MASTER

Cargo revenue management for synchromodal transportation

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Cargo Revenue Management for Synchromodal Transportation

Master Thesis

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Abstract

A logistics service provider that offers two synchromodal transportation services with a 1- and 2-day shipment window faces a single-leg revenue management problem. The service provider seeks to maximize the expected profit by guaranteeing that its capacity is utilized by committing to allotment contracts or reserving capacity for spot market sales, while coping with limited capacity, stochastic demand, and stochastic spot market freight rates and simultaneously accounting for the transportation services' shipment windows. In this study, we present a stochastic integer program and a simulation-based optimization model to solve the revenue management problem optimally. We use the model to show that the expected profit function is concave in the capacity and that the optimal allocation distribution depends on the capacity, contractual and spot demand and freight rates, the shipment windows, the spot market demand volatility, and the customer's forecast reliability. Next, we show that the optimal capacity reserved for spot market sales is independent of the spot freight rate volatility, provided that the service provider is risk-neutral. A sensitivity analysis is conducted to examine the allocation mechanisms, and to assess managerial insights.

Executive summary

This project presents a single-leg cargo revenue management problem of a logistics service provider with two synchromodal transportation services that seeks to maximize its profit by optimizing the capacity allocation to allotment contracts and spot market demand. The research is conducted at a container terminal operator in Rotterdam, which is pioneering with synchromodal transportation in order to develop efficient hinterland transportation.

Problem Statement

A logistics service provider offers two mode-free transportation services: Express and Standard with a 1- and 2-day shipment window respectively. The shipment window indicates the allowed delivery time in days, such that the service provider should deliver Standard shipments either today or tomorrow. The logistics service provider can sell its transportation services in advance to freight forwarders via allocation contracts or sell it on the spot market. The cargo allotment contract is an agreement between the carrier and the customer that specifies pre-determined freight rates for transportation services within the contract period. The customer is only charged for the realized shipment volume and does not face any capacity restrictions on their shipment volume. By committing to allotment contracts, the logistics service provider is obliged to accommodate the contractual demand throughout the booking horizon. The spot market, on the other hand, consists of shipment requests from customers without allocation contracts. The logistics service provider can utilize these shipment requests and receives the current spot freight rate for the service. Serving the spot market provides an option on demand because the service provider is allowed to reject the incoming spot order. However, spot market demand is volatile, which exposures the logistics service provider to the risk that capacity is underutilized. Therefore, to maximize profit, the logistics service provider should determine the optimal mix between medium-term allocations contracts and reserving capacity for spot market demand, while accounting for the spot market demand volatility. The synchromodal service provider should also account for the effects of the differentiated transportation services (Express and Standard) on its profit and operational performance. Although Express services generate more revenue per shipment, the Standard services have more planning flexibility, which enables network optimization.

The synchromodal service provider faces a revenue management problem, which is an economic trade-off between guaranteeing that capacity is utilized by committing to allocation contracts or reserving capacity for spot market sales, with the objective to maximize profit while coping with its transportation service characteristics, limited capacity, stochastic demand, and stochastic spot freight rates. Therefore, in order to maximize profit, the logistics service provider must:

1. Determine the optimal contract allocation to multiple freight forwarders;
2. (optionally) Reserve capacity for spot market demand;
3. Account for the optimal cargo mix between the transportation service types.

The company's current sales strategy focuses on maximizing the asset utilization, which holds that sales targets to maximize utilization without directly considering the operational implications. The objective of this research is to define a cargo revenue management model that maximizes the expected profit by optimizing the capacity allocation, to develop insights on the optimal allocation mechanisms, and to provide the company with practical recommendations. Therefore, based on the problem statement, the following research question was defined:

How can the introduction of a revenue management model that optimizes the capacity allocation to allotment contracts and spot market demand support EGS's performance in terms of profit and asset utilization?

Analysis

In order to answer the research question, two simulation-based optimization models are developed. The objective of both models is to maximize the expected profit, by determining the optimal capacity distribution to allotment contracts and spot market demand. First, a stochastic integer program is defined to optimally solve the capacity allocation problem, while coping with the shipment windows of the transportation services, limited capacity, stochastic demand, and deterministic spot freight rates. Second, a simulation-based optimization model is defined to extend the stochastic integer program by assuming stochastic spot freight rates, which exhibit mean-reverting properties and are modeled by an Ornstein-Uhlenbeck process. The models evaluate the performance of an allocation portfolio by providing the expected profit, asset utilization, and excess shipments. Next, a method is defined to determine the minimum acceptable freight rate per shipment of a rejected contract, such that it is profitable to accept the contract and offsets other more profitable business opportunities, which supports sales during negotiations.

The capacity allocation problem is solved optimally for small-sized numerical problems, a case study is conducted and a sensitivity analysis is performed to extend the insights on the allocation dynamics. The numerical analysis revealed that the profit function is concave in the capacity since the profit increases when additional demand is allocated to underutilized capacity, while it decreases as capacity is overutilized due to penalty costs owing to excess shipments. The case study showed that the optimization algorithm results on average in 3.68% more profit compared to the allocation decisions taken by experienced sales representatives.

Furthermore, the sensitivity analysis illustrated that the optimal capacity allocation distribution depends on the capacity, the contractual and spot demand, the corresponding freight rates, the transportation services' shipment windows, and on the spot demand volatility. The optimal capacity allocation is independent of the spot freight rate volatility, provided that the service provider is risk-neutral.

Moreover, it is shown that it is profitable to include Standard services in the allocation portfolio when the revenue per shipment is at most 30% lower than the revenue of Express shipments. The additional shipment day of Standard services provides the service provider with planning flexibility, which reduces the probability of excess orders. The smaller the freight rate, the more profitable to increase the share of Standard orders in the allocation portfolio. Next, extending the shipment window of the Standard service saves penalty costs, and allows to allocate more demand, which yields additional profit. The service provider could compensate the customers for the extended shipment window with the obtained profit.

Besides, the sensitivity analysis showed that it is profitable to substitute Express shipments for spot shipments, while it is only profitable to substitute Standard shipments if the spot freight rate compensates the profit loss due to the reduced planning flexibility. It turns out that the optimal capacity reserved for the spot market depends on the freight rates and the spot demand volatility.

Finally, this study showed that the customer's forecast reliability affects the profit of the service provider. The forecast reliability reflects in what degree the customer's shipment volume matches with the volume indicated in the allotment contracts. Reliable forecast positively contributes to the profit. It follows that the freight rates charged to unreliable customers should compensate the profit loss.

Based on the conducted research, it is obtained that a revenue management model that optimizes the capacity distribution to allotment contracts and spot market demand, and copes with fixed capacity, the shipment windows, stochastic demand, freight rates, and stochastic spot freight rates provides the opportunity to improve the company's profit. That is, numerical experiments and the sensitivity analysis showed the dependency of the optimal allocation on the demand, shipment windows and freight rate characteristics. The optimal asset utilization depends on the allocation portfolio that maximizes profit. Consequently, maximizing the profit may not imply maximized asset utilization. Furthermore, this study showed that profit opportunities may exist by reserving capacity for spot market sales. Quantifying the profit opportunity was not possible, due to a lack of available company data.

By addressing the cargo revenue management problem of a synchromodal service provider, we contribute to the limited existing literature in three ways. First, this study provides a model to solve the capacity allocation problem with multiple transportation services optimally, while coping with stochastic influences and constraints. We showed that the shipment windows affect the optimal cargo distribution. Second, we show that profit opportunities exist by serving spot market demand, but notice that the optimal capacity reserved for spot sales depends on the spot demand volatility. Third, this paper studies the capacity allocation problem with stochastic spot freight rates, by modeling it as an Ornstein-Uhlenbeck process. We show that the optimal capacity allocation is not affected by the spot rate volatility, provided that the service provider is risk-neutral.

Recommendations

This study showed that the optimal capacity allocation that would maximize profit depends on the stochastic contractual and spot demand, the freight rates, the limited capacity, and the customer's forecast reliability. In order to maximize profit, it is recommended to shift from a strategy that focuses on maximizing the asset utilization to a strategy that focuses on profit maximization, by applying the defined optimization models that cope with the limited capacity, the transportation services' shipment window, stochastic demand, the spot demand volatility, and the customer's forecast reliability.

Second, this study showed that reserving capacity for spot market sales provides an opportunity to improve the profit. While the demand from allotment contracts must be accommodated, the logistics service provider could optionally accept or reject spot shipment requests. The sensitivity analysis illustrated that substituting capacity reserved for Express shipments with spot shipments yields additional profit while substituting Standard shipments is only profitable if the spot freight rate compensates the profit loss due to reduced planning flexibility. Additionally, the sensitivity analysis showed that less capacity should be reserved for spot demand when the volatility increases. Therefore, it is recommended to reserve capacity for spot market sales but to account for the spot demand volatility in the allocation process. Moreover, it is recommended to survey the spot market freight rate and demand characteristics since this study did not analyze the actual spot demand characteristics, because of data unavailability.

Third, we recommend that the service provider should focus on allocating Express services, but also include lower-priced Standard services in the allocation portfolio to account for planning flexibility, such that the profit is maximized. Although the revenue reduces by allocating Standard services instead of Express shipments, the penalty costs savings outweigh the revenue opportunity, which implies a higher profit. Including Standard services becomes more profitable as the freight rate difference between Express and Standard shrinks.

Finally, it is recommended to measure and incorporate the customer's forecast reliability in the capacity allocation process. This study showed that unreliable customers with uncertain demand negatively affect profit. The forecast reliability is especially of importance in the case of Express shipments because this service has a relative tight planning flexibility, which increases the exposure to demand uncertainty. Moreover, we recommend reflecting the customer's forecast reliability in the freight rates, such that unreliable customers are charged higher freight rates that compensate the expected profit loss. In order to incorporate the forecast reliability in the allocation process, the company should start measuring the reliability of its current customers.

Preface

The thesis that you are about to read marks the end of my time at the Eindhoven University of Technology and is the final chapter of an amazing student life. It has been a sequence of great moments, and I am honored to have shared them with great people. I would like to take a moment to express my gratitude to the people that supported me along this journey.

First of all, I want to state my acknowledgment to my university supervisors dr. Arun Chockalingam and dr. Nevin Mutlu for their collaborative support, useful insights, recommendations during the execution of this project, and for the time and effort you invested in me. I enjoyed our conversations and your excitement for this project. Arun, it was an honor to have you as a mentor. You were invaluable in the process that has resulted in this master thesis. You continuously challenged me to push my limits and to develop myself professionally. You always asked the right questions that forced me to improve my work. Moreover, you supported me through the ups and downs of this project. Nevin, your door was always open, and you were always willing to provide critical feedback. Your knowledge on revenue management was incredibly beneficial for understanding the context of this project.

Secondly, I want to thank European Container Terminal Rotterdam, NWO, and TKI Dinalog for the opportunity of conducting this research project about revenue management opportunities conducive to synchromodal transportation. I particularly want to thank Willemien Akerboom, champion of this project. You gave me full responsibility to structure the research the way I wanted. During the process, you guided me with critical thinking which helped me to rethink the choices made. Moreover, I am grateful for your lessons and advices on company politics. It was nice to experience that you also became excited about the subject of this project. I profoundly enjoyed this fascinating learning trajectory, and I am looking forward to keep evolving in these knowledge areas.

As said, the fulfillment of this master thesis also implies that my life as a student is finished. It closes a great period and marks the beginning of an exciting new one. During my time in Eindhoven, I had the privilege to meet and work with incredible people. I want to thank all my friends for this unforgettable time.

Finally, I want to express my gratitude to my family, in particular, my parents. You always supported me on the road to this point, which was not always smooth as it contained highs and lows. You always wanted the best for me, and always encouraged me to achieve my potential. Thanks for your love, your unconditional support and for providing me a place that I call home.

Stan Fransen

Contents

List of Figures

List of Tables

List of Abbreviations

CAP	Capacity Allocation Problem
ECT	European Container Terminal
EGS	European Gateway Services
GA	Genetic Algorithm
LSP	Logistics Service Provider
NPV	Net Present Value
OU-process	Ornstein-Uhlenbeck process
PoR	Port of Rotterdam

List of Variables

$B = \{i : b_1, \ldots, b_n\}$	Set of n allotment contracts with b_i the bid contract of bidder i
$P = \{E, S\}$	Set of transportation service types (Express and Standard)
$X_i^P \sim Poisson(\lambda_i^k)$	Number of shipments of bidder i of service type P
$X_s \sim Poisson(\lambda_s)$	Number of shipments on spot market
$F(x)$	Poisson cumulative distribution function
C	Capacity
E_s	Excess shipments
x_i	Binary decision variable to grant contract to bidder i
n_{spot}	Booking limit of spot market shipment requests
r_i^P	Revenue per shipment of bidder i and service type P
r^{spot}	Revenue per shipment of spot market sale
r_{max}	Maximum freight rate of all allotment contracts
p	Penalty costs of excess shipments
D_E	Expected cumulative Express demand
D_S	Expected cumulative Standard demand
D_{spot}	Expected cumulative spot demand
π_j	Probability of postponing j shipments
η	Expected asset utilization
r_f	Risk-free interest rate
$T = \{t : 1, \ldots, T\}$	Time periods t in booking horizon T
S_t	Spot freight rate at time t
κ	Mean reversion rate of spot market freight rates
μ	Long term mean of spot market freight rates
σ	Volatility of spot market freight rates
W_t	Wiener process of spot market freight rates

List of Definitions

Booking limit	The maximum number of shipment requests to accept of a transportation service type for a single day.
Carrier	Company that provides transportation services.
Corridor	Link between origin and destination that are connected by one or more modes of transportation.
Freight forwarder	Company that manages the freight shipment of a shipper but that outsources the actual transportation to one or more carriers.
Freight rate	Revenue per shipment.
Logistics service provider	Company that manages the freight flows between origin and destination.
Shipment window	The maximum number of days the carrier has to ship the goods, e.g., a two-day shipment window allows the carrier to transport the shipment today or tomorrow.
Shipper	Company or person that wants to ship freight between an origin and destination but does not have the resources to transport the shipment by itself.
Transportation mode	The way of transportation, e.g., road, rail, waterway.

Chapter 1

Introduction

This report presents the results of a revenue management study to maximize the profit of a logistics service provider that offers synchromodal transportation services by optimizing the capacity allocation to allotment contracts and spot market demand. The capacity allocation problem with spot market demand has been solved optimally incorporating the characteristics of the synchromodal products. This project is realized with the cooperation of European Container Terminal Rotterdam and European Gateway Services, pioneers in synchromodal transportation.

1.1 Synchromodal transportation

Synchromodal transportation is a logistics concept that focuses on the integration and cooperation of transport services and modes in order to provide service operators more transportation possibilities (Zhang & Pel, 2016). Characteristic of the synchromodal concept is that shippers allow the network operator to select the modality of the shipment. The shipper and the logistics service provider agree only on the delivery of products at a specified price, time, quality and sustainability, and gives the service provider freedom to decide on how to deliver the product (Haller, Pfoser, Putz & Schauer, 2015).

The logistics service provider functions as the network orchestrator that manages the transportation operations in the network. Synchromodality enables the network orchestrator to optimize the network transportation plan by exploiting the extra planning flexibility and by efficiently utilizing all available resources given the current state of the network. Moreover, the service operator can optimize the transportation plans by bundling the flow of goods from different customers (Pfoser, Treiblmaier & Schauer, 2016).

As planning flexibility is essential to enable synchromodal planning, logistics network operators, i.e., carriers, have an incentive to introduce differentiated transport services with different tariff classes depending on the shipment window and flexibility (Van Riessen, Negenborn & Dekker, 2015). Shippers could provide the logistics service provider with this additional flexibility by leaving the mode selection to the service provider (Gorris et al., 2011; Lucassen & Dogger, 2012). Logistics service providers should offer shippers an incentive to book synchromodal by transferring a proportion of the financial benefit of synchromodality to shippers (Behdani, Fan, Wiegmans & Zuidwijk, 2016). This way, the service level and the level of flexibility of the transportation service is reflected by the price of the product.

Synchromodality is promised as the future of transport, having benefits for logistics companies, consumers and the environment (Singh, van Sinderen & Wieringa, 2016). Shippers demand higher levels of service, in terms of delivery time and reliability, while supply chains get more global and increasingly interconnected (Crainic, 2000; Crainic & Laporte, 1997; Veenstra, Zuidwijk & Van Asperen, 2012). Cost reductions, improved reliability, flexible and integrated supply chains, reduction of CO_2-emissions and reduced pressure on roads are promising benefits of the synchromodal concept (Singh et al., 2016). Furthermore, synchromodal transportation results in reduced delivery times, increased capacity utilization and buffering effects between the alternative modes yielding a more flexible, reliable and robust transport system (Zhang & Pel, 2016).

Furthermore, maritime terminals also benefit from synchromodal transportation as it contributes to hinterland accessibility. In turn, efficient hinterland transport may result in faster container release and reduced terminal congestions at seaports (Franc & Van der Horst, 2010). Hinterland accessibility is an essential contributor to the seaport's competitiveness (De Langen & Pallis, 2006; Wiegmans, Hoest & Notteboom, 2008). Therefore, Notteboom and Rodrigue (2005) state that "the development of the hinterland network is a new dimension for competition between seaports."

1.2 Project environment

Company background

European Container Terminal (ECT), is the leading container terminal operator in Europe and part of Hutchison Ports, which in turn is the world's leading port network. ECT operates two maritime container terminals located in the Port of Rotterdam: ECT Delta Terminal and Euromax Terminal Rotterdam. The Port of Rotterdam (PoR) is a major European port that functions as central node and connects Europe with the rest of the world. The Rotterdam-based terminals processed 7.5 million twenty-foot equivalent units (TEU) in 2015 (ECT Rotterdam, 2016). Furthermore, ECT owns and operates four inland terminals: MCT Moerdijk and Hutchison Ports Venlo in the Netherlands, Hutchison Ports Duisburg in Germany and Hutchison Ports in Belgium, which are connected by rail and waterway connections.

In 2007, ECT founded European Gateway Services (EGS) to provide more efficient and sustainable hinterland transportation with the goal to improve hinterland accessibility. EGS is a Dutch-based logistics service provider that provides synchromodal network solutions for European hinterland transport. As a subsidiary of ECT, EGS offers barge and rail transportation services between the maritime and inland terminals of ECT and an expanding network of partnered terminals. The company has a strong European network that contains 22 terminals located in the Netherlands, Germany, Belgium, Austria and Switzerland (European Gateway Services, 2018), see Figure A.1 in Appendix A. EGS is committed to providing qualitative, reliable, cost-efficient, innovative and sustainable logistics solutions for its customers. Moreover, EGS offers Extended Gate services, which allow customers to delay customs formalities until its cargo arrives at an ECT inland terminal, resulting in additional time savings and increased efficiency. Other services of EGS's product portfolio include Terminal services, E-services, and Deepsea Liner services. By having the flexibility to switch between transportation modes and providing extra services, EGS is a principal competitor in the field of container hinterland transportation. Table A.1 in Appendix A provides EGS's key figures.

