing and Logistics Optimization, bologna, Italy.

[Bontekoning et al., 2004] Bontekoning, Y., Macharis, C., and Trip, J. (2004). Is a new applied transportation research field emerging? - A review of intermodal rail-truck freight transport literature. *Transportation Research Part A: Policy and Practice*, 38(1):1–34.

[Braekers et al., 2013] Braekers, K., Caris, A., and Janssens, G.K. (2013). Optimal shipping routes and vessel size for intermodal barge transport with empty container repositioning. *Computers in Industry*, 64(2):155–164.

[Caris et al., 2011] Caris, A., Macharis, C., and 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 et al., 2012] Caris, A., Macharis, C., and Janssens, G.K. (2012). Corridor network design in hinterland transportation systems. *Flexible Services and Manufacturing Journal*, 24(3):294–391.

[Chouman and Crainic, 2014] Chouman, M. and Crainic, T.G. (2014). Cutting-plane matheuristic for service network design with design-balanced requirements. *Transportation Science*, 49(1):99–113.

[Christiansen et al., 2007] Christiansen, M., Fagerholt, K., Nygreen, B., and Ronen, D. (2007). Maritime transportation. In Barnhart, C. and Laporte, G., editors, *Transportation*, volume 14 of *Handbooks in Operations Research and Management Science*, pages 189–284. North-Holland, Amsterdam.

[Christiansen et al., 2004] Christiansen, M., Fagerholt, K., and Ronen, D. (2004). Ship routing and scheduling: Status and perspectives. *Transportation Science*, 38(1):1–18.

[Cordeau et al., 1998] Cordeau, J.-F., Toth, P., and Vigo, D. (1998). A survey of optimization models for train routing and scheduling. *Transportation Science*, 32(4):380–404.

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

[Crainic, 2003] Crainic, T.G. (2003). Long-haul freight transportation. In Hall, R.W., editor, *Handbook of Transportation Science*, pages 451–516. Kluwer Academic Publishers, Norwell, MA, second edition.

[Crainic et al., 1984] Crainic, T.G., Ferland, J.-A., and Rousseau, J.-M. (1984). A tactical planning model for rail freight transportation. *Transportation Science*, 18(2):165–184.

[Crainic et al., 1993] Crainic, T.G., Gendreau, M., and Dejax, P.J. (1993). Dynamic stochastic models for the allocation of empty containers. *Operations Research*, 41(1):102–126.

[Crainic et al., 2000] Crainic, T.G., Gendreau, M., and Farvolden, J. (2000). A simplex-based tabu search method for capacitated network design. *INFORMS Journal on Computing*, 12(3):223–236.

[Crainic et al., 2014] Crainic, T.G., Hewitt, M., Toulouse, M., and Vu, D.M. (2014). Service network design with resource constraints. *Transportation Science*, 50(4):1380–1393.

[Crainic and Kim, 2007] Crainic, T.G. and Kim, K.H. (2007). Intermodal transportation. In Barnhart, C. and Laporte, G., editors, *Transportation*, volume 14 of *Handbooks in Operations Research and Management Science*, chapter 8, pages 467–537. North-Holland, Amsterdam.

[Crainic and Rousseau, 1986] Crainic, T.G. and Rousseau, J.-M. (1986). Multicommodity, multimode freight transportation: A general modeling and algorithmic framework for the service network design problem. *Transportation Research Part B: Methodological*, 20:225–242.

[Crainic and Roy, 1988] Crainic, T.G. and Roy, J. (1988). O.R. tools for tactical freight transportation planning. *European Journal of Operational Research*, 33(3):290–297.

[Crevier et al., 2012] Crevier, B., Cordeau, J.-F., and Savard, G. (2012). Integrated operations planning and revenue management for rail freight transportation. *Transportation Research Part B: Methodological*, 46(1):100–119.

[Douma et al., 2011] Douma, A., Schuur, P., and Jage, R. (2011). Degrees of terminal cooperativeness and the efficiency of the barge handling process. *Expert Systems with Applications*, 38(4):3580–3589.

[European Commission, 2011] European Commission (2011). White paper 2011: Roadmap to a single European transport area - Towards a competitive and resource-efficient transport system. Technical report, Directorate for Mobility and Transport, European Commission.

[Eurostat, 2015] Eurostat (2015). *Energy, transport and environment indicators - 2015 edition*. Luxembourg: Publications Office of the European Union.

[Fazi et al., 2015] Fazi, S., Fransoo, J.C., and van Woensel, T. (2015). A decision support system tool for the transportation by barge of import containers: A case study. *Decision Support Systems*, 79:33–45.

[Feng et al., 2015] Feng, B., Li, Y., and Shen, Z.-J. (2015). Air cargo operations: Literature review and comparison with practices. *Transportation Research Part C: Emerging Technologies*, 56:263–280.

[Frémont and Franc, 2010] Frémont, A. and Franc, P. (2010). Hinterland transportation in Europe: Combined transport versus road transport. *Journal of Transport Geography*, 18(4):548–556.

[Gelareh and Pisinger, 2011] Gelareh, S. and Pisinger, D. (2011). Fleet deployment, network design and hub location of liner shipping companies. *Transportation Research Part E: Logistics and Transportation Review*, 47(6):947–964.

[Ghamlouche et al., 2003] Ghamlouche, I., Crainic, T.G., and Gendreau, M. (2003). Cycle-based neighbourhoods for fixed-charge capacitated multicommodity network design. *Operations research*, 51(4):655–667.

[Ghamlouche et al., 2004] Ghamlouche, I., Crainic, T.G., and Gendreau, M. (2004). Path relinking, cycle-based neighbourhoods and capacitated multicommodity network design. *Annals of Operations research*, 131(1-4):109–133.

[Glover, 1997] Glover, F. (1997). A template for scatter search and path relinking. In Hao, J., Lutton, E., Ronald, E., Schoenauer, M., and Snyers, D., editors, *Artificial Evolution*, volume 1363 of *Lecture Notes in Computer Science*, pages 13–54. Berlin: Springer.

[Kasilingam, 1997] Kasilingam, R. (1997). Air cargo revenue management: Characteristics and complexities. *European Journal of Operational Research*, 96(1):36–44.

[Konings, 2007] 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 et al., 2013] Konings, R., Kreutzberger, E., and Maraš, V. (2013). Major considerations in developing a hub-and-spoke network to improve the cost performance of container barge transport in the hinterland: The case of the port of Rotterdam. *Journal of Transport Geography*, 29:63–73.

[Lai, M.F. and Lo, H.K., 2004] Lai, M.F. and Lo, H.K. (2004). Ferry service network design: Optimal fleet size, routing and scheduling. *Transportation Research Part A: Policy and Practice*, 38:305–328.

[Li et al., 2015] Li, L., Lin, X., Negenborn, R., and De Schutter, B. (2015). Pricing intermodal freight transport services: A cost-plus-pricing strategy. In F. Corman et al., editor, *Computational Logistics*, volume 9355 of *Lecture Notes in Computer Science*, pages 541–556. Springer.

[Liu and Yang, 2015] Liu, D. and Yang, H. (2015). Joint slot allocation and dynamic pricing of container sea-rail multimodal transportation. *Journal of Traffic and Transportation Engineering (English Edition)*, 2(3):198–208.

[Lium et al., 2009] Lium, A.-G., Crainic, T.G., and Wallace, S.W. (2009). A study of demand stochasticity in service network design. *Transportation Science*, 43(2):144–157.

[Macharis and Bontekoning, 2004] Macharis, C. and Bontekoning, Y.M. (2004). Opportunities for OR in intermodal freight transport research: A review. *European Journal of Operational Research*, 153(2):400–416.

[Meng et al., 2012] Meng, Q., Wang, T., and Wang, S. (2012). Short-term liner ship fleet planning with container transshipment and uncertain container shipment demand. *European Journal of Operational Research*, 233(1):96–105.

[Moccia et al., 2011] Moccia, L., Cordeau, J.-F., Laporte, G., Ropke, S., and Valentini, M. (2011). Modeling and solving a multimodal transportation problem with flexible-time and scheduled services. *Networks*, 57(1):53–68.

[Notteboom, 2012] Notteboom, T. (2012). Challenges for container river services on the Yangtze river: A case study for Chongqing. *Research in Transportation Economics*, 35(1):41–49.

[Pedersen et al., 2009] Pedersen, M.B., Crainic, T.G., and Madsen, O.B.G. (2009). Models and tabu search meta-heuristics for service network design with asset-balance requirements. *Transportation Science*, 43(2):158–177.