Synchromodal network

EGS operates a synchromodal network with rail and barge connections, depending on the accessibility of the destination. At this point, the company's network does not include truck connections, but if necessary, the company charters a truck from an external partner. The availability of multiple modalities provides the opportunity to optimize the network by selecting the most efficient modality for each shipment. Furthermore, the EGS network allows for redirecting freight via multiple corridors to its final destination, which contributes to the planning flexibility. Next, being a subsidiary of a container terminal operator, EGS could temporality store containers at a terminal and ship the container later if this contributes to the network's performance. The company deploys a synchromodal planning algorithm that optimizes the network planning.

Synchromodal services

As a pioneer in synchromodal transportation, EGS is currently developing a synchromodal product portfolio. EGS translated the synchromodal concept into two mode-free logistics products with varying service levels: Express and Standard. The service level indicates the shipment window, where the Express product has a tighter window than the Standard product. Accordingly, EGS charges a premium on Express services, as this product has less planning flexibility compared to the Standard product.

It should be highlighted that the logistics service provider (EGS) determines the modality of the shipment. The shipper and EGS only agree in advance on the price and shipment window, and it is up to EGS to select the optimal modality given the agreed shipment window and given the current state of the network. A pilot study with a major customer showed that the synchromodal service portfolio improves the on-time delivery reliability and asset utilization.

1.3 Problem statement

Capacity allocation problem

A logistics service provider could sell its transportation services in advance to freight forwarders via medium-term allotment contracts or sell it on the spot market. Since the capacity of the logistics service provider is relatively fixed, managing inventory involves capacity allocation and booking control (Billings, Diener & Yuen, 2003).

Capacity allocation involves distributing capacity between allotment contracts and spot market demand. An allotment contract is a pre-determined agreement between the logistics service provider and a customer to transport the customer's shipments for a fixed shipment compensation within the contract period. The logistics service provider optimizes its capacity allocation before the start of the booking horizon by determining which allotment contracts to accept and reserving capacity for spot market sales. Accordingly, the service provider is obliged to transport the contractual demand throughout the booking horizon, while it sells the remaining capacity on the spot market. The medium-term allocation decisions therefore effectively reduce the capacity for spot market shipments (Billings et al., 2003). The optimal allocation of capacity is challenging due to exaggerated demand information of forwarders and uncertain spot market demand (C. Liu, Jiang, Geng, Xiao & Meng, 2012).

Allotment contracts

Logistics service providers commit to mid-term allocation contracts with shippers and freight forwards to assure capacity utilization and mitigate cash flow risks (Hellermann, 2006). Shippers and freight forwarders, on the other hand, try to secure capacity access while pressing for favorable terms, strengthened by its market domination. The cargo allotment contract is an agreement between the carrier and the customer that specifies pre-determined rates for transportation services within a fixed term, typically a year. The settled rate per shipment reflects the discount that the customer negotiated, based on the volume that the customer expects to ship in the contract period. The customer is only charged for the realized shipment volume, and not penalized if it falls short or exceeds the expected shipment volume as defined in the contract. Accordingly, the customer does not face any capacity restrictions on their shipment volume. In fact, by committing to the medium-term allocation contracts, the customer acquires options on transportation services of the carrier. That is, the customer has the right but not the obligation to ship demand via the carrier at a specified strike price that may be exercised at any time within the contract period. As a result, the pricing decisions and the management of the cargo contracts with customers, all having unique contracts, are two key factors that affect the carrier's profitability (Billings et al., 2003).

Spot market

The logistics service provider could also sell its transportation services on the spot market, i.e., it could serve the demand of customers without granted capacity via allotment contracts. Although EGS currently does not serve the spot market, management has some aspirations to serve the spot market in the future.

The container freight industry is especially appropriate to serve the spot market due to standardized transportation units, and the relatively fixed transportation schedules (Gorman, 2015). The advantage of serving the spot market is that the logistics service provider could accept demand continuously, instead of allocating capacity for an extended period via contracts. Moreover, the spot market is commonly more profitable than contractual shipments. However, spot market demand is volatile, which exposures the logistics service provider to the risk that capacity is underutilized. Therefore, to maximize profit, the logistics service provider should determine the optimal mix between medium-term allocations contracts and reserving capacity for spot market demand, while accounting for the spot market demand volatility.

Cargo mix

Furthermore, while determining the optimal contract portfolio, the synchromodal service provider should account for the effects of the differentiated transportation services (Express and Standard) on its profit and operational performance. The service provider should sell the right set of products to their customers in order to develop cost-efficient transportation plans, while also maximizing revenue. Although Express services generate more revenue per shipment, the Standard services provide more planning flexibility, enabling network optimization. Consequently, relatively low-priced Standard services with high planning flexibility are not inferior to Express services (Van Riessen, Negenborn & Dekker, 2017). The contract allocation decision thus involves determining the optimal cargo mix given the characteristics of synchromodal transportation services, such that profit is maximized.

EGS is currently testing a synchromodal product portfolio with a major customer. The objective of the pilot is to examine the customer behavior to synchromodal transportation services and to examine the operational effects. Preliminary results suggest that the company should consider the optimal mix between the synchromodal products in an early stage of the sales process such that it could contribute to the operational performance. The conclusions that follow from this master thesis project contribute to the further development of the synchromodal project of EGS.

In short, the cargo capacity allocation problem of a logistics service provider is an economic trade-off between guaranteeing that capacity is utilized by committing to allocation contracts or reserving capacity for spot market sales, given its transportation service characteristics, such that profit is maximized. To maximize profit, the logistics service provider must:

1. Determine the optimal contract allocation to multiple freight forwarders;
2. (optionally) Reserve capacity for spot market demand;
3. Account for the optimal cargo mix between the transportation service types.

Revenue management opportunities

Revenue management entails strategies and tactics to manage demand with the objective to maximize revenue or yield. Revenue management is practiced in industries or markets that face high fixed costs and low margins, with the goal of efficiently selling perishable resources or products (Cross, 1997; McGill & Van Ryzin, 1999; Talluri & Van Ryzin, 2006). The cargo business is such an industry, and cargo revenue management, therefore, involves maximizing profit by optimizing the prices of transportation services and asset utilization given a relatively fixed capacity. Billings et al. (2003) highlight the need for cargo revenue management: "Cargo carriers must adopt revenue management or face the consequences of revenue opportunity loss and being competitively disadvantaged."

Capacity is valuable for logistics service providers, and the efficiency with which it is utilized should be maximized (Freeland, 2007). Especially when demand keeps growing, while the options for increasing capacity are limited. The company involved in this research currently experiences capacity limitations, which emphasizes the need for a revenue management strategy to maximize profit by optimizing the capacity distribution. Barnhart, Belobaba and Odoni (2003) state that a revenue management model is required to balance customer demand and transportation options.

EGS's current sales strategy focuses on maximizing asset utilization, which holds that sales targets to maximize utilization without directly considering the operational implications. Shifting from an emphasis on maximizing asset utilization to maximizing profit is the first impact of revenue management, given that higher profitability may be realized with a lower utilization (Billings et al., 2003). Agatz, Campbell, Fleischmann, Van Nunen and Savelsbergh (2013) state that "Revenue management has shown that companies can do much better than a one-size-fits-all first-come-first-served strategy when selling scarce capacity to a heterogeneous market." So a revenue management strategy that focuses on maximizing profit rather than on asset utilization could yield improved profitability and operational performance. The synchromodal service provider faces a revenue management problem, as it is challenged to select those allotment contracts, and to reserve the optimal amount of capacity for spot market demand such that profit is maximized. Billings et al. (2003) note that sales should have the tools to determine the optimal space allocation via medium-term contracts.

Minimum bid-price

Furthermore, revenue management systems contain information that sales can use to explain why specific freight arrangements cannot be accepted (Freeland, 2007). The logistics service provider seeks to maximize the expected profit by optimizing the capacity allocation, given the contract terms that are negotiated by the sales offices. Optimizing the capacity allocation is a trade-off between the allotment contracts, and the service provider will only accept those contracts that maximize profit and reject all other contracts. Revenue management practices could provide sales with a minimum bid-price of a rejected contract, such that it is profitable to accept the contract. That is, the minimum bid-price is the minimum acceptable price per shipment such that it offsets other more profitable business opportunities (Billings et al., 2003). In other words, the minimum bid-price tells how much the revenue per shipment of a rejected contract should increase such that it compensates the opportunity costs of accepting other more profitable contracts. It indicates the floor price, which sales representatives can use to (re-)negotiate a contract. Further profitability is achieved as the renegotiated price exceeds the bid price. This study presents a method to determine the minimum bid-price of rejected contracts, based on the optimal allocation contract portfolio that follows from the revenue management model.

1.4 Scope

As discussed above, the sales department of EGS faces the challenge of optimally allocating its capacity to contract or spot market demand such that the expected profit is maximized. This research should provide the sales department with a model that supports them in the capacity allocation problem when selling the cargo capacity. All aforementioned aspects motivate the research, and its objective is the development of a mathematical model and its solution algorithm to the capacity allocation problem. The target of the solution algorithm is to provide sales representatives with (near-) optimal solutions to the problem, such that the tool is practical to use. The research is conducted in the Product Development department of ECT Rotterdam, with the cooperation of the Sales and Operations departments of EGS. This section introduces the scope that is used as input to model and analyze the capacity allocation problem of a synchromodal logistics service provider.

Medium-term contract allocation

Billings et al. (2003) mention that four fundamental issues should be addressed to achieve profit maximization: cargo product definition, contract pricing, medium-term allocation, and short-term booking control. In general, there are three levels of revenue management decisions: strategic, tactical and booking control (Phillips, 2005). Decisions on the strategic level involve market segmentation, cargo product definition, and contract pricing. Tactical decisions are concerned with medium-term allocations, while short-term booking control implies determining which shipment requests to accept and which to reject.

This study focuses on the tactical medium-term allocation level by solving the capacity allocation problem of a synchromodal logistics service provider. The capacity allocation problem involves optimizing the medium-term contract portfolio and allocating capacity to spot market demand with the objective to maximize profit. More specifically, we develop a model that determines which contracts to grant, and that determines the optimal static spot market booking limit while coping with the available capacity. The spot market booking limit indicates the maximum number of spot market shipment requests the service provider should accept on a day such that its expected profit is maximized in the long run.

Transportation services

As already stated, the synchromodal product portfolio of EGS includes two shipment service types: Express and Standard. Express shipments are fast-delivery services with a relatively tight shipment window, while the shipment window flexibility characterizes the Standard services. It follows that the freight rates reflect the shipment window flexibility of the product, viz. Express shipments are more expensive than Standard shipments. Accordingly, the scope of this research includes both transportation services, which holds that the model to be developed should incorporate both products and its characteristics.

Single corridor

We limit ourselves to focus on optimizing the capacity allocation of a single corridor. More specifically, the Rotterdam – Venlo corridor is selected as the primary focus of this research, as this is a typical synchromodal corridor connected by road, rail and waterways. Additionally, EGS is currently testing the synchromodal portfolio with a major customer on this corridor. It is likely that the knowledge and information of this pilot study could contribute to our research.

Bid contracts

This study focuses on optimizing the contract portfolio, and it is, therefore, assumed that all bid contracts are known. Next, each bid contract specifies the expected daily number of Express and Standard shipments and a fixed rate for each shipment type. As argued before, the contractual agreement does not limit the customer on shipment volume, i.e., they are not penalized if the realized shipment volume exceeds or falls short. The contractual shipment prices are exogenous as the prices are a result of negotiations between the service provider and the customer. Furthermore, for the sake of simplicity, it is assumed that the contract periods have the same length, covering the entire booking horizon.

Constraints and uncertainties

The capacity allocation problem should respect the following constraints and uncertainties:

- **Limited capacity**: The service provider has a limited daily container capacity, measured per TEU. The standardization of shipping containers allows transporting the containers with different modes without handling and unloading the individual cargo packed in the containers. Therefore, it is assumed that all containers are homogenous, i.e., all containers have the same characteristics and cover exactly one TEU.
- **Commodities**: The service provider does not distinguish between the type of commodities. Although some commodities require special services such as refrigerated containers, these special requirements are managed on the operational level. Therefore, we assume that all commodities require exactly the same service. Additionally, we assume that the freight rates are independent of the commodity types.
- **Shipment disturbances**: Shipment delays caused by the network operator or beyond their control during logistics and transport operations are out of scope. Delays are a day-to-day process and potentially caused by different actors, which increases the complexity to control the disturbances. Although disturbances are business as usual, we assume that disturbances are handled on the operational level. Therefore, we exclude the shipment disturbances effects since we distribute capacity on a tactical level for the medium-term, e.g., a year.
- **Stochastic demand**: Contractual and spot market demand are stochastic. Although the bid contracts specify an expected number of shipments per service type, the realized demand is uncertain. This research excludes seasonality patterns in demand, due to unavailable data to verify the seasonality patterns and in order to reduce the problem complexity.
- **Stochastic spot prices**: Related to stochastic demand is the uncertainty of the spot freight rates, influenced by demand and supply mechanisms. The service provider should account for this uncertainty as it may influence the capacity allocation decision. Therefore, we account for stochastic spot freight rates in this research.

1.5 Research goal

This research aims to support logistics service providers in their capacity allocation decision process with the goal to maximize profit. Following from the Problem Statement in Section 1.3 and from the Scope in Section 1.4, the research goal is derived as follows:

Develop a **mathematical model** that **maximizes profit** by determining the **optimal contract allocation portfolio** and **spot market booking limit**, while coping with the **shipment windows** of the differentiated synchromodal products, **stochastic contract and spot market demand**, **fixed revenue of contractual transportation services**, **stochastic spot market freight rates** and **fixed capacity**.

The mathematical model and its solution algorithm should determine the optimal contract allocation and the optimal spot market booking limit with respect to the shipment windows of the differentiated products and the fixed capacity. The spot market booking limit indicates the maximum number of spot orders to accept on a day. That is, on a given day, all incoming spot shipment requests are accepted up to the fixed booking limit. The target of the solution algorithm is to provide the sales department with a decision support tool to evaluate the optimal set of contracts to accept. Next, the solution algorithm should provide insights into the cargo service types mix and the minimum acceptable freight rates of rejected contracts.

1.6 Research question

The main research question follows from the Problem Statement, Research Goal and according to all aspects mentioned above:

How can the introduction of a revenue management model that optimizes the capacity allocation to allotment contracts and spot market demand support EGS's performance in terms of profit and asset utilization?

Underlying research questions

The following sub-questions were defined to answer the research question. First, the characteristics of the differentiated transportation products should be studied to establish a definition of the transportation services, leading to the following sub-question:

I What are the characteristics of the differentiated synchromodal transportation services (Express and Standard)?

To define a revenue management model that maximizes profit, we need to determine which modeling types are the best suitable to define and optimize the capacity allocation problem with deterministic and stochastic spot freight rates. Therefore, we need to analyze the model requirements, resulting in the following sub-question:

II What type of modeling is the best fit to model the capacity allocation process of the synchromodal transportation provider, given stochastic demand, limited capacity and stochastic spot market prices?

Next, this study focuses on a capacity allocation problem with stochastic spot market freight rates. The following research question is defined to determine how to represent the stochastic spot freight characteristics:

III What type of modeling is the best fit to model the stochastic spot market freight rates?

Subsequently, we will derive the revenue management models by answering the following sub-questions:

IV How to determine the optimal capacity allocation to allotment contracts and spot market demand that would maximize profit given stochastic demand, limited capacity, and **deterministic** spot market rates?

V How to determine the optimal capacity allocation to allotment contracts and spot market demand that would maximize profit given stochastic demand, limited capacity, and **stochastic** spot market rates?

As discussed in Section 1.3, the minimum bid-price indicates the required freight rate of a rejected allotment contract that offsets other more profitable business opportunities. By answering the following sub-question, we can determine the minimum bid-price based on the results that follow from the optimization models:

VI How to determine the minimum bid price of a rejected allotment contract?

Finally, this research will focus on the development of a solution algorithm to provide a practical tool to the sales offices that optimizes the capacity distribution to allotment contracts and spot market demand within a reasonable computation time. Therefore, the following research question is defined:

VII What type of solution algorithm is practical in providing a (near-) optimal solution to the capacity allocation problem?

1.7 Methodology

A methodology is defined to achieve the research goals and is structured according to the reflective cycle, a design theory of Van Aken (1994) see Figure 1.1. The case class that will help to position the research in literature is defined as a cargo capacity allocation problem. The selected case is the capacity allocation problem of a synchromodal logistics service provider, as described in Section 1.2. The problem selection and diagnosis of the selected case are summarised in Section 1.3 by describing the Problem Statement and in Section 1.4 by discussing the Project Scope. This research tries to develop generic design knowledge for similar cases within the case class. The results of the problem-solving process, the regulative cycle, are used in the reflective cycle to reflect and to determine the design knowledge.

The insights gained by answering sub-questions 1-6 capture the design step of the regulative cycle. To answer sub-question 1, current literature on synchromodal transportation is examined, and the product development team of ECT is consulted to specify the characteristics of the synchromodal transportation services. Although part of this research question is already answered in Section 1.1, it is found significant to investigate the requirements of the synchromodal services, which should be reflected by the mathematical model to be developed. To answer sub-question 2, current cargo revenue management literature, in particular cargo capacity allocation problems, is investigated to examine which mathematical models and modeling techniques are used to optimize the profit of the capacity allocation problem. Next, maritime literature on freight rates is examined to answer sub-question 3.

The knowledge gained by answering sub-questions 1-3 serves as input for the design of the mathematical model and to answer sub-questions 4 and 5. Based on these insights, the decision variables will be determined, an objective function will be constructed, and the set of restrictive conditions are defined. First, deterministic spot market prices will be assumed to reduce the complexity of the model. The cargo capacity allocation problem with spot market demand is modeled as a stochastic integer problem incorporating the characteristics of the synchromodal services. Second, we incorporate the stochastic spot freight rate by defining a simulation model. It should be noted that the development of the mathematical model is an iterative process and revisions of the models or its solutions algorithms could happen in each step.

To increase the practicability of the mathematical model for sales representatives, it is tried to determine the minimum bid-price, which answers sub-question 6. The minimum bid-price will be derived from the solution of the mathematical model of sub-question 4.

After the mathematical models are defined, a solution algorithm that optimally solves the mathematical models will be developed. The models will be encoded in Python. A genetic algorithm is developed to increase the practicability of the model to the sales representatives since it significantly decreases the required computation time. The development of the genetic algorithm answers sub-question 7.

The developed mathematical model is solved in the implementation step of the regulative circle. The model is evaluated by submitting it to a sensitivity analysis to assess the effects of the input parameters on the results. Unfortunately, due to the lack of company data, it is not possible to optimally solve the cargo capacity allocation problem for the selected case. Therefore, all data to evaluate the model is constructed by estimations from experienced sales representatives. The sensitivity analysis in the evaluation step finalizes the regulative cycle.

The reflection step in the reflective cycle also assesses the practicality of the cargo capacity allocation model. During the reflection step, it is examined how the model could support EGS management in its decision-making process. Furthermore, the reflection step assesses if the case-specific design knowledge gained by completing the regulative cycle is generally applicable.

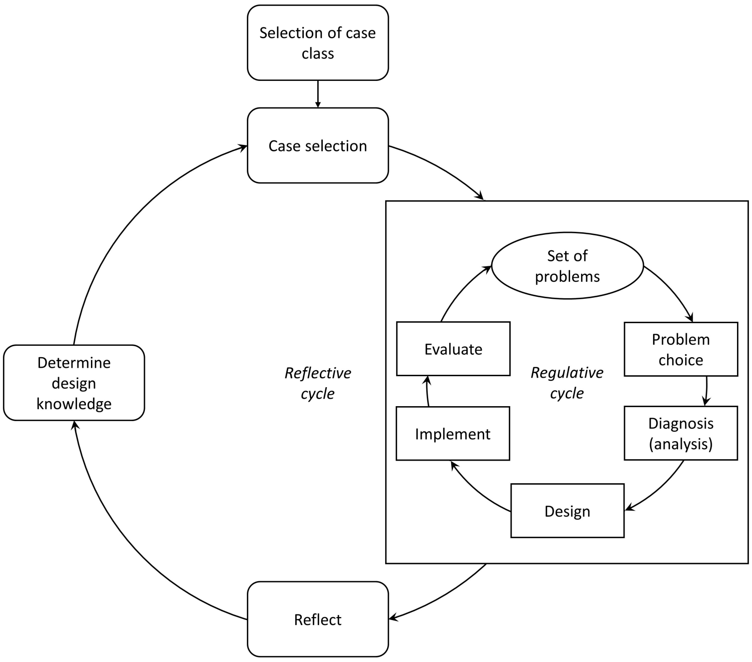


Figure 1.1: Reflective Cycle

1.8 Report outline

The remainder of this report is structured based on the Methodology as defined in Section 1.7. In Chapter 2 we review current literature on cargo revenue management and related concepts with the aim to conceptualize the revenue management problem, identify existing mathematical models and to position our research in the current literature. Chapter 3 presents the mathematical model with deterministic spot market freight rates, the simulation model that incorporates stochastic spot freight rates, and a method to determine the minimum bid-price. Next, Chapter 4 presents a genetic algorithm that functions as a solution algorithm to the mathematical model. In Chapter 5 we perform a sensitivity analysis on the model, thereby setting the stage for a detailed assessment from which practical recommendations will be derived. Last, Chapter 6 presents the research conclusions, limitations of this research and future research directions.

Chapter 2

Literature Review

This chapter provides an overview of current literature on cargo revenue management in general and related to synchromodal transportation. The goal of this section is twofold. First, it provides a theoretical foundation on the subjects relevant to this research. Second, it supports positioning the contributions of this research against the gap observed in the current literature.

The chapter is structured as follows. First, an overview of (cargo) revenue management literature is provided to introduce the concept and the research area. Next, current revenue management literature on synchromodal transportation is examined. Thirdly, literature on cargo capacity allocation problems is presented to determine modeling techniques and to identify gaps in current literature. Fourth, the literature on stochastic freight rates is examined to determine the necessary modeling techniques. Finally, the contribution of this paper to current literature is provided.

2.1 Revenue management

Revenue management comprises strategies and tactics to manage demand with the objective to maximize revenue or yield. The goal of revenue management is to sell the right product to the right customer at the right price and at the right time (Cross, 1997). Revenue management strategies focus on the identification of customer segments, based on the customer's perceived value of a product, and subsequently aligning the product's characteristics and price to target each customer segment (Phillips, 2005; Cross, 1997). Revenue management commonly involves data-driven analyses to predict customer behavior and to optimize product availability and prices. The revenue management discipline is all about prioritizing service to the most profitable customer (Agatz et al., 2013).

Next to focusing on revenue maximization, revenue management strategies could also contribute to costs savings, while helping to maintain quality (Elliott, 2003). For example, by introducing premiums and discounts on delivery fees, groceries try to encourage customers to select a particular time slot for home delivery with the objective to facilitate cost-efficient routing (Agatz, Campbell, Fleischmann, van Nunen & Savelsbergh, 2008).

Business conditions

The following business conditions conducive to revenue management strategies are identified in literature, see Weatherford and Bodily (1992), Talluri and Van Ryzin (2006) and Phillips (2005):

- Capacity is fixed, perishable and booked prior to departure;
- Stochastic demand;
- Price as a signal of quality;
- The seller can divide capacity into fare classes (e.g., Express and Standard services);
- The fare class availability can be changed over time.

It turns out that the business context of the synchromodal logistics service provider complies with the identified conditions. The presence of revenue management enabling conditions supports the purpose of this research, which focuses on a revenue management strategy to optimize the medium-term capacity distribution with the objective to maximize profit.

Context

Revenue management is classically separated into four subproblems: forecasting, inventory control, pricing and overbooking (Belobaba, 1987; Chiang, Chen & Xu, 2006; Talluri & Van Ryzin, 2006). This revenue management study targets the inventory control problem of a logistics service provider. A short overview of the revenue management subproblems is included below to provide the context of the inventory control problem related to the other problems.

The inventory control problem of a logistics service provider involves efficiently distributing capacity to customers over time such that profit is maximized, i.e., quantity-based revenue management. Pricing is a critical aspect of revenue management models since incorrectly pricing could cause revenue management systems to make incorrect decisions (Ingold, Yeoman & McMahon-Beattie, 2000). The challenge of price-based revenue management is to determine the appropriate magnitude of discounts and premiums (Agatz et al., 2013). It should be noted that quantity-based revenue management rather supplements than replaces price-based revenue management (Phillips, 2005). Overbooking strategies are applied to guarantee that capacity is fully utilized, while coping with no-shows and cancellations. Forecasting functions as a critical input to the optimization models for inventory control, pricing, and overbooking. It determines to a large degree the performance of a revenue management system. Reducing the forecast error of a revenue management system by 20% could result in a 1% revenue increase (Pölt, 1998).

Inventory and booking control

As already argued in Section 1.3, logistics service providers commit to mid-term allocation contracts with shippers and freight forwards, to ensure capacity utilization and to mitigate cash flow risks. These allocation contracts specify a pre-determined price per shipment but do not specify the shipment volume. The relationship between the carrier and the freight forwarder has parallels with the wholesaler and the retailer, because the carrier has the transportation resources, while the forwarder has the marketing expertise and long-term contracts with shippers (Gupta, 2008). Alternatively, the logistics service provider could also (partly) utilize its capacity by serving the spot market, i.e., serving demand of customers without an allocation contract.

The logistics service provider faces a trade-off between distributing capacity to allocation contracts with key customers or to spot market demand. Therefore, inventory control of a logistics service provider involves capacity allocation management and spot market booking control (Billings et al., 2003; Hoffmann, 2013). The challenge of capacity allocation management is to determine the optimal cargo mix between medium-term allocations and spot market shipments that maximizes profit. Medium-term contract and spot market demand utilize the same capacity, implying that the allocation decisions affect the remaining available capacity to sell on the spot market. Next, capacity allocation management is concerned with optimizing the contract portfolio that would maximize profit, i.e., determining which key customers the service provider should contract. The allocation decisions significantly impact the carrier's profitability (Billings et al., 2003).

Spot market booking control is concerned with managing incoming shipment requests from contracted customers and the spot market on a daily basis, that is, managing the utilization of capacity. Since the logistics service provider is obliged to satisfy the contractual demand, booking control involves deciding whether a spot booking request should be accepted or not. Logically, a spot market booking request is only accepted if the service provider has sufficient capacity available. This decision is a dynamic problem because the service provider must consider the current bookings on hand, incoming shipment requests prior to departure, no-shows and cancellations.

This research exclusively focuses on the cargo capacity allocation problem of the cargo revenue management system, as the logistics service provider involved in this research currently encounters the problem, see Section 1.3. To answer the research questions in Section 1.6, the capacity allocation problem will be studied in the context of a synchromodal logistics service provider. This study contributes to the cargo revenue management research field, and in particular to the limited studies available on the medium-term capacity allocation problems.

2.2 Cargo capacity allocation problem

This subsection provides an overview of current literature available on the cargo capacity allocation problem.

Levin, Nediak and Topaloglu (2012) study the cargo capacity allocation problem with allotments and spot market demand. The article considers an airline that offers transportation services on a number of parallel flights between a particular origin and destination pair, where customers exhibit choice behavior between flights. The problem involves a multi-dimensional capacity: volume and weight. They propose a model to simultaneously select the optimal allotment contracts and find a booking control policy that maximizes the total expected profit. First, they formulate a dynamic program to the booking control problem and approximate the expected profit from the spot market. Next, the spot market profit approximation is used to determine the optimal allotment contract portfolio by defining multiple linear mixed-integer programs. The work of Moussawi-Haidar (2014) is close to that of Levin et al. (2012). In contrast to Levin et al. (2012), the solution to their dynamic program depends on the accepted spot market bookings. Next, they account for no-shows and cancellations by allowing overbooking.

This work also addresses the cargo capacity allocation problem as in Levin et al. (2012) and Moussawi-Haidar (2014) as we consider a logistics service provider that seeks to optimize its capacity distribution among allotment contracts and spot market demand. However, the work in this study distinguishes from their work as we account for two transportation services with different shipment windows, of which one service allows postponing the shipment to the next day. Next, we only focus on the static allocation problem by introducing a static booking limit on spot market shipment requests. Furthermore, the logistics service provider considered in our work has a one-dimensional capacity defined per TEU, while the work of Levin et al. (2012) and Moussawi-Haidar (2014) incorporates a two-dimensional capacity.

D. Liu and Yang (2015) address joint slot allocation and dynamic pricing for multi-node container sea-rail multimodal transport. They propose a two-stage model to the problem. The first stage involves determining the optimal long-term slot allocation and empty container allocation, while the second stage is concerned with booking control and price settling. Their work involves a single transportation line and a single transportation service. Our work focuses on the first stage problem without the empty container allocation problem but considers the effects of multiple transportation services with varying service levels.

Lee, Chew and Sim (2007) propose a revenue management model for a single-leg ocean carrier that serves contracted customers and the spot market, while also considering the postponement opportunity of shipments. The carrier involved is allowed to ship demand from the contracted customer immediately or postpone it to the next shipment, while spot demand must be shipped immediately. They present a stochastic dynamic programming model to the problem and show that a threshold policy defines the optimal allocation. The problem addressed in our work also reflects the shipment postponement effects but distinguishes itself in that not all contracted sales can be postponed. Next, our work considers two different transportation services sold to allotment customers, Express and Standard, of which postponing is only allowed for a single service. Furthermore, the work of Lee et al. (2007) mainly focus on the allocation of containers to ships on a daily basis, while we focus on the allocation of capacity on the medium-term.

Ang, Cao and Ye (2007) focus on the sea cargo problem for the carrier in a multi-period planning horizon. The objective is to optimize the cargo mix and shipping schedule that would maximize the total profit generated given limited capacity. Cao, Gao and Li (2012) study the capacity allocation problem of a container rail operator by taking into account matches in supply and random demand. Amaruchkul and Lorchirachoonkul (2011) propose a dynamic program to select the allotments that maximize the expected total profit. They propose a discrete Markov Chain to derive a probability distribution of the actual volume usage.

2.3 Current revenue management literature on synchromodal transportation

Even though several studies focus on synchromodal transportation, their results focus mainly on the operational implications of the logistics concept. Less attention has been paid to the revenue management opportunities for synchromodal transportation, including pricing and demand management. Therefore, current revenue management literature conducive to synchromodal transportation is examined to identify the revenue management need related to synchromodal transportation, to identify the gap in literature and to position our research. In this study, we address the gap by focusing on demand management strategies that incorporate the synchromodal concept characteristics.

Central in the synchromodal concept is that shippers order mode-free shipments (Gorris et al., 2011; Lucassen & Dogger, 2012). The cargo products of the service provider are service-bound. The shipper and the logistics service provider agree only on the delivery of shipments at a specified cost, time, quality and sustainability (Haller et al., 2015). As planning flexibility is crucial for cost-efficient transportation plans, network operators have an incentive to introduce differentiated transport products with different tariff classes depending on the shipment window and flexibility (Van Riessen et al., 2015). Therefore, Van Riessen et al. (2015) state that pricing and operations are strongly linked since promoting planning flexibility improves the network performance if the additional flexibility leads to cost-efficient transportation plans. However, they also argue that not all customers are willing to transfer planning flexibility to the network operator due to company policy, habituation, and pricing mechanisms. Behdani et al. (2016) identify "synchromodal service pricing as a strategic topic of synchromodality since part of the financial benefits should be transferred to customers by a fair pricing scheme to guarantee a sustainable operation of synchromodal freight systems. Next, Pfoser et al. (2016) recognize pricing, cost, and service as a critical success factor to ensure the effective implementation of synchromodal transportation.

Current revenue management studies in the synchromodal context focus mainly on the pricing problem. For example, Li, Lin, Negenborn and De Schutter (2015) study the pricing problem of a differentiated product portfolio in a synchromodal network, by developing a model that determines whether a booking request should be accepted or rejected. Next, Ypsilantis and Zuidwijk (2013) study the pricing and network problem jointly by determining the shipment prices during network design. Van Riessen et al. (2017) focus on the demand management (inventory control) problem by proposing the Cargo Fare Class Mix model. The objective of the model is to determine the optimal mix between transportation services that maximize profit. They conclude that low-priced products with high planning flexibility are not inferior to high-priced products, because the extra planning flexibility could be exploited to optimize the network planning. Furthermore, they show that increasing the shipment windows of the low-priced flexible service relative to the high-priced Express product yields additional costs savings.

Although pricing, cost, and service are identified as a critical success factor, there are currently only limited studies on these revenue management subjects available. Therefore, in this research, we target to contribute to the limited literature available on revenue management strategies for synchromodal transportation.

Cargo Fare Class Mix problem

The research of Van Riessen et al. (2017) has parallels with our research. Therefore, we will discuss the model they propose and argue the limitations of the study that shall be tried to bridge.

The Cargo Fare Class Mix problem is concerned with optimizing the cargo mix such that profit is maximized. Van Riessen et al. (2017) propose a booking limit on two differentiated synchromodal services: Express and Standard. The Express service has a 1-day shipment window and the Standard product a 2-day window. The booking limit reflects the number of shipments of a service type that should be accepted on a daily basis. That is, incoming shipment requests are accepted up to the booking limit and rejected otherwise. The objective of the model is to determine the optimal booking limits of both services that would maximize the profit given stochastic demand. Accepted shipments generate revenue and penalty costs are incurred if capacity is exceeded. Bear in mind that the Standard product has a 2-day shipment window, which holds that the service provider is allowed to transship the shipment either today or tomorrow.

Although Van Riessen et al. (2017) already study the optimal cargo mix between differentiated synchromodal products, they focus on the booking control problem of a logistics service provider that only serves the spot market. That is, they assumed that the logistics service provider could accept or reject any incoming order. Consequently, they neglect the effects of the medium-term allocation contracts between the shipper and the carrier. The model of Van Riessen et al. (2017) does not answer the optimal cargo allocation problem between allocation contracts and spot market demand but only focus on the cargo mix between the transportation services. As argued in Section 1.3, logistics service providers commit to medium-term allocation contracts to ensure asset utilization. Due to the existence of these contracts, the service provider is not able to reject a shipment request from a contracted customer if the booking limit is exceeded. Our study targets the limitations of the Cargo Fare Class Mix problem by focusing on the optimal cargo mix between allocation contracts and spot market demand while considering the characteristics of the synchromodal products.

The work of Van Riessen et al. (2017) is used as a guideline to shape our research. In line with their work, we also define two transportation services with the same shipment window characteristics. Next, they defined a Markov Chain to model the expected excess orders on a daily basis. We opt to select the same modeling technique and adjust the Markov Chain such that it applies to our research focus.

2.4 Stochastic freight rates

Lastly, the literature review focuses on the existing literature regarding stochastic freight rates. The objective of this study is to model the stochastic properties inherent to the spot freight rates by incorporating an existing stochastic model in the cargo capacity allocation problem, which is to the best of our knowledge not studied yet.

A mean-reverting property characterizes the evolution of the stochastic freight rates. Koekebakker, Adland and Sødal (2006) conclude, based on empirical results and in line with maritime economic theory, that the freight rates in both dry-bulk and tanker markets are non-linear stationary. That is, freight rates tend to revert to the long-run mean level. Adland (2003) concludes that extraordinarily high or low freight rates in a perfectly competitive market are not sustainable due to the potential of supply adjustments. They argue that shippers would substitute forms of transportation at extremely high freight rates. In reverse, meager freight rates will lead to supply adjustment in the form of scrapping capacity. The freight rates cannot display explosive behavior, because of the existence of a lower and upper bound (Koekebakker et al., 2006). Modeling the stochastic freight rate process by the mean reversion property is dominating in literature, see Strandenes (1984) and Tvedt (1997). Although most studies that include stochastic freight rates focus on the dry-bulk shipping market, we assume that the same price mechanisms apply in the hinterland transportation market as we assume a perfectly competitive market. Therefore, the spot freight rates in the capacity allocation problem will be modeled following the mean reversion property.

The Ornstein-Uhlenbeck process is a mean reverting stochastic process that describes the evolution of prices over time, see Vasicek (1977). It is used to simulate the movements in freight rates over time and is modeled by i.a. Bjerksund and Ekern (1995); Sødal, Koekebakker and Aadland (2008) and Jørgensen and De Giovanni (2010). The mean-reverting property of the process reflects the tendency of the freight rates to revert to the long-term mean over time. The drift of the freight rates depends on the current value of the price. That is, the drift term will be positive if the current freight rate is lower than its long-term mean, and the price will move back to its long-term mean if the current freight rate exceeds the mean. The drift of returning to the mean is stronger if the current value of the process is further away from the mean. The OU-process is Gaussian, Markov and stationary (Vasicek, 1977). Tvedt (1997) concludes that the OU-process is a stochastic differential equation that is analytically solvable, although the process does not describe the best fit Markov specification of the freight rates. Considering the current literature on freight rates, we will model the stochastic spot freight rates by an Ornstein-Uhlenbeck process. For completeness, see Figure F.1 in Appendix F that represents three samples price paths that follow an Ornstein-Uhlenbeck process.

2.5 Contribution to current literature

The topic addressed in this study integrates two fields of research: cargo revenue management and synchromodal transportation. In relation with the bodies of literature examined, our contributions to current literature are as follows.

First, we propose a stochastic integer program to the cargo capacity allocation problem with allotment contracts, spot market demand, and shipment windows. To the best of our knowledge, there are no studies that consider the effects of shipment service levels, i.e., which allow postponing shipments to the next day, while determining the optimal distribution of capacity between allotment contracts and spot market. We address this gap by optimally solving the capacity allocation problem. This study contributes to the cargo revenue management field by determining the optimal cargo mix given multiple transportation services, where it is allowed to postpone orders to the next shipment.