[Powell, W.B. and Topaloglu, H., 2005] Powell, W.B. and Topaloglu, H. (2005). Fleet management. In Wallace, S. and Ziemba, W., editors, *Applications of Stochastic Programming*, Math Programming Society - SIAM Series on Optimization, pages 185–216. SIAM, Philadelphia, PA.

[Ropke and Pisinger, 2006] Ropke, S. and Pisinger, D. (2006). An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows. *Transportation science*, 40(4):455–472.

[Sharypova, 2014] Sharypova, M.B. (2014). *Optimization of hinterland intermodal container transportationl*. PhD thesis, Technical University of Eindhoven, The Netherlands.

[Sharypova et al., 2012] Sharypova, M.B., Crainic, T.G., van Woensel, T., and J.C., F. (2012). Scheduled service network design with synchronization and transshipment constraints for intermodal container transportation networks. Publication CIRRELT-2012-77, Centre interuniversitaire de recherche sur les réseaux d'entreprise, la logistique et le transport, Montréal, QC, Canada.

[Smilowitz et al., 2003] Smilowitz, K.R., Atamtürk, A., and Daganzo, C.F. (2003). Deferred item and vehicle routing within integrated networks. *Transportation Research Part E: Logistics and Transportation*, 39:305–323.

[Stålhane et al., 2014] Stålhane, M., Andersson, H., Christiansen, M., and Fagerholt, K. (2014). Vendor managed inventory in tramp shipping. *Omega*, 47:60 –72.

[SteadieSeifi et al., 2014] SteadieSeifi, M., Dellaert, N., Nuijten, W., van Woensel, T., and Raoufi, R. (2014). Multimodal freight transportation planning: A literature review. *European Journal of Operational Research*, 233(1):1–15.

[Talluri and van Ryzin, 2004] Talluri, K. T. and van Ryzin, G. J. (2004). The theory and practice of revenue management.

[Tavasszy et al., 2015] Tavasszy, L., Behdani, B., and Konings, R. (2015). Intermodality and synchromodality. *Available at SSRN 2592888*.

[Taylor et al., 2005] Taylor, G.D., Whyte, T.C., DePuy, G.W., and Drosos, D.J. (2005). A simulation-based software system for barge dispatching and boat assignment in inland waterways. *Simulation Modelling Practice and Theory*, 13(7):550–565.

[Teypaz et al., 2010] Teypaz, N., Schrenk, S., and Cung, V.-D. (2010). A decomposition scheme for large-scale service network design with asset management. *Transportation Research Part E: Logistics and Transportation Review*, 46(1):156–170.

[Thapalia et al., 2012] Thapalia, B.K., Wallace, S.W., Kaut, M., and Crainic, T.G. (2012). Single source single-commodity stochastic network design. *Computational Management Science*, 9(1):139–160.

[van Riessen et al., 2015a] van Riessen, B., Negenborn, R., and Dekker, R. (2015a). Synchromodal container transportation: An overview of current topics and research opportunities. In *Computational Logistics*, pages 386–397. Springer.

[van Riessen et al., 2015b] van Riessen, B., Negenborn, R., and Dekker, R. (2015b). The cargo fare class mix problem - Revenue management in synchromodal container transportation. Technical report.

[Vu et al., 2013] Vu, D.M., Crainic, T.G., and Toulouse, M. (2013). A three-phase matheuristic for the capacitated multi-commodity fixed-cost network design with design-balance constraints. *Journal of Heuristics*, 19(5):757–795.

[Wang et al., 2015] Wang, S., Wang, H., and Meng, Q. (2015). Itinerary provision and pricing in container liner shipping revenue management. *Transportation Research Part E: Logistics and Transportation Review*, 77:135–146.

[Wang et al., 2014] Wang, Y., Bilegan, I.C., Crainic, T.G., and Artiba, A. (2014). Performance indicators for planning intermodal barge transportation systems. *Transportation Research Procedia*, 3(0):621–630.

[Ypsilantis and Zuidwijk, 2013] Ypsilantis, P. and Zuidwijk, R. (2013). Joint design and pricing of intermodal port-hinterland network services: Considering economies of scale and service time constraints. ERIM Report Series Research in Management.

[Zuidwijk, 2015] Zuidwijk, R. (2015). Are we connected? ERIM Inaugural Address Series Research in Management.