Second, the findings of this project contribute to the limited literature available on cargo revenue management for synchromodal transportation providers. Synchromodal shipment services have various shipment windows, affecting the cargo allocation process and the corresponding profit. Van Riessen et al. (2015) argue that operations and sales are strongly linked. In this study, we try to link those departments by considering the operational effects while optimizing the capacity distribution such that profit is maximized.

Third, the focus of our research distinguishes from conventional cargo revenue management models as we incorporate stochastic spot freight rates in the cargo mix decision process.

Chapter 3

Optimization Models

This chapter is dedicated to the development of two optimization models to solve the cargo capacity allocation problem optimally. First, we present the problem formulation, define the allotment contact terms and define the underlying assumptions. Next, we formulate the stochastic integer program with deterministic spot market freight rates. Later in this chapter, we formulate a simulation-based optimization program that extends the cargo capacity allocation problem by incorporating stochastic spot market freight rates. Last, we formulate equations to derive the minimum-acceptable bid price based on the results of the stochastic integer program.

3.1 Problem formulation

A logistics service provider operates scheduled transportation services between an origin-destination pair with a fixed daily capacity in a specific booking horizon. It offers two synchromodal transportation services with varying service levels to its customers: Express and Standard, with a 1-day and 2-day shipment window respectively. The 2-day shipment window of the Standard service holds that the service provider could ship the shipment immediately or postpone it to the next day. The transportation services are mode-free, i.e., the logistics service provider determines the modality deployed for the shipment.

To maximize the expected profit, the service provider faces the problem of distributing its capacity between allotment contracts with freight forwarders and spot market demand, while also accounting for the capacity distribution between the transportation services. That is, the service provider should determine which allotment contracts to grant and reserves capacity for spot market sales by determining the daily spot market booking limit.

Allotment contracts are signed before the start of the booking horizon and remain valid throughout the booking horizon. Therefore, the logistics service provider decides on its capacity distribution to allotment contracts and spot market sales before the start of the booking horizon. Contractual and spot shipment requests occur continuously in the booking horizon. The service provider reserves capacity for spot market sales by determining a static spot market booking limit. The static booking limit is fixed throughout the booking horizon and indicates the number of spot orders to accept on a day.

The logistics service provider is obliged to transport all accepted demand and is penalized for excess shipments, which are charted to an external party and do not invoke the capacity of a subsequent day. Penalty costs include for example the costs of alternative transportation and loss of goodwill.

In short, the objective is to determine the optimal allocation of capacity to allotment contracts with multiple freight forwarders and reserving capacity for spot market demand that would maximize the total expected profit, while coping with the shipment windows, capacity constraints, stochastic demand and optionally stochastic spot freight rates.

3.1.1 Allotment contract definition

The mutual allotment contract agreement between the logistics service provider (seller) and the freight forwarder (buyer) specifies the following terms:

- The buyer orders mode-free transportation services, which holds that the contract does not specify the modality to be deployed for the shipment;
- A specified freight rate per container shipment per service type;
- The buyer is only charged for the realized shipment volume;
- The buyer has no volume restrictions.

In other words, the logistics service provider commits to serve all the customer's shipment demand in the agreed contract period for a fixed freight rate per service type, which is a common agreement within the freight business, see Section 1.3.

3.1.2 Assumptions

To model the cargo capacity allocation problem the following assumptions are defined:

- The cargo capacity allocation problem is optimized for a single corridor. That is, the logistics service provider allocates its capacity on a single origin-destination pair, which holds that network effects are excluded.
- The complete set of allotment contract bids are known. That is, all allotment contracts to choose from are known when optimizing the capacity allocation.
- The logistics service provider is risk-neutral, which holds that the service provider is only concerned with maximizing the expected profit and is indifferent to risk when distributing its capacity to allotment contracts and spot market demand. More specific, the logistics service provider is neither risk-averse nor risk-seeking. That is, it does not attempt to reduce the exposure to demand and freight rate uncertainty by accepting an allocation portfolio with more certainty but with lower expected profit. Additionally, it does not try to exploit risk opportunities by accepting an allocation portfolio with more uncertainty but with lower expected profit to take the probability of a higher payoff.
- The contractual demand for Express and Standard services and spot market demand are Poisson distributed and are statistically independent of each other.
- An allotment contract cannot be partially accepted, i.e., the complete shipment package of a freight forwarder must be accepted.
- The booking horizon equals one year, such that the logistics service provider must optimize its capacity allocation each year for the next year.
- We consider a one-period allocation model, and therefore we assume that the allotment contract period covers the entire period.
- No-shows and cancellations are excluded and out of scope, as we assume that these are handled on an operational level.
- The capacity of the logistics service is measured in number of containers (TEU).
- No restrictions exist regarding the type of commodities, see Section 1.4.
- Spot market demand consists exclusively of Express shipment requests, i.e., they require same-day delivery immediately once accepted.
- Shipments allocated to any modality are delivered on the same day.
- There are no shipment disturbances, i.e., shipment delays that may occur during logistics and transportation operations are out of scope, see Section 1.4.

- Standard shipments are shipped immediately or optionally postponed to the next day without any penalty costs, whereby postponing is only allowed once.
- Contractual shipment freight rates are deterministic and exogenous since they are specified in the negotiated bid contract.
- Express shipments have less planning flexibility than Standard shipments due to a shorter shipment window, which is reflected by the freight rates. Consequently, revenue generated by Express shipments (r_i^E) of bidder i are higher than or at least equal to the revenue of Standard shipments (r_i^S) of bidder i:

$$r_i^S \leq r_i^E \quad \forall i \tag{3.1}$$

- The penalty costs p of excess shipments are always higher than the generated revenue of both contractual and spot market shipments. Hence,

$$r^P < p \quad P \in \{E, S, spot\} \tag{3.2}$$

3.2 Stochastic integer program with deterministic spot freight rates

The logistics service provider has a fixed daily capacity of C units, which it could allocate to key customers via allotment contracts or reserve for spot market sales. The service provider must decide on its capacity distribution before the start of the booking horizon, by granting contracts and setting a static booking limit on spot market sales. Appendix B.1 provides an overview of the stochastic integer program.

3.2.1 Allotment contracts

Consider a finite set of allotment contract biddings B that consists of the contracts that the logistics service provider can select to include in its contract portfolio. Let $B = \{b_1, \ldots, b_n\}$ with n allotment contracts and b_i the bidding contract of bidder i. Let $P = \{E, S\}$ be the set of transportation service types offered by the service provider in which E and S represent the Express and Standard transportation service types respectively.

Each bidding contract b_i specifies an expected daily number of shipments $\mathbb{E}(X_i^P)$ per service type in P, which follows a stochastic demand distribution. Based on the work of Moussawi-Haidar (2014) we assume that $\mathbb{E}(X_i^P) \sim Poisson(\lambda_i^P)$, where λ_i^P is the average daily arrival rate of allotment bookings of bidder i and of service type P. Next, each contract b_i indicates the revenue r_i^P generated per realized shipment of service type P. Let x_i the binary decision variable to represent the contract allocation decision of bidder i, such that a contract is granted to bidder i if $x_i = 1$ and rejected if $x_i = 0$. Next, let $\overrightarrow{\boldsymbol{x}} = [x_1, x_i, \ldots, x_n]$ the contract allocation portfolio with n contract allocation decision variables x_i to represent the accepted and rejected allotment contracts in the portfolio.

3.2.2 Spot market

The daily spot market demand is represented by $X_s \sim Poisson(\lambda_s)$, with λ_s the average daily arrival rate of spot market shipment requests. At this point, we assume that the revenue generated by a spot market shipment is deterministic and is represented by r^{spot}. Later we relax this assumption by assuming stochastic spot market freight rates, see Section 3.3.

Let n_{spot} be the booking limit decision variable, which is an integer that indicates the maximum number of spot shipment requests to accept for a day in the booking horizon. The booking limit is static, which holds that it is forecast-based, valid and unaltered in the entire booking horizon.

The introduction of the booking limit implies that the demand function of the accepted spot market shipments is not Poisson distributed, because it is constrained above by the booking limit.

Therefore, a truncated distribution of the spot market sales is formulated as in Van Riessen et al. (2017). To determine the expected number of realized spot market shipments, we should account for the booking limit. The following two situations can be distinguished:

1. The number of shipment requests is less than n_{spot};
2. The number of shipment requests is equal or greater than n_{spot}.

The realized spot market demand is the minimum of the spot market shipment requests X_s and the booking limit n_{spot}, because all shipment requests above the booking limit are rejected.

$$D_{spot}(t) = \min\big(X_{spot}(t), n_{spot}\big) \tag{3.3}$$

The probability that k shipment requests are accepted in situation 1 follows from the Poisson density function for k smaller than n_{spot}.

$$P\big(X_{spot}(t) = k\big) = e^{-\lambda}\frac{\lambda^x}{x!}, \qquad k = 0, 1, 2, \ldots, n_{spot} - 1 \tag{3.4}$$

The probability that n_{spot} shipment requests are accepted (situation 2) is $P(X_{spot} \geq n_{spot})$, because there arrive more shipment requests than accepted, Equation (3.5). In other words, spot orders are accepted up to the booking limit and are rejected from that point. The probability of accepting n_{spot} orders is equal to $1-F(n_{spot})$, where $F(n_{spot})$ is the cumulative Poisson distribution function.

$$P\big(X_{spot}(t) = n_{spot}\big) = 1 - \sum_{k=0}^{n_{spot}-1} e^{-\lambda}\frac{\lambda^x}{x!} = 1 - F(n_{spot}) \tag{3.5}$$

It follows that the expected number of realized spot market shipment requests, given booking limit n_{spot}, is the sum of the expected number of shipments that arrive in situation 1 and 2.

$$\mathbb{E}\big(X_{spot}|n_{spot}\big) = \sum_{k=1}^{n_{spot}-1} kP(X_s = k) + n_{spot}[1 - F(n_{spot})] \tag{3.6}$$

3.2.3 Objective function

The logistics service provider seeks to maximize its total expected profit by optimizing its contract portfolio and determining the optimal static spot market booking limit given its fixed daily capacity, see Equation (3.7). The service provider is obliged to transport all accepted demand, and penalty costs of size p are charged over excess shipments (E_s). The first part of the objective function formulates the expected revenue generated from the accepted contract sales, the second part represents the expected profit from the spot market sales and the last part accounts for the penalty costs of the excess shipments.

The booking limit n_{spot} is constrained by the available daily capacity because it is assumed that the penalty costs always outweighs the revenue generated by a spot market shipment. That is, the revenue of a spot market shipment does not offset the penalty costs, which holds that it does not make sense to accept more spot market shipments as the daily capacity.

$$\max_{\vec{x}, n_{spot}} \quad \sum_{i \in B} x_i\big(\lambda_i^E r_i^E + \lambda_i^S r_i^S\big) + r^{spot}\mathbb{E}(X_{spot}|n_{spot}) - p\mathbb{E}(E_s) \tag{3.7}$$

s.t.

$$\begin{aligned} & n_{spot} \leq C \\ & x_i \in \{0, 1\} && \forall x \in B \\ & n_{spot} \in \mathbb{N} \end{aligned}$$

This reasoning does not hold for contractual demand. Since it is not allowed to accept an allotment contract partially, the additional revenue of accepting an allotment contract could compensate the penalty costs. Consider the case that a carrier has some shipment capacity left, but insufficient capacity to satisfy all demand of a single allotment contract. In order to accept the contract, the additional expected revenue generated by accepting the contract should offset the penalty costs of the excess shipments. Hence, the penalty costs of the excess shipments in the objective function account for the contractual capacity constraints. Therefore, we need to derive an equation to determine the expected excess shipments.

3.2.4 Expected excess shipments

Excess shipments occur when the logistics service provider has insufficient capacity available to satisfy the accepted demand. More specifically, excess shipments are Express shipments, spot shipments, and postponed Standard shipments, that cannot be transported within a day due to capacity limitations. The number of excess orders E_s on day t depends on the demand patterns of the Express contractual sales of day t (D_E), on the demand patterns of the spot market shipments of day t (D_{spot}) given booking limit n_{spot}, on the number of Standard shipments that are left over from day $t-1$ (R_S) and the available capacity C.

$$E_s(t) = \max\big(D_E(t) + D_{spot}(t) + R_S(t) - C, 0\big) \tag{3.8}$$

In order to derive an equation to determine the expected excess orders on a given day t, we are required to formulate equations for D_E and R_s, while we already provided a derivation to determine D_{spot} in Equation (3.3).

Cumulative allotment demand per service type: D_E, D_S

First, we derive equations to determine the cumulative demand of the contractual sales per service type, D_E and D_S. It is assumed that the contractual demand of both service types are Poisson distributed and that the distributions of the individual contracts per service types are mutually independent. To determine the cumulative demand distribution per service type, we sum the Poisson demand distributions of all accepted contracts, Equation (3.9) and Equation (3.10). Consequently, the cumulative Express allotment demand is the sum of the daily average arrival rate λ_i^E of each allotment contract multiplied with the decision variable x_i of each customer i. The resulting demand distributions for D_E and D_S are Poisson distributed, because if the sum of two independent variables are Poisson distributed then the sum of those variables are also Poisson distributed, see Grimmett and Welsh (1986).

$$D_E = \sum_{i=1}^{n} x_i \lambda_i^E \sim Poisson(\lambda_1^E, \ldots, \lambda_n^E) \tag{3.9}$$

$$D_S = \sum_{i=1}^{n} x_i \lambda_i^S \sim Poisson(\lambda_1^S, \ldots, \lambda_n^S) \tag{3.10}$$

Expected postponed Standard shipments: R_S

In order to determine the expected number of excess orders, we need to know the available capacity on a given day t, which depends on the number of Standard orders that are postponed from the day before (R_S^t). As in Van Riessen et al. (2017), we formulate a Markov Chain with R_S^t as the Markov state to determine the expected number of orders that are postponed on the long-term. The state of the transportation system is fully described by R_S^t, memoryless and independent from previous states. We derive the transition probabilities of the Markov Chain based on the work of Van Riessen et al. (2017), but account for (1) the demand distributions of the contractual sales per service type and (2) the truncated spot market demand distribution. The steady-state distribution indicates the probability of postponing j Standard orders on average to the next day and follows from the transition probabilities.

Transition probabilities

First, we need to derive the transition probabilities $p(i,j)$ to determine the remaining demand for the next day (R_S^{t+1}) given the remaining demand from the day before (R_S^t), Equation (3.11). That is, given the number of orders i that are postponed the day before, we need to derive the transition probability that there are j orders postponed to the next day.

$$P(R_S^{t+1} = j | R_S^t = i) \tag{3.11}$$

Van Riessen et al. (2017) note that we could differentiate between the situation with excess shipments ($E_s > 0$) and without excess shipments ($E_S = 0$) to determine the transition probabilities:

$$p(i,j) = P(R_S^{t+1} = j, E_S > 0 | R_S^t = i) + P(R_S^{t+1} = j, E_S = 0 | R_S^t = i) \tag{3.12}$$

Given the current state of the system ($R_S^t = i$) we distinguish between the following situations:

1. Capacity is sufficient to transport all demand, including D_E, D_{spot}, the remaining demand of the day before (R_S^t) and all today's Standard demand (D_S). Consequently, there are no excess shipments ($E_s = 0$) and there are zero orders postponed to the next day ($R_S^{t+1} = 0$).
2. Capacity is sufficient to transport D_E, D_{spot}, R_S^t, and there is capacity left to transport part of D_S, while the leftovers from D_S are postponed to the next day. Hence, there are no excess orders ($E_s = 0$) and $R_S^{t+1} = D_s - (C - D_E - D_{spot} - R_S^t)$.
3. Capacity is insufficient to transport D_E, D_{spot} and R_S^t. Hence, there are excess shipments ($E_s > 0$) and all Standard shipments on day t are postponed to the next day, i.e., $R_S^{t+1} = D_s$.

Given situations 1 and 2 with no excess demand ($E_S = 0$) there might capacity left to transport (partly) today's Standard demand (D_S). That is, there are s slots available to transport D_S, which effectively reduces the number of orders postponed to the next day. The probability that there are s slots available depends on the available capacity, D_E, D_{spot}, and the remaining demand of the day before R_S^t.

$$P(S = s) = P(D_E + D_{spot} + R_S^t = C - s) \tag{3.13}$$

The probability that there is sufficient capacity available to ship all demand (situation 1) is the probability that D_E and D_{spot} are smaller than the available capacity after satisfying the i leftovers from the day before, and the required slots s to transport D_S, provided the probability that D_S is smaller than or equal to the s remaining slots. The truncated spot market demand distribution (D_{spot}) prevents us from summing the spot and Express demand distributions, as the resulting distribution is not Poisson distributed. Therefore, the probability that there are no excess shipments depends on the probability that D_E is smaller than or equal to the remaining available capacity, given the probability that there are z spot orders, Equation (3.14).

$$\sum_{s=0}^{C-i} P(D_E + D_{spot} = C - i - s) P(D_S \leq s) = \sum_{s=0}^{C-i} \sum_{z=0}^{n_{spot}} P(D_E = C - i - s - z) P(D_{spot} = z) P(D_S \leq s) \tag{3.14}$$

Next, consider situation 2 without excess orders ($E_S = 0$), there is capacity left such that today's Standard demand (D_S) is partly allocated to the s remaining slots. Consequently, the remaining demand that is postponed to the next day $R_s^{t+1} = D_S - s$. Hence, the probability that j shipments are postponed to the next day given that there are i remaining shipments from the day before is derived as:

$$\sum_{s=1}^{C-i} \sum_{z=0}^{n_{spot}} P(D_E = C - R_S^t - z - s) P(D_{spot} = z) P(D_S = s + j) \tag{3.15}$$

Thus, the probability of postponing j orders to the next day, given i remaining orders of the day before and given that there are no excess orders follows from situation 1 and 2:

$$P(R_S^{(t+1)} = j, E_S = 0 | R_S^t = i) = \begin{cases} \sum_{s=0}^{C-i} \sum_{z=0}^{n_{spot}} P(D_E = C - i - z - s) P(D_{spot} = z) P(D_S \leq s) & \text{if } j = 0, \\ \\ \sum_{s=0}^{C-i} \sum_{z=0}^{n_{spot}} P(D_E = C - i - z - s) P(D_{spot} = z) P(D_S = s + j) & \text{if } j > 0. \end{cases} \tag{3.16}$$

The probability that there are excess shipments (situation 3) occurs when capacity is insufficient to transport today's Express demand (D_E), spot demand (D_{spot}), and yesterday's remaining Standard shipments (R_S^t).

$$P(E_S > 0) = P(D_E + D_{spot} + R_S^t > C) = P(D_E + D_{spot} > C - R_S^t) = \sum_{z=0}^{n_{spot}} P(D_E > C - R_S^t - z) P(D_{spot} = z) \tag{3.17}$$

If capacity is insufficient to satisfy the required demand on day t, then all incoming Standard shipments of day t are postponed to the next day $(t+1)$. Consequently, the transition probability that there are j orders postponed to the next day, given i leftovers from the day before, depends on the probability that there are excess orders, Equation (3.17), and the probability that there are precisely j Standard shipments on day t.

$$P(R_S^{t+1} = j, E_S > 0 | R_S^t = i) = P(E_S > 0) P(D_S = j) = P(D_S = j) \sum_{z=0}^{n_{spot}} P(D_E > C - i - z) P(D_{spot} = z) \tag{3.18}$$

Substituting Equation (3.16) and Equation (3.18) in Equation (3.12) results in the following transition probability function:

$$\pi_{(i,j)} = \begin{cases} P(D_S = 0) \sum_{z=0}^{n_{spot}} P(D_E > C - i - z) P(D_{spot} = z) \\ \quad + \sum_{s=0}^{C-i} \sum_{z=0}^{n_{spot}} P(D_E = C - i - z - s) P(D_{spot} = z) P(D_S \leq s) & \text{if } j = 0, \\ \\ P(D_S = j) \sum_{z=0}^{n_{spot}} P(D_E > C - i - z) P(D_{spot} = z) \\ \quad + \sum_{s=0}^{C-i} \sum_{z=0}^{n_{spot}} P(D_E = C - i - z - s) P(D_{spot} = z) P(D_S = s + j) & \text{if } j > 0. \end{cases} \tag{3.19}$$

Steady-state probabilities

To determine the expected number of shipments that are postponed in the long run, we need to derive the steady-state distributions of the Markov state R_s. Let $\pi_j = P(R_s^{\infty} = j)$, where π_j reflects the long term probability of postponing j orders to the next day. The steady-state probability follows from solving the Markov equilibrium equation given the transition probabilities $p(i,j)$ in Equation (3.19):

$$\pi_j = \sum_i \pi_i p(i,j) \tag{3.20}$$

$$\sum_i \pi_i = 1 \tag{3.21}$$

Expected excess shipments: $\mathbb{E}(E_S)$

As we have defined equations to determine D_E, D_{spot} and the steady-state distribution of the average number of Standard orders postponed to the next day R_S, we can derive the expected number of excess shipments. In order to determine the expected number of excess orders, we follow the same approach as in Van Riessen et al. (2017), but account again for (1) the contractual Express and Standard demand from multiple freight forwarders and (2) the truncated spot market demand.

Excess shipments (E_S) occur when there is insufficient capacity available to transport today's Express demand (D_E), today's spot demand (D_{spot}) and the remaining Standard shipments of the day before (R_S). Therefore, the probability of excess orders depends on the probability distribution of D_E, D_{spot} and R_S, see Equation (3.22). Again, the truncated spot market demand distribution (D_{spot}) prevents us from summing the spot and Express demand distributions, because the resulting distribution is not Poisson distributed. Therefore, we account for the truncated spot demand distribution by determining the probability that capacity is insufficient to transport D_E after satisfying R_S and z spot orders, given the spot market booking limit n_{spot} and given the probability that there are z spot orders. Hence, we take the sum over z spot orders to determine the probability of excess demand:

$$P(E_S > 0) = P(D_E + D_{spot} + R_S > C) = \sum_{z=0}^{n_{spot}} P(D_E > C - R_S - z)P(D_{spot} = z) \tag{3.22}$$

Subsequently, the probability of having m excess orders follows from Equation (3.22):

$$P(E_S = m) = \begin{cases} P(D_E \leq C - R_S^t - z)P(D_{spot} = z) & \text{if } m = 0, \\ \\ P(D_E = C + m - R_S^t - z)P(D_{spot} = z) & \text{if } m > 0. \end{cases} \tag{3.23}$$

To determine the expected number of excess orders we need to sum over the probability that $m > 0$. Consequently, given the probability π_q of postponing j orders in the long-run, which follows from the steady-state distribution in Equation (3.20) and Equation (3.21), the expected number of excess Standard orders is:

$$\mathbb{E}(E_S) = \sum_{m=1}^{\alpha+\beta+n_{spot}} m \sum_{z=0}^{n_{spot}} \sum_{q=1}^{\beta} P(D_E = c + m - z - q)P(D_{spot})\pi_q \tag{3.24}$$

Where α is the upper bound of the Express demand Poisson distribution and β the upper bound of the Standard demand Poisson distribution. These upper bound are determined based on Chebyshev's inequality (1867), which state that the probability that the distribution values are within k standard deviations of the mean is at least $1 - \frac{1}{k^2}$. Hence, we set the upper bound such that it is within k standard deviations from the mean, $\alpha = \mu + k\sigma$. This holds that, given Poisson distributed demand, the upper bound is $\alpha = \mu + k\sqrt{\lambda}$. We target to set $k = 10$ such that the cumulative probability over the range is at least 0.99. For example, consider $\lambda = 100$ then $\alpha = 100 + 10\sqrt{100} = 200$.

3.2.5 Utilization

We determine the expected utilization η as in Van Riessen et al. (2017), but account for the expected spot demand:

$$\eta = \frac{\mathbb{E}(D_E) + \mathbb{E}(D_S) + \mathbb{E}(X_{spot}|n_{spot}) - \mathbb{E}(E_S)}{C} \tag{3.25}$$

3.3 Simulation-based optimization model with stochastic spot freight rates

This section extends the capacity allocation problem with stochastic freight rates by formulating a simulation model. As argued in Section 2.4, the stochastic freight rates exhibit mean-reverting behavior, which is modeled by the Ornstein-Uhlenbeck process. A drawback from this approach is that the optimization model defined in Section 3.2 is not valid anymore, as the spot market freight rates are time-dependent. Therefore, a simulation model is formulated that optimizes the capacity allocation such that profit is maximized given limited capacity, stochastic demand and stochastic freight rates. First, the Ornstein-Uhlenbeck process and its parameters are presented, followed by the derivation of the simulation model. Appendix B.2 provides an overview of the formulated simulation-based optimization model.

3.3.1 Ornstein-Uhlenbeck process

The spot freight rate evolution over time is reflected by a stochastic Ornstein-Uhlenbeck process in Equation (3.26), where S_t is the spot price at time t, θ the long-term mean freight rate, σ the volatility, W_t a Wiener process with mean 0 and variance dt, and κ the mean reversion rate at which the process reverts.

$$dS_t = \kappa(\theta - S_t)dt + \sigma dW_t \tag{3.26}$$

The drift term $\big(\kappa(\theta - S_t)dt\big)$ is the difference between the current spot freight rate (S_t) and the long-term mean (θ) and pushes the spot freight rate back to the long-term mean. The constant κ indicates the rate at which the freight rate reverts back to the long-term mean - the higher the rate, the faster it returns back. The drift rate is negative as the current freight rate is higher than the long-term mean, which forces the spot freight rate to evolve back to the mean value. The second term $\big(\sigma dW_t\big)$ reflects the volatility of the mean-reverting process.

The exact solution to the stochastically differential equation can be approximated by Equation (3.27), where t is the time-step, see Bjerksund and Ekern (1995). The approximation to the exact solution is used to simulate the evolution of S^t.

$$S_{t+1} = S_t e^{-\kappa t} + \theta(1 - e^{-\kappa t}) + \sigma \int_0^T e^{-\kappa(T-t)} dW_s \tag{3.27}$$

The mean of the stochastic freight rate equals θ and the variance of the mean-reverting process increases in the volatility σ and is bounded by the reversion rate κ, see Appendix F.2 for a mathematical derivation of the mean and the variance.

$$\lim_{T\to\infty} E[S_t] = \theta$$

$$\lim_{T\to\infty} Var[S_t] = \frac{\sigma^2}{2\kappa}$$

3.3.2 Simulation-model

The objective of the simulation model is to find the optimal cargo capacity allocation to allotment contracts with multiple freight forwarders and to spot market demand, given the limited daily capacity, stochastic demand and stochastic freight rates. In contrast to the stochastic integer program in Section 3.2, we introduce a time-component. Let $T = 0, 1, \ldots, t$ be the number of days in the booking horizon. The introduction of time holds that we should account for the value of money over time. Therefore, we determine the optimal contract portfolio based on its net present value (NPV), by continuously discounting the revenue streams with the annual risk-free interest rate (r_f). Let $B = \{b_1, \ldots, b_n\}$ with n allotment contracts and b_i the bidding contract of bidder i. The binary decision variable x_i represents if the bid contract of customer i is included in the allocation portfolio, i.e., contract i is accepted if $x_i = 1$. Next, let $\overrightarrow{x} = [x_1, x_i, \ldots, x_n]$ the contract allocation portfolio with n contract allocation decision variables x_i to represent the accepted and rejected allotment contracts in the portfolio. Furthermore, let n_{spot} the decision variable that represents the spot market booking limit. The objective is to maximize profit by optimizing the contract portfolio and the spot market booking limit.

$$\max_{\overrightarrow{x}, n_{spot}} NPV_{allotment} + NPV_{spot} - NPV_{excess} \tag{3.28}$$

NPV: Spot market sales

Let r^t_{spot} be the stochastic spot market freight rate at time t that follows an Ornstein-Uhlenbeck process and let D^t_{spot} be the spot market demand at time t . Spot market demand is again constrained by the booking limit n_{spot} such that $D^t_{spot} = \min(X^t_{spot}, n_{spot})$, where X^t_{spot} reflects the number of spot market shipments that follows from a demand distribution. It is assumed that $X^t_{spot} \sim Poisson(\lambda_{spot})$, where λ_{spot} is the average daily arrival rate of spot shipment requests. However, notice that all theoretical distributions fit. The NPV of spot market sales is then:

$$NPV_{spot} = \sum_{t \in T} r^t_{spot} D^t_{spot} e^{-\frac{r_f t}{252}} \tag{3.29}$$

NPV: Allotment contract sales

Furthermore, let $D^t_{E,i} \sim Poisson(\lambda_{E,i})$ be the Express shipment demand of customer i at time t, where $\lambda_{E,i}$ is the average daily arrival rate of a shipment request. Equivalently, let $D^t_{S,i} \sim Poisson(\lambda_{S,i})$ be the Standard shipment demand of customer i at time t. Again, notice that all theoretical distributions fit. Next, let $r_{E,i}$ and $r_{S,i}$ the revenue per shipment of customer i of the Express and Standard service types respectively. The revenue per shipment is fixed throughout the booking horizon and therefore independent of time. Hence, the NPV of the contract sales is the sum of the revenue generated from all accepted contracts:

$$NPV_{allotments} = \sum_{t \in T} \sum_{i \in B} x_i (r_{E,i} D^t_{E,i} + r_{S,i} D^t_{S,i}) e^{-\frac{r_f t}{252}} \tag{3.30}$$

NPV: Excess shipments

Next, we derive an equation to determine the number of Standard shipments that are postponed to the next day. Let R^t_S be the number of Standard shipments at day t that are postponed to the next day $(t + 1)$. Hence, at day t the logistics service provider is obliged to transport the remaining Standard shipments of the day before, R^{t-1}_S.

After satisfying today's Express shipment demand (D^t_E), today's spot shipments (D^t_{spot}), and the remaining Standard shipments from the day before (R^{t-1}_S), there may some remaining capacity slots s available to ship (partly) today's Standard demand (D^t_E), Equation (3.31). Consequenlty, the number of Standard orders that are postponed to the next day depends on the remaining capacity slots s, Equation (3.32)

$$s^t = \max\Big(C - R^{t-1}_S - \sum_{i \in B} D^t_{E,i} - D^t_{spot}, 0\Big) \tag{3.31}$$

$$R^t_S = \max\Big(\sum_{i \in B} D^t_{S,i} - s^t\Big) \tag{3.32}$$

Next, we derive an equation to determine the penalty costs that are charged over the excess shipments. It is assumed that the penalty costs include the costs for alternative transportation, which depends in turn on the current spot market freight rates and a premium. That is, if the logistics service provider is forced to outsource the excess shipments to a third party, it pays the current spot freight rate plus a premium on this rate. The premium is introduced such that the spot prices never exceed the penalty costs and includes for example commission or administration costs. The purpose of including the penalty costs is to constrain the model in its allocation decisions. Therefore, we assume that the penalty costs are bounded below by the highest contractual Express freight rate plus a premium as excess shipments will otherwise always result in profit. That is, if the penalty costs are lower than the revenue of contractual Express shipments, the service provider will make a profit on each excess shipment of the size revenue minus penalty costs by outsourcing it. Therefore, given stochastic freight rates, we assume that the penalty costs p at day t are equal to the maximum of the spot freight rate or the revenue of an Express shipment on day t multiplied with a premium percentage on this price, such that the freight rates never offset the penalty costs.

$$r_{max} = \max_{i \in B}(r_{E,i}) \tag{3.33}$$

$$p^t = \min(r_{max}, S^t) * (1 + premium) \tag{3.34}$$

Excess orders occur when there is insufficient capacity available to transport Express shipments, the remaining Standard orders from the day before and spot market shipments. The logistics service provider is charged a penalty of size p over each excess order:

$$NPV_{excess} = \sum_{t \in T} p^t \max\Big(\sum_{i \in B} D^t_{E,i} + D^t_{spot} + R^{t-1}_S - C, 0\Big) e^{-\frac{r_f t}{252}} \tag{3.35}$$

Objective function

Consequently, the objective function of the simulation follows from all above-defined equations:

$$\max_{x_i, n_{spot}} \sum_{t \in T} \left(\sum_{i \in B} x_i \big(r^t_{E,i} D^t_{E,i} + r^t_{S,i} D^t_{S,i} \big) + r^t_{spot} D^t_{spot} - p^t \max\Big(\sum_{i \in B} D^t_{E,i} + D^t_{spot} + R^{t-1}_S - C, 0\Big) \right) \tag{3.36}$$

3.4 Minimum bid-price

The optimization models in Section 3.2 and Section 3.3 determine the optimal contract portfolio that maximizes profit. The results that follow from the model can also be exploited to determine the minimum bid-price of those contracts that are rejected. Assumed that the shipment volumes of the proposed contracts are fixed, the minimum bid-price per shipment of the excluded contract i should offset the profit loss between the optimal contract portfolio and the contract portfolio that includes contract i. The required minimum bid-price increase is zero if a specific contract is already included in the optimal contract portfolio because there do not exist any more profitable business opportunities.

Let $f^*(x_1, x_2, \ldots, x_n, n_{spot})$ be the value of the optimal contract portfolio with spot market booking limit n_{spot}. Next, let $\bar{f}(x_1', x_2, \ldots, x_n, n_{spot})$ be the value of the contract portfolio with the highest value containing contract x_1' of which we want to determine the minimum bid-price. It should be noted that the contracts in portfolio $\bar{f}$ are not necessarily included in the optimal contract portfolio f^*. This way, we exclude capacity constraints, because simply adding the excluded contract portfolio might imply that capacity is exceeded, yielding penalty costs.

To determine the required freight rate increase per shipment (Δr_i) we subtract the profit of the optimal contract portfolio f^* with the profit of contract portfolio $\bar{f}$ and divide it by the total expected number of shipments, Express and Standard, $(X^E_i + X^S_i)$ as defined in contract x_1', see Equation (3.37).

$$\Delta r = \frac{f^* - \bar{f}}{(X^E_i + X^S_i)} \tag{3.37}$$

The minimum bid-price per shipment per service type is the initial negotiated freight rate plus the necessary profit increase, see Equation (3.38).

$$r_i^{p'} = r_i^p + \Delta r_i \tag{3.38}$$

It is also feasible to determine the minimum bid-price for a specific service type P, Express or Standard, by dividing the value difference between the portfolios by the expected number of shipments of the service type, see Equation (3.39) and Equation (3.40). The minimum bid-price per service type could be useful for sales offices when there is for example only room to renegotiate the Express rates.

$$\Delta r_i^P = \frac{f^* - \bar{f}}{X_i^P} \tag{3.39}$$

$$r_i^{P'} = r_i^P + \Delta r_i^P \tag{3.40}$$

Minimum bid-price example

Consider two contracts with similar demand, yet one contract consists majorly of Express shipments and the other of Standard shipments. The initial negotiated Express and Standard freight rates per service type in both contracts are \$100 and \$80, respectively. The penalty costs equal \$150, and the service provider does not serve the spot market. The logistics service provider has a limited daily capacity of 20 TEU, such that only one contract can be accepted.

Assumed that the logistics service provider is risk-neutral, it will grant contract 1 and ignores contract 2, because the former contract yields more profit than the latter, see Table 3.1.

To offset the profit opportunity of accepting contract 1, the shipment freight rates of contract 2 should increase with \$4.25, see Equation (3.41). Hence, the service provider should renegotiate contract 2 observing the minimum bid-prices of \$104.25 and \$84.25 for Express and Standard shipments respectively, see Table 3.1. Alternatively, it could either charge an additional fee of \$16.98 for Express shipments or \$5.66 for Standard shipments, while keeping the shipment freight rate for the other service unchanged.

$$\Delta r = \frac{1724.68 - 1639.76}{6 + 14} = 4.25 \tag{3.41}$$

Table 3.1: Minimum bid-price example with 2 initial bid contracts and penalty costs of 150. To offset the revenue opportunity of accepting contract 1, the freight rates of contract 2 should increase with 4.25, or alternatively the freight rate of Express shipments or Standard shipments with 16.98 and 5.66 respectively.

Contract	**Demand**		**Freight Rate**		**Profit**	η	$\mathbb{E}(E_s)$
	Express	Standard	Express	Standard	f(x)	[%]	
1	15	5	100	80	1725	94	1.77
2	5	15	100	80	1640	98	0.40
$\bar{2}$ (All)	5	15	104.25	84.25	1725	98	0.40
$\bar{2}$ (Exp)	5	15	116.98	80.00	1725	98	0.40
$\bar{2}$ (Std)	5	15	100.00	85.66	1725	98	0.40

Chapter 4

Genetic Algorithm

This section presents a heuristic to solve the capacity allocation problem (CAP) with spot market demand. We show that a Genetic Algorithm (GA) provides (near-) optimal solutions within a reasonable computation time. First, the GA concept is introduced, followed by a definition of the GA problem, its components, and the associated parameter settings. A pseudo-code of the algorithm is provided in Appendix C.1. Finally, the performance of the GA is benchmarked against the exact solution in terms of profit and computation time.

4.1 Genetic algorithm design

Finding the exact solution to the capacity allocation problem with spot market demand is a time-consuming task as the number of solutions grows exponentially with the number of contracts. Although exact solutions to the problem are preferred, the required computation time is undesirable. Therefore, a Genetic Algorithm (GA) is developed as heuristic with the goal to find optimal or near-optimal solutions to the CAP within a reasonable computation time.

GAs are global search heuristics that imitate the principals of human evolution and survival of the fittest, see Holland (1992). The goal of the GA is to find the optimal allocation portfolio that maximizes the output of the CAP. The rationale behind the GA is to exploit information of examined solutions to search the solution space intelligently. The effectiveness of the heuristic is a tradeoff between exploration and exploitation. Exploring the solution space to a high degree increases the accuracy, but negatively affects computation time. While a too small coverage of the solution space provides fast results, it might not lead to high-quality solutions. Hence, contrary to exactly solving the problem, heuristics provide relative fast solutions but do not guarantee the optimal solution.

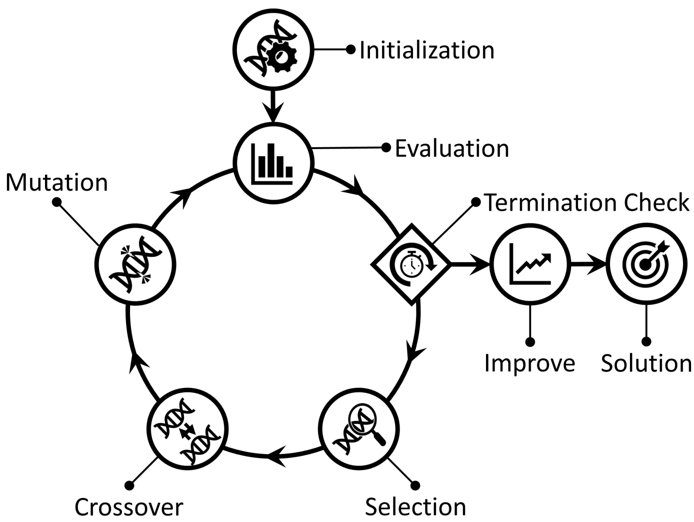


Figure 4.1: Genetic algorithm evolution process

Representation

The decision variables of the CAP are encoded into chromosome representation, i.e., a binary string, to make them suitable for evolution operations. An individual is a chromosome with genes that represents a single solution to the CAP. The genes of an individual encode the set of decision variables in the GA, where each gene determines a distinct property. It is decided to encode the spot market booking limit following the binary alphabet rather than an integer to standardize chromosome coding and evolution operations.

Chromosome $\hat{X} : x_1, x_2, \ldots, x, x_{k+n}$ represents the decision variables of the CAP, where k is the number of contracts available and n the length of a binary string that encodes the spot market booking limit upper bound γ, which is determined as in Section 3.2. The solution vector $x_i (i = 1, 2, \ldots, k)$ represents the contracts of the CAP as binary decision variables, where a '1' indicates that a contract is included and a '0' that a contract is excluded from the allocation portfolio. The solution vector $x_i (i = k+1, k+2, \ldots, k+n)$ represents the spot market booking limit as a binary string. The length n of the binary booking limit string depends on the required bits to represent the spot demand upper bound. For example, three binary bits are required to represent a spot market upper bound of 5, e.g., the binary string '101' equals 5. To illustrate, the chromosome in Table 4.1 indicates to accept contract 1 and 2, reject contract 3 and a booking limit of 5 spot shipments.

Table 4.1: Chromosome representation: accept contract 1 and 2, reject contract 3 and a spot market booking limit of 5 orders.

	Contracts			Booking limit		
Element	x_1	x_2	x_3	x_4	x_5	x_6
Chromosome	1	1	0	1	0	1
Binary				2^2	2^1	2^0

Initialization

The initialization process launches the evolution process, which randomly generates a population of individuals. Diversity of candidate solutions in the initial generation is necessary to prevent premature convergence towards suboptimal solutions. Therefore, each candidate solution in the solution space has equal selection probability.

Evaluation

The evaluation process assesses the performance of all individuals in a generation by calculating the fitness. The fitness of an individual is the expected profit given the allocation portfolio, as stated in Section 3.2. Evaluation of the fitness value guides the evolution of individuals from generation to generation because, analogous to evolution theory, healthy individuals with a high expected profit are likely to pass its inheritance to next generations. Due to the randomness of the evolution operators, it is plausible that precisely the same individuals exist in a consecutive generation. Therefore, we store the performance of examined individuals such that a duplicate does not require reexamination, because assessing the fitness performance is a time-consuming task.

Selection

Selection is the process of determining which individuals in the current generation participate in producing an offspring for the next generation. In other words, selected individuals are parents of the children in the next generation. The goal of selection is to identify fit individuals for reproduction such that strong genes of the parents are passed onto the next generation, and unfit solutions are eliminated (Sivaraj & Ravichandran, 2011).

The tournament selection method is used to select individuals for reproduction. Two individuals from the current generation are randomly drawn to participate in a tournament. The selected individuals are compared on the fitness value, and the winning individual is inserted into the mating pool. Tournament selection provides selection pressure based on fitness differences between individuals and guides the GA to improve the fitness of succeeding generations (Sivanandam & Deepa, 2008).

However, unfit solutions should also have a probability to participate in the mating process to prevent premature converge towards a suboptimal optimum. In other words, the genes of unfit individuals promote exploration of the solution space. Therefore, a stochastic probability p_s is introduced that determines the probability that an individual is selected based on its fitness. The strongest individual makes it into the mating pool with probability p_s, and the weak individual is the lucky one with probability $(1 - p_s)$.

Multiple tournaments are organized to select the required number of parents. A non-replacement strategy is used, which holds that previously drawn individuals could not participate in next tournaments to prevent that individuals are excluded by chance. However, the whole generation is replaced if all individuals are selected once, or if there is only a single individual left.

Crossover

Crossover pushes the GA to converge to an optimum and exploits the solution space. It is an iterative process where the genes of two parents are exchanged to create a child, such that the decision variables of the child is a combination of both parents.

A uniform crossover process is applied, which hold that both parents have equal probability to pass a specific gene to the child. That is, to determine the value of each gene x_i^C, a coin is flipped to determine if the child's gene value is determined by parent 1 (x_i^{P1}) or parent 2 (x_i^{P2}), see Figure 4.2.

	Contracts			Booking Limit		
Elements	X_1	X_2	X_3	X_4	X_5	X_6
Parent 1 $(\hat{X}^{P1})$	0	1	1	0	1	1
Parent 2 $(\hat{X}^{P2})$	1	1	0	1	0	1
Child $(\hat{X}^{C})$	0	1	0	0	1	1

Figure 4.2: Crossover example

Mutation

Mutation randomly alters the value of a gene, i.e., the value of a decision variable changes, resulting in another allocation portfolio. It promotes exploration of the search domain and escaping from local optima. Mutation prevents, therefore, loss of diversity (Holland, 1992). Mutation is a rare event and occurs with probability p_m per gene of an individual. A high probability ensures sufficient coverage of the search domain but could prevent the algorithm to converge to an optimum, i.e., a random walk. On the other hand, a low mutation rate might result in premature convergence to a local optimum.

A random number between 0 and 1 is sampled to determine if a gene mutates. If the random number is smaller than or equal to p_m, the value of the gene is altered. Subsequently, if gene x_i with value 1 is selected for mutation its value will change into $x_i = 0$, see Figure 4.3. Again, we check for the spot market upper bound. If the upper bound limit is violated, the mutation process starts from scratch with the unmutated child.

Termination criteria

The evolution process terminates after a certain number of generations have been generated.

	Contracts			Booking Limit		
Elements	X_1	X_2	X_3	X_4	X_5	X_6
Original child	0	1	1	0	1	1
Mutated child	0	1	0	0	1	1
Random number	0.4	0.5	0.1	0.4	0.8	0.3

Figure 4.3: Mutation example with $p_m = 0.1$

Improvement

Prototyping the GA revealed that the algorithm was often able to find the right contract portfolio, but sometimes failed to find the optimal spot market booking limit. Therefore, we define an improvement process to determine the booking limit that would maximize profit. We select the optimal contract portfolio observed by the GA for improvement operations and try to increase or decrease the spot booking limit. In other words, it is verified if profit opportunities exist by altering the booking limit while keeping a fixed contract portfolio. Improvement is an iterative process where the spot market booking limit is increased with one shipment in each iteration until the expected profit decreases. The same procedure is followed to analyze the effects of lowering the booking limit, with a booking limit lower bound of 0 spot shipments.

Solution

The optimal solution found by the GA after the improvement process is the contract portfolio with the highest expected profit observed by the GA, but is not necessarily the optimal solution to the CAP.

4.2 Parameter tuning

The effectiveness of the evolution operators depends on multiple parameters. The parameter values influence the performance and effectiveness of the algorithm regarding finding (near-) optimal solutions and computation time (Eiben, Hinterding & Michalewicz, 1999). As tuning the parameters is a time-consuming task, it is decided to set the parameters based on recommendations in literature or by logical reasoning. The primary motivation to develop a GA is to show the effectiveness of a heuristic to the CAP. The following parameter settings are applied in the remainder of this paper.

Selection probability

A static selection probability is applied, which holds that the probability of selecting the strongest individual is equal in all generations. The probability is set to 80%, such that fit individuals are promoted, but ensure genetic diversity by including a survival probability of the weaker individual:

$$p_s = 0.80 \tag{4.1}$$

Mutation probability

Typically it is recommended to set the mutation rate p_m to $1/l$, where l denotes the number of elements in a chromosome (Back, 1993). As the CAP chromosome consists of $n + k$ elements, where k are the number of contracts and n the binary string length of the spot upper bound, the mutation probability of each element equals:

$$p_m(k, n) = \frac{1}{k + n} \tag{4.2}$$

Population size

The population size indicates the number of individuals in a generation. The optimal population size is a trade-off between accurate results and computation time. The population size must be large enough such that the search domain is sufficiently covered, however, too large populations negatively affect computation time. The optimal population size $S_{opt}(n)$ depends on the number of decision variables n in the chromosome and is bounded below by n and above by $2n$ (Alander, 1992). Consequently, we set the population size S to two times the number of elements in the chromosome:

$$S_{opt}(k, n) = 2(k + n) \tag{4.3}$$

Number of children

This parameter determines the number of children that each couple of parents produces and is related to the number of parents. The number of children multiplied by the number of parents should equal the population size to preserve stable population sizes. The number of children C is set to 2 children per couple:

$$C = 2 \tag{4.4}$$

Number of parents

This parameter determines which individuals are selected from the current generation to participate in the reproduction for the next generations. The parameter value depends on the population size S and the number of children C:

$$P(S, C) = \frac{S}{C} \tag{4.5}$$

Number of generations

This parameter regulates the termination criteria of the algorithm. The optimal number of generations is a trade-off between accuracy and effectiveness. A large number of generations increases the probability of finding the optimal solution because more candidate solutions are examined but negatively affect the computation time. An analysis of the number of generations parameter showed that the number of generations depends on the population size and the theoretical number of candidate solutions covered, see Appendix C.2. Based on this analysis, we fix the number of generations such that 60% of the solution space is covered. That is, we determine the total number of solutions, which depends on the number of contracts k and the spot demand upper bound γ, and divide it by the population size S and rounded above.

$$G_{opt}(S, k, \gamma) = \frac{(2^k \gamma) * 60\%}{S} \tag{4.6}$$

4.3 GA performance analysis

In order to examine the GA's performance, the heuristic is applied to multiple capacity allocation problems with spot market demand. We determine the performance by comparing the allocation decision found by the GA with the optimal solution, which is found by exactly solving the CAP as in Section 3.2. The second performance indicator involves the algorithm's accuracy, which is defined as the number of times that the GA was able to find the optimal solution. Next, we examine the GA's computation time relative to the required time to exactly solve the CAP. The GA is coded in Python, and the performance is examined using an Intel(R) Core(TM) i7-3630QM CPU2.40 GHz processor. We run the GA five times for each scenario and determine the average performance, to improve the reliability and consistency of the performance indicators. This way, the randomness effects of the evolution processes are reduced. First, we examine the GA's performance given the problem size. Secondly, we address the performance regarding the capacity sensitivity.

Problem size

The CAP problem size equals $2^k\gamma$, with k allotment contracts and γ spot demand upper bound. Multiple scenarios with varying problem sizes are defined, while we fix the capacity to 15 TEU. We apply a demand to capacity ratio of 1.80, which indicates that there are 180% more shipment requests as capacity available. Demand is randomly allocated to the contracts, but we fix the average spot market shipment requests to 2 orders per day, while it is fixed to 1 order when there are more than 8 contracts due to computation time limitations. Next, we apply the GA parameter settings as defined in Section 4.2. An overview of the scenarios and the associated parameter values can be found in Table C.2 in Appendix C.3.

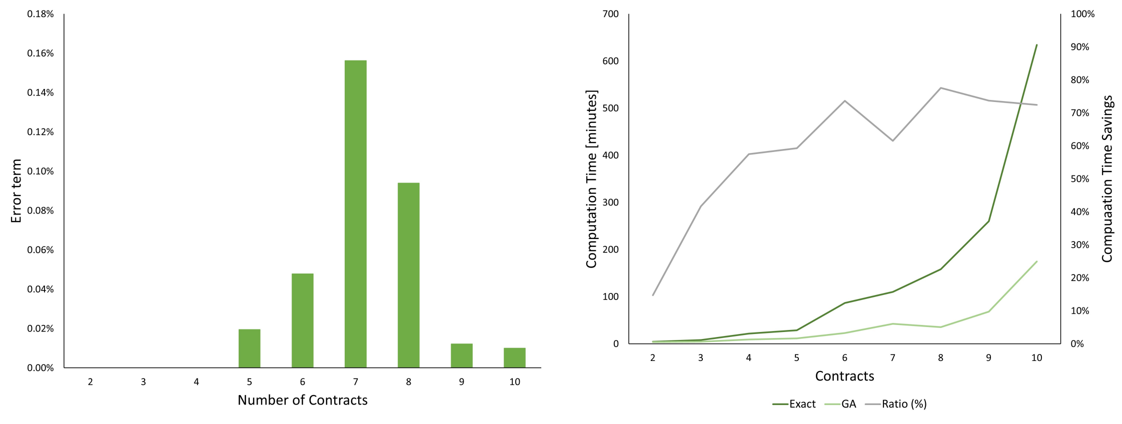
Figure 4.4a presents the average GA error term given the number of contracts. The error term indicates the profit difference between the optimal solution and the solution found by the GA. It turns out that the error term increases with the problem size. Increasing the problem size implies a larger solution space with more candidate solutions, which reduces the probability that a single candidate solution is selected. Although the algorithm was not always able to find the optimal solution, the error term is rather small. Overall, the average profit difference is equal to 0.038%, while the maximum average error term is equal to 0.156%.

Furthermore, the GA has an accuracy of 84.44%. That is, out of the 45 trial runs, the algorithm was able to find 38 times the optimal solutions. A detailed overview of the results is provided in Table C.4 in Appendix C.3.

Moreover, Figure 4.4b shows that the GA achieves significant computation time savings, with an average time reduction of 59%. The GA computation time increases, analogous to exactly solving the problem, in the problem size, because the termination criteria depend on the problem size. Figure 4.4b also indicates the fraction of time required to solve the GA compared to the required time to solve the cargo capacity allocation problem exactly. It follows that computation time savings increments proportionally to the problem size.

Capacity

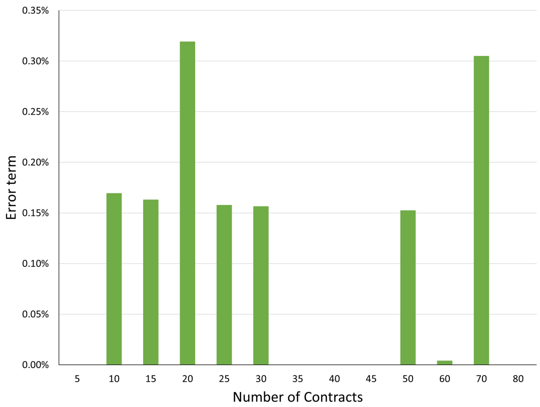
The computation time of exactly solving the CAP depends on the capacity size. Therefore, we examine the GA's computation time sensitivity to the capacity. We define scenarios with different capacity sizes and set the demand to capacity ratio again to 1.80 with 1 spot shipment request per day. A detailed overview of the scenario and the corresponding parameters settings are presented in Table C.3 in Appendix C.3.



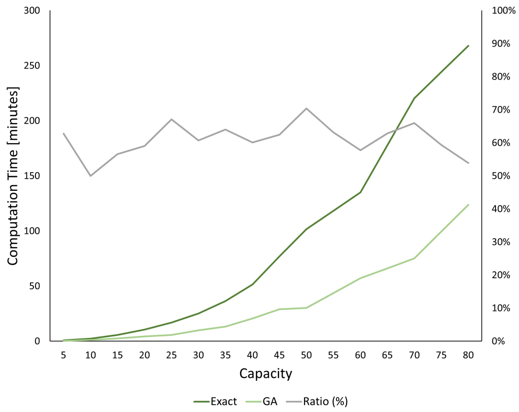
(a) Error term.

(b) Computation time.

Figure 4.4: Error term and computation time given the problem size against exactly solving the capacity allocation problem.



(a) Error term.



(b) Computation time.

Figure 4.5: Average error term and computation time given the capacity against exactly solving the capacity allocation problem.

Figure 4.5a shows that the GA results in an average error term of 0.11%, yielding (near-) optimal solutions. A relatively small error-term was obtained, and the results do not indicate that the error term increases with the capacity, which implies that the GA is insensitive to the capacity size. The results report an accuracy of 84.62%.

Furthermore, the GA achieves on average time savings of 60.81% compared to exactly solving the problem, see Figure 4.5b. Increasing the capacity size negatively affects the computation time. Calculating the objective function is the most time-consuming task of both the GA and the exact optimization model, which increments with the capacity.

4.4 Chapter conclusion

The GA performance analysis demonstrated that the algorithm is an effective heuristic to the capacity allocation problem, as it provides optimal or near-optimal solutions within a reasonable computation time. Scenario-based analyses showed that the GA has an average error term of 0.08%, i.e., 0.04% and 0.11% in the problem and capacity size scenario respectively. The error term increases with the problem size but is insensitive for the capacity size. The GA obtains on average 60% faster results compared to exactly solving the model. The computation time increases in the problem size and capacity. Based on the results, we conclude that the GA is a practical approach to find high-quality solutions to the capacity allocation problem.

Chapter 5

Analysis

This chapter presents an analysis of the proposed optimization models. In the remainder of this chapter, we assume that all demand is Poisson distributed unless stated otherwise. We start this chapter by demonstrating the stochastic integer optimization model by applying it to a capacity allocation problem. The second section is dedicated to the results that followed from a case study in which experienced sales representatives were challenged to beat the optimization model. The chapter finishes with a sensitivity analysis to evaluate the impact of the input parameters on the allocation behavior.

5.1 Results for a small-size capacity allocation problem

In this section, we apply the stochastic integer optimization problem to a capacity allocation problem. Consider a capacity allocation problem with 3 bids, spot market demand, and a fixed capacity of 25 TEU. All bids have an expected daily demand of 10 TEU, but different distributed Express and Standard demand. More specifically, one contract includes especially Express shipments, one mainly Standard shipments, while the last contract has equal demand for Express and Standard services, such that $\lambda_E = \{8, 5, 2\}$ and $\lambda_S = \{2, 5, 8\}$. The service provider negotiated equal shipment rates per service type for all contracts, i.e., $r^E = \{100, 100, 100\}$ and $r^S = \{80, 80, 80\}$. Next, there are on average 8 daily spot shipment requests, i.e., $\lambda_{spot} = 8$, with a deterministic and fixed revenue ($r^{spot} = 120$). Excess orders are outsourced to a third-party that charges the spot market freight rate with a 25% premium, i.e., $p = 150$. The logistics service provider seeks to maximize its expected profit by determining the optimal contract portfolio and spot market booking limit.

Table 5.1 summarizes the results of the allocation decisions, by providing the expected profit, utilization, demand, and excess shipments. The vector $x_A = [x_1, x_2, x_3]$ represents the allocation portfolio, where x_i reflects the decision to allocate contract i. Figure 5.1 shows the expected profit of the 224 possible solutions to the allotment problem. It follows that accepting all contracts, $x_A = [1, 1, 1]$, is less profitable compared to allocating two contracts with reserving capacity for spot market demand. That is, accepting all allocation contracts implies an expected demand of 30 TEU, while there is only 25 TEU daily capacity available, resulting in excess orders and penalty costs. Furthermore, granting a single contract and serving the spot market results in underutilized capacity, providing a revenue opportunity by allocating additional demand. To maximize profit, the service provider should accept contract 1 and 2, reject contract 3 and set the spot market booking limit (n_{spot}) to 7 shipments per day. That is, the service provider should focus on allocating Express shipments and reserve capacity for Spot orders to maximize the profit. Notice that a higher expected profit is realized with lower asset utilization.

Table 5.1: Results of a numerical experiment with 3 allotment contracts, spot market demand and 25 TEU capacity. With $\lambda_E = \{8, 5, 2\}$, $\lambda_S = \{2, 5, 8\}$, $\lambda_{spot} = 8$, $r^E = \{100, 100, 100\}$, $r^S = \{80, 80, 80\}$, $(r^{spot} = 120)$ and $p = 150$

Allocation	n_{spot}	Profit	Utilization	$\mathbb{E}(D_E)$	$\mathbb{E}(D_S)$	$\mathbb{E}(D_{Spot})$	$\mathbb{E}(E_S)$
$[1, 1, 0]$	7	2365	98.4	13	7	6.3	1.7
$[1, 0, 1]$	7	2325	98.9	10	10	6.3	1.6
$[0, 1, 1]$	7	2280	99.2	7	13	6.3	1.5

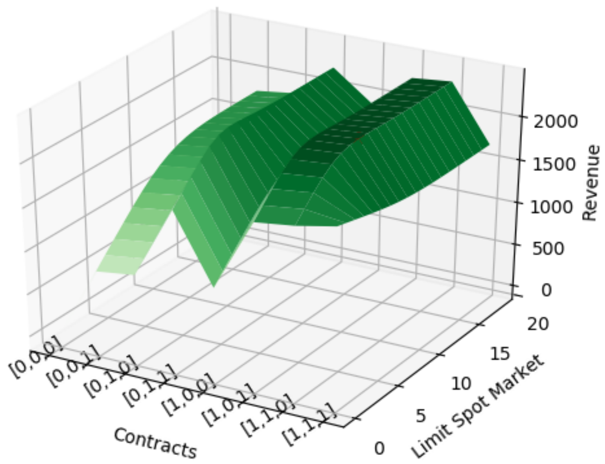


Figure 5.1: Expected profit given contract allocation portfolio and spot market booking limit. Allocation portfolio $x_A = [1, 1, 0]$ represents to accept contract 1 and 2, and reject contract 3.

5.2 Case study

A case study was developed to compare the decisions generated by the optimization model and the ones that were taken by experienced sales and operations representatives. The case study was conducted during a workshop with the objective to introduce the cargo capacity allocation problem, to create awareness of the relation between the allocation decisions and the performance in terms of profit, asset utilization and excess shipments, and to identify shortcomings of the optimization model. First, a small-sized cargo capacity allocation problem was submitted to the representatives to get familiar with the subject and its complexities. Once familiar, the representatives were asked to solve a more significant and more challenging allocation problem with the goal to maximize profit.

5.2.1 Case description

A logistics service provider with a fixed daily capacity of 200 TEU seeks to maximize its expected profit by optimizing its capacity distribution between freight forwarders and spot market demand.

The case involves 15 bids, which specify the expected number of daily shipments and a fixed freight rate specified per service type. A structured scheme defines the relation between the demand and revenue parameters of the Express and Standard services, such that variance among the parameters is guaranteed, see Table D.1 in Appendix D.1. The contract parameters are randomly assigned given the defined demand and revenue relations. Table D.2 in Appendix D.1 provides an overview of the contract terms.

Furthermore, there are on average 4 spot market shipment requests per day with a deterministic and fixed revenue of $150 per shipment. Next, excess orders require alternative transportation, resulting in penalty costs that include the spot price with a 33% premium, i.e., $p = 200$. Planners were informed to account for demand uncertainty and the spot market booking limit. The cargo capacity allocation problem has 786,432 unique solutions.

5.2.2 Results

Six experienced sales and operations representatives were asked to solve the capacity allocation problem. The allocation decisions obtained by the representatives are compared with the optimal allocation that follows from the optimization model. The results revealed that the optimization model outperforms the allocation decisions of the representatives, resulting in 4.8% more profit on average, see Figure 5.2. The profit difference between the optimal solution and the ones taken by the participants vary between 0.7% and 11.5%. One participant was able to find the optimal contract allocation, yet additional profit (+0.7%) could have been realized by increasing the spot market booking limit. Table D.3 in Appendix D.2 provides a summary of the resulting performance of all allocation portfolios.

The main conclusion that follows from the case study is that the optimization model that solves the capacity allocation problem can improve the expected profit. Furthermore, the workshop contributed to the awareness, among the representatives, of the allocation decision consequences on the profit. The representatives mentioned the complexity of the problem and noted that more factors influence the profit than solely focusing on asset utilization. Next, the participants noticed the awareness of the shipment windows of the synchromodal products on the operational performance. Pfoser et al. (2016) identify 'Awareness' and 'Mental Shift' as a critical success factor to ensure effective implementation of synchromodal transportation. It is believed that the capacity allocation problem workshop contributes to the awareness factor, as it shows the trade-offs between the synchromodal transportation services.

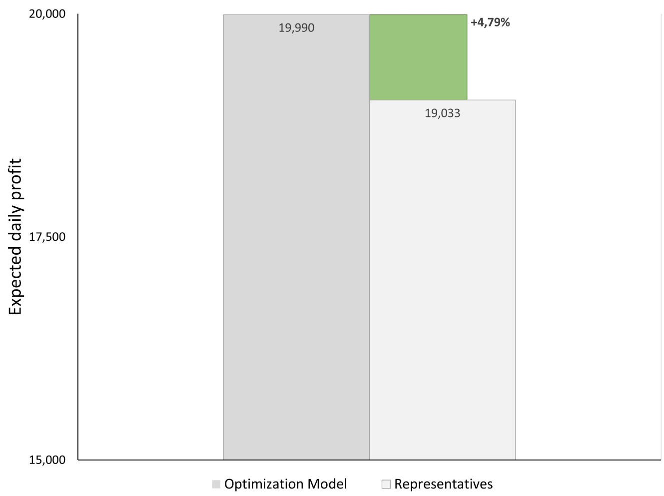


Figure 5.2: Expected profit given the optimal allocation portfolio and the average profit of the allocation decisions taken by experienced sales and operations representatives.

5.3 Sensitivity analysis

This section discusses the results obtained from the sensitivity analysis. The section first addresses the model behavior given the capacity and demand size to validate if the model exhibits the expected behavior. Second, we examine the sensitivity of the freight rates on the allocation decision. The third section focuses on the spot market demand and volatility and its effects on the allocation decision. Next, we analyze the penalty costs sensitivity. Fourth, we show that increasing the shipment window of the Standard service yields additional profit. Last, we study the influence of the forecast reliability of contractual sales on profitability.

5.3.1 Capacity and demand size

First, we examine the behavior of the stochastic integer model regarding the demand and capacity size. In order to assess the model behavior, we define three scenarios in which we scale the demand proportionally to the capacity, see Table E.1 in Appendix E.1. We solve the capacity allocation problem and analyze the performance of each allocation decision.

Figure 5.3 shows the expected profit of each possible allocation portfolio for all scenarios, where the contract allocations are represented by $[x_1, x_2]$, e.g. $[1, 0]$ indicates that contract 1 is accepted and contract 2 is rejected. Since the spot limit upper bound γ increases with the mean shipment arrival rate, we visualize the booking limit relative to its upper bound γ. For example, a 60% ratio with a spot demand upper bound of 25 shipments in scenario 1 indicates that the booking limit equals 15 orders. Besides, we determine the profit of a single allocation portfolio relatively to the optimal profit of the scenario, such that we are able to compare the results of the scaled scenarios.

It turns out that the model exhibits the same behavior given the allocation decisions. That is, the expected profit function is concave in all situations. As expected, allocating demand to underutilized capacity increases the expected profit, because it generates additional revenue, while it does not result in excess orders. However, allocating demand to scare capacity results in excess shipments, which in turn negatively affects the profit. Hence, the profit function is concave upwards if there is capacity left to be utilized and concave downwards if capacity is exceeded.

The optimal contract portfolio involves in all cases accepting contract 1, rejecting contract 2 and fixing the booking limit to about 50% of the spot market demand upper bound γ. As expected, increasing the booking limit up to 50% results in additional profit in the cases $[0, 1]$ and $[1, 0]$, as additional spot demand is allocated to underutilized capacity. However, the profit decreases as too many shipments are accepted, resulting in excess shipments and penalty costs. Only serving the spot market, case $[0, 0]$, consequences low asset utilization such that revenue opportunities exist.

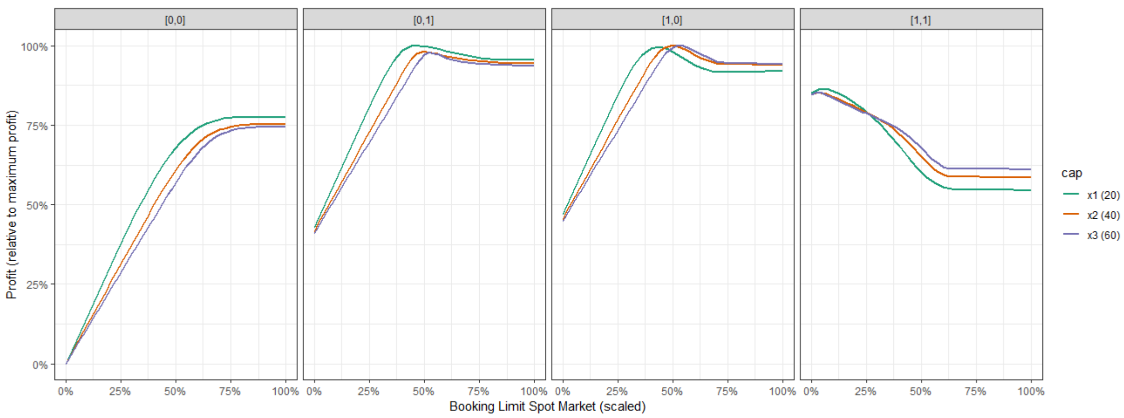


Figure 5.3: Model behavior of proportionally scaling capacity and demand size.

It should be noticed that the incremental increase of the expected number of spot shipments slows as the booking limit goes to the spot demand upper bound because the range that is covered by the booking limit contains all random variables. More specific, the probability that more spot orders arrive than the booking limit decreases as the booking limit is close to the upper bound. Next, accepting both contracts, case $[1, 1]$, and increasing the booking limit negatively affects the profit, as there is insufficient capacity to satisfy all demand.

To conclude, the profit that follows from solving the stochastic integer model exhibits the expected behavior. The small differences in the model behavior, compared to the other scenarios, is caused by the variance of the Poisson distribution, which increases with the mean arrival rate. The model also exhibits the same behavior when there are more contracts or when there is only a single shipment service defined, see Figures E.1 and E.2 in Appendix E.2. Since the computation time increases in the capacity/demand size, we will use relatively small capacity and demand sizes (± 20) in the remainder of this chapter.

5.3.2 Freight rates

This section analyzes the sensitivity of the freight rates on the allocation mechanisms. First, we examine the cases with fixed and deterministic freight rates. Second, we determine the optimal capacity distribution to Express and Standard orders given the freight rate spread. The freight rate spread indicates the revenue difference of Standard and/or spot services relative to Express shipments, e.g., a $100 Express freight rate with a 10% spread indicates a $90 and $110 Standard and spot freight rate respectively.

Fixed deterministic freight rates

We examine the sensitivity of the freight rates on the allocation decision mechanisms, by altering the freight rate spread between the transportation services. Consider a capacity allocation problem with two contracts and an expected daily spot market demand of 13 shipments. The first contract contains mainly Express orders, while the other mainly Standard orders: $\lambda_E = \{8, 2\}$, $\lambda_S = \{2, 8\}$. The logistics service provider has a daily capacity of 20 TEU, and penalty costs that include the spot freight rate with a 10% premium.

First, we increase the freight rate spread of the Standard and spot services relative to the Express rate, adhered to the following rate structure: $r^S \leq r^E \leq r^{spot}$. Table 5.2 shows the dependency of the optimal allocation on the freight rate spread. It turns out that the logistics service provider should allocate capacity to Standard shipments if the freight rate spread is smaller than 7.5%, but should focus on Express demand as the spread exceeds 7.5%, see Table 5.2.

The 2-day shipment window of the Standard service results in less excess demand, which offsets the revenue opportunity of allocating the contract with mainly Express shipments. That is, the trade-off freight rate spread between contract I with mainly Express shipments and contract II with mainly Standard shipments depends on the profit equilibrium:

$$Profit\big(contract\ \ I\big) = Profit\big(contract\ \ II\big)$$

Table 5.2: Freight rate analysis with variable deterministic spot freight rates and 20 TEU capacity, and Poisson distributed Express, Standard and spot demand, with $\lambda_E = \{8, 2\}$, $\lambda_S = \{2, 8\}$, $\lambda_{spot} = 13$, and penalty costs include spot rate with 10% premium.

Freight rates				**Penalty**	**Allocation portfolio**		**Profit**	**Utilization**	**Excess**
Spread	Express	Standard	Spot		contracts	n_{spot}			**shipments**
0.0%	100.00	100.00	100.00	110.00	[0,1]	13	1971	99.4%	1.7
7.5%	100.00	92.50	107.50	118.20	[0,1]	13	1984	99.4%	1.7
7.6%	100.00	92.40	107.60	118.36	[1,0]	13	1985	97.4%	2.1
10.0%	100.00	90.00	110.00	121.00	[1,0]	13	2002	97.4%	2.1

Allocating contract I results in 2.1 expected excess shipments, while allocating contract II results in 1.7 expected excess shipments. Hence,

$$Penalty\big(contract\ \ I\big) > Penalty\big(contract\ \ II\big)$$

Consequently, allocating contract I is only profitable if the Express freight rates compensate the profit loss owing to more excess shipments. Therefore, if the freight rate spread increases, the benefit of the 2-day shipment window disappears because the additional revenue for Express shipment compensates the penalty costs:

$$Revenue\big(contract\ \ I\big) - Penalty\big(contract\ \ I\big) > Revenue\big(contract\ \ II\big) - Penalty\big(contract\ \ II\big)$$

On the other hand, as the freight rate spread decreases, the profit obtained from the Standard shipments outweighs the revenue opportunity of allocating contract I. Although contract I results in a higher revenue, the penalty costs reduces the profit, such that it is more profitable to accept contract II:

$$Revenue\big(contract\ \ I\big){-}Penalty\big(contract\ \ I\big) < Revenue\big(contract\ \ II\big) \uparrow {-}Penalty\big(contract\ \ II\big)$$

Second, we analyze the trade-off between Express and Standard orders given the freight rate spread and a fixed and deterministic spot freight rate. We determine a break-even freight rate spread in which both contracts are even profitable. That is, at the break-even point, the expected profit that follows from accepting contract I equals the expected profit of allocating contract II.

Figure 5.4 shows the break-even freight rate spread given the spot rate relative to the Express rate. Contract II, with mainly Standard orders, is allocated if the freight rate spread is smaller than the break-even point, while contract I is accepted if the spread exceeds the break-even point. The break-even spread is more significant when the spot rate increases relative to the Express rate because the penalty costs grow proportionally to the contractual freight rates, which disadvantages contract I as it leads to more expected excess shipments. The freight rates of Express shipments must compensate the additional penalty costs, which explains a larger freight rate spread. It should be highlighted that this observation only holds when the penalty costs depend on the spot freight rate.

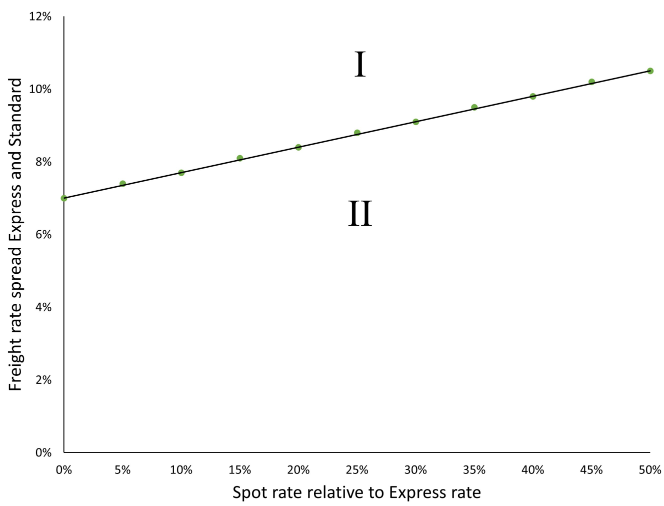


Figure 5.4: Break-even freight rate spread between Express and Standard transportation services, with $\lambda_E = \{8, 2\}$ and $\lambda_E = \{2, 8\}$. Allocate contract II if the freight rate spread is smaller than the break-even point, allocate contract I otherwise.

Finally, we show how the spot freight rate affects the allocation decision given fixed Express and Standard freight rates. In other words, we increase the spot freight rate, and in turn also the penalty costs, subject to fixed contractual shipment rates. Considering the freight rate spread findings above, we distinguish between a spread rate of 5% and 15% such that we exclude the allocation trade-off effects. Table 5.3 reflects that the allocation decision is not affected by the spot freight rate, as the penalty costs increase with the spot rates. The additional revenue of allocating extra demand does not outweigh the penalty costs. Notice that capacity is underutilized if we only serve the spot market, which holds that the optimal allocation portfolio contains at least one contract.

Table 5.3: Spot freight rate analysis with variable deterministic spot freight rates, fixed contract freight rates, 20 TEU capacity, and Poisson distributed Express, Standard and spot demand, with $\lambda_E = \{8, 2\}$, $\lambda_S = \{2, 8\}$, $\lambda_{spot} = 13$, and penalty costs include spot rate with 10% premium.

Freight rates				**Penalty**	**Allocation portfolio**		**Profit**	**Utilization**	**Excess**
$\Delta Spot$	Express	Standard	Spot		contracts	n_{spot}			**shipments**
+0%	100	100	85	110	[1,0]	13	1899	97.4%	2.1
+30%	130	100	85	143	[1,0]	13	2178	97.4%	2.1
+0%	100	100	95	110	[0,1]	13	1931	101.9%	1.2
+30%	130	100	95	143	[0,1]	13	2222	101.9%	1.2

Optimal capacity allocation to Express and Standard shipments
In this section, we examine the optimal capacity allocation distribution between Express and Standard shipments given the freight rate spread between the transportation services and provided that there are no spot market sales. We assume that there is infinite demand for Express and Standard shipments, and finite and fixed capacity. Additionally, we assume that there are infinite contracts with a demand for precisely one Express or one Standard shipment, such that there are no contractual volume restrictions. Next, the penalty costs are two times the Express freight rate to avoid excess orders.

Figure 5.5 presents the optimal allocation between Standard and Express orders given the freight rate spread and a 1- and 2-day Express shipment window policy. In the first, we examine the 1-day shipment policy, which is the primary focus of this research.

Considering a freight rate spread between 3% and 30%, it turns out that the optimal allocation portfolio consists majorly of Express services, but also includes Standard services. While Express services generate more revenue per shipment, Standard services provide planning flexibility, which reduces the probability of excess shipments. The shipment window of the Standard service hedges against demand uncertainty, because it is allowed to postpone Standard orders in case of insufficient capacity, while Express shipments require immediately alternative transport, yielding penalty costs. More specifically, Standard surplus demand is postponed to the next day that may face low demand, such that demand is balanced over the days. Although Standard shipments generate less revenue, the penalty costs savings outweigh the revenue loss, designating the essence of including Standard shipments. The share of Standard services in the optimal allocation increases as the freight rate spread decreases, because the revenue-opportunity of allocating Express reduces, while allocating Standard demand also saves on penalty costs.

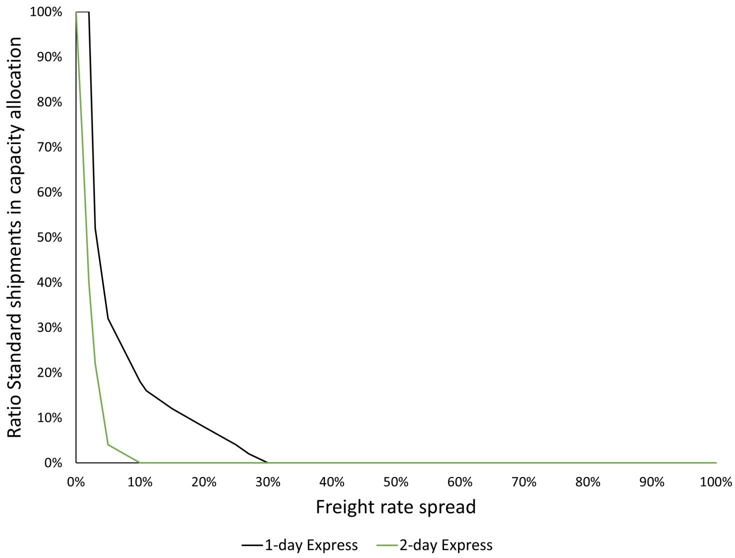


Figure 5.5: Optimal capacity distribution between Express and Standard shipments

Furthermore, the optimal distribution in Figure 5.5 reflects that the service provider should exclusively allocate Express shipments as the freight rate spread exceeds 30%. From this point, the penalty costs savings do not compensate the revenue loss. More specifically, it is more profitable to take the penalty costs, than trying to reduce the excess orders by substituting capacity reserved for Express shipments by lower-priced Standard shipments.

A small freight rate spread (0-2%) indicates that the service provider should only focus on utilizing Standard demand. In this case, the freight rate does not reflect the extended shipment window of the Standard service, as it equals the Express freight rate. Therefore, the Standard service is preferred above Express services as it reduces the probability of excess orders and results in lower penalty costs, while it generates equal revenue.

Moreover, Figure 5.5 indicates to prefer the allocation of Express shipments over Standard services, when extending the Express and Standard shipment window to a 2- and 4-day policy respectively. In this case, the extended shipment window of the Express service provides the opportunity to postpone shipments and hedges therefore against demand uncertainty. It follows that there is less need to include Standard shipments in the portfolio since the Express service already provides the opportunity to smooth demand. However, Standard services are still preferred as the freight rate decreases, since the 4-day shipment window provides more flexibility, yielding lower penalty costs compared to the 2-day Express shipment window.

The optimal allocation distribution provides the opportunity to benchmark the company's current service portfolio with the optimal one. A deviation from the optimal distribution indicates that any shift towards substituting Express or Standard shipments in the allocation portfolio results in additional profit. For example, consider a logistics service provider with a demand that consists for 2% of Standard shipments with a freight rate spread of 20% and a 1- and 2-day shipment window for Express and Standard services respectively. Figure 5.5 indicates that the optimal allocation portfolio consists for 8% of Standard shipments, which is a discrepancy with the current situations. Consequently, the logistics service provider should include more Standard services in its allocation portfolio, by substituting it with Express demand. More specific, the service provider should increase the share Standard orders and reduce the share Express orders to maximize its expected profit.

Notice that the allocation distribution does not provide any detail about the demand size relative to capacity. Additionally, the optimal distribution is based on a fixed freight rate spread between all shipments and does not account for differences in rates between individual contracts. Consider for example an average freight rate of \$100 and \$90 for Express and Standard services respectively, i.e., a 10% freight spread. Next, consider a single contract with demand for one Express order that represents less than 1% of the total demand with a relatively high revenue of \$180 for Express shipments, which is twice the Standard shipment rate. The optimal distribution indicates that the service provider should exclusively accept Standard orders. However, it is likely that it is profitable to accept the contract as it replaces two Standard shipments.

Therefore, although the optimal distribution provides a biased view by neglecting the freight rates of individual contracts, the framework provides a generic policy guideline.

5.3.3 Spot market

In this section, we address the spot allocation decision sensitivity for spot market demand. First, we evaluate the effects of the spot demand size and examine the profit opportunity of substituting contractual demand with spot demand. Second, we show how spot demand volatility affects the allocation decision.

Spot market demand allocation

In this section, we evaluate the spot demand volume effects on the allocation decision, given fixed and deterministic spot rates as in Section 5.3.2. Furthermore, we examine the effects of substituting Express and Standard shipments with spot shipments.

Table 5.4 summarizes the allocation results when increasing the spot demand, by providing the average spot market demand, the contract portfolio, and the spot market booking limit. It turns out that more capacity is reserved for spot sales as the average demand on the spot market increases. Notice, that it is assumed that the spot market and contractual demand are both Poisson distributed, which implies that the volatility increases with the expected number of shipments. Consequently, as there is no significant difference between the average spot, Express, and Standard shipment demand size, the contractual and spot demand are even volatile.

The results in Table 5.4 show that reserving capacity for spot demand is profitable, even when spot demand is rather low since spot shipments are more profitable than Express and Standard shipments. That is, the case with $\lambda = 7$, with a total demand of 17 shipments, outweighs the profit of accepting both contracts, which accommodates 20 expected shipments. The booking limit reduces the probability of excess orders relative to Express contractual demand, because it bounds the accepted spot shipments requests. That is, spot shipments are only accepted up to the booking limit, while Express and Standard shipments are always accepted. Therefore, given equal demand volatility, reduced excess orders and a higher revenue, it is profitable to reserve more capacity for spot shipments as the spot shipment demand increases.

Table 5.4: Spot demand analysis with Express and Standard transportation services and 20 TEU capacity. Poisson distributed Express, Standard en Spot demand, with $\lambda_E = \{8, 2\}$, $\lambda_S = \{2, 8\}$, $r^E = 100$, $r^S = 80$, $r^{spot} = 120$, and $p = 150$.

Spot Demand λ_{spot}	**Contracts**	n_{spot}	**Profit**	**Utilization** [%]	**Excess** [orders]
0	[1,1]	0	1702	96.7	0.66
7	[1,0]	11	1730	82.6	0.38
13	[0,1]	12	1982	99.1	1.21
26	[0,0]	20	2369	98.7	0.00

Substituting demand

To examine the effects of reserving capacity for spot sales at the expense of Express and Standard shipments, we substitute contractual shipment demand with spot market demand. Notice that spot and Express shipments have both a 1-day shipment window, while Standard shipments are either shipped today or tomorrow.

Figure 5.6 shows the change in profit given the Express substitution rate, which indicates the ratio of Express shipments that are replaced with spot shipments, e.g., a 50% substitution rate with 10 initial Express shipments indicates an expected demand of 5 shipments for both Express and spot services. To evaluate the substitution effects, we assume equal Express and spot freight rates, because if we can prove that substituting Express demand is profitable given equal freight rates, then substituting is even more profitable when the spot rate increases. We apply the same logic by setting equal freight rates for spot and Standard shipments, when we substitute Standard demand with spot market demand. We optimize the resulting capacity allocation problem and compare the scenarios on profit. It should be highlighted that we assume that Express, Standard and spot market demand are Poisson distributed. Later in this section, we relax this assumption and analyze the allocation decision given volatile spot demand.

It turns out that additional profit is obtained as more Express shipments are substituted. The spot booking limit provides an upper bound on the spot sales, while the service provider is obliged to accept all incoming Express demand. As a consequence, the spot market prevents against excess shipments, yielding penalty cost savings, see Figure 5.7. On the other hand, substituting Express shipments results in less revenue, because Express shipments are not constrained above. That is, given equal expected demand, the expected number of spot sales is lower than the expected number of Express orders, and generates thus less revenue, see Equation (3.6). Nevertheless, the penalty cost savings offset the revenue loss, yielding more profit.

The profit opportunity increases as the share of Express shipments in the initial case increments, especially when there are only Express orders, see Figure 5.6. The shipment window of Standard shipments hedges against demand uncertainty, because it is allowed to postpone Standard shipments. Replacing Standard orders with Express orders in the initial allocation portfolio with a 0% Express demand substitution rate increases the exposure to excess shipments, yielding more expected penalty costs. Therefore, the advantage of substituting Express demand for spot demand increases when there are relatively few Standard shipments in the allocation portfolio.

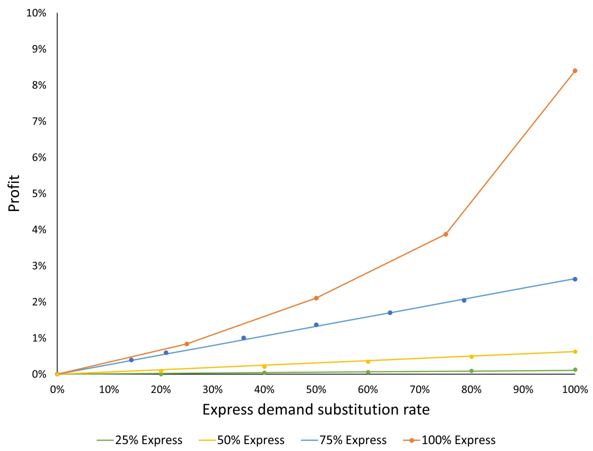


Figure 5.6: Simulation results of substituting Express demand with spot market demand, with 20 TEU capacity, $r^E = r^{spot} = 100$, $r^S = 80$, $p = 150$, and Poisson distributed demand.

Furthermore, it turns out that substituting Standard shipments for spot market shipments reduces the expected profit, provided equal freight rates, see Figure 5.8. Substituting Standard shipments cause additional excess shipments, due to reduced planning flexibility. Besides, the booking limit constraints the spot shipments above, while excess Standard shipments are postponed to the next day, such that they still generate revenue. That is, the service provider can accommodate more shipments, yielding additional revenue, while it does not lead to excess shipments and thus positively contributes to the expected profit. Accordingly, in order to substitute Standard shipments for spot shipments, the revenue generated by spot sales should offset profit loss. Figure 5.9 indicates the required spot freight rate, which increases with the substitution rate, such that it is profitable to substitute capacity reserved for Standard shipments with spot market demand.

In short, the substitution analysis showed that it is profitable to substitute Express shipments for spot shipments while substituting Standard shipments is only profitable if the spot freight rate compensates the profit loss.

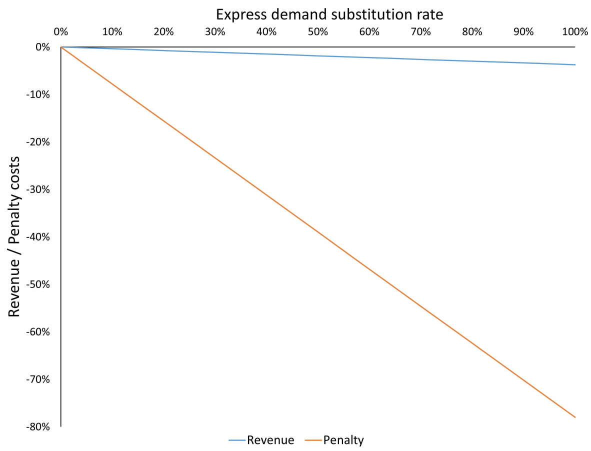


Figure 5.7: Revenue and penalty costs of substituting Express demand for Spot market demand with 75% initial Express demand, with 20 TEU capacity, $r^E = r^{spot} = 100$, $r^S = 80$, $p = 150$, and Poisson distributed demand.

Figure 5.8: Simulation results of substituting Standard demand for Spot market demand, with 20 TEU capacity, $r^E = r^{spot} = r^S = 100$, $p = 150$, and Poisson distributed demand.

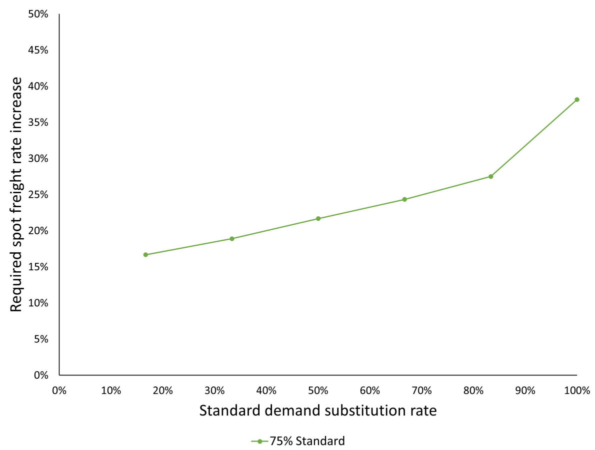


Figure 5.9: Required spot freight rate increase to offset the profit loss due to substituting Standard demand.

Spot market demand volatility

In contrast to the previous spot market analysis, we examine the allocation decision mechanisms by increasing the spot demand volatility relative to the Express and Standard demand volatility, i.e., we assume more uncertain spot demand. In Section 3.1.2 we assumed Poisson distributed spot demand, with a mean arrival rate of λ shipments and a variance of λ, i.e., a standard deviation of $\sqrt{\lambda}$. However, in order to alter the spot demand volatility, we assume a Normal distribution with mean λ and standard deviation $\sqrt{\lambda}$, which approximates the Poisson distribution for $\lambda > 10$, provided that a continuity correction is applied. The accuracy of the approximation increases with λ. We alter the standard deviation of the Normal distribution to assess the spot demand volatility. The reference case follows a Normal distribution with a standard deviation of $\sqrt{\lambda}$ and we compare it with more volatile spot demand by increasing the standard deviation.

Figure 5.10 shows the expected profit given the increased spot demand volatility relative to the initial case, in which spot and Express demand are even volatile. Increasing the spot demand volatility negatively affects the profit as the exposure to capacity underutilization increases. The realized shipment demand deviates further from the mean when the standard deviation, i.e., the demand uncertainty, increments. Consequently, there is an increased probability that there arrive less spot shipment requests as the booking limit allows, which results in underutilization and revenue loss. On the other hand, the upward demand risk, i.e., there are more incoming spot shipment requests as expected, does not influence the profit since the booking limit prevents to accept more shipments as the booking limit. The exposure to spot demand volatility increases as more capacity is reserved for spot sales.

Notice that we assumed that the Normal distribution approximates Poisson distributed spot demand, which holds that the standard deviation equals $\sqrt{\lambda}$, with λ the mean expected spot shipments. This implies that a larger mean results in a relatively larger standard deviation. Therefore, given Poisson distributed demand, the larger the expected number of spot orders, the stronger the profit is influenced by the volatility.

To analyze the spot demand volatility effects, consider the following scenario that is optimized by the simulation-based optimization model, as defined in Section 3.3. A service provider with a capacity of 150 TEU, with a demand for 50 Express, 50 Standard and 100 spot shipments, seeks to maximize the expected profit. The service provider is forced to reject demand due to capacity limitations. Based on the observation in Section 5.3.3, we assume that it is only allowed to substitute Express demand for spot demand. The contractual demand is variable, such that the service provider can substitute Express demand one by one, i.e., there are no contractual volume constraints. Next, we assume deterministic and fixed freight rates of \$100 for spot and Express shipments and \$90 for Standard shipments. The penalty costs comprise the spot freight rate with a 10% premium, i.e., $p = 110$, and the risk-free rate r_f equals 1%.

Table 5.5 summarizes the results of the optimal capacity distribution to spot, Express, and Standard demand. A standard deviation of $\sqrt{\lambda}$ reflects a Normal distribution that approximates the Poisson distribution. Notice that the Express and Standard demand follow a Normal distribution that approximate the Poisson distribution, such that we only increase the spot demand volatility. It turns out that less capacity is reserved for spot market sales as the volatility surges. The risk of underutilization increases with the spot demand volatility, because realized spot demand could disappoint, while Express demand provides more certainty. The spot market booking limit prevents overutilization because all demand above the booking limit is rejected. It follows that the logistics service provider should allocate less spot demand as the spot demand uncertainty increases.

In Figure 5.6, we observed that substituting capacity reserved for Express shipments by spot shipments positively contributes to the profit, and that the contribution increases with the substitution rate. We now analyze the volatility effects on the profit while we substitute Express demand for spot demand.

Figure 5.11 shows the expected profit given the spot demand volatility and the Express substitution rates, relative to a portfolio that only includes Express shipments. Profit opportunities exist in the initial case with equal volatile Express and spot demand by substituting Express demand with spot shipments, because the spot market booking limit prevents against excess orders, see Section 5.3.3.

Table 5.5: Simulation results of determining the optimal spot market booking limit given volatile spot demand, with $\lambda_{spot} = 100, \lambda_E = 50, \lambda_S = 50$.

Spot demand volatility	n_{spot}	D_E	D_S	**Profit**	**Revenue**	**Penalty**
$1.00\sqrt{\lambda}$	89	12	50	14,907	15,032	125
$1.10\sqrt{\lambda}$	87	14	50	14,904	15,036	132
$1.50\sqrt{\lambda}$	81	20	50	14,893	15,028	135
$2.00\sqrt{\lambda}$	71	30	50	14,878	15,037	159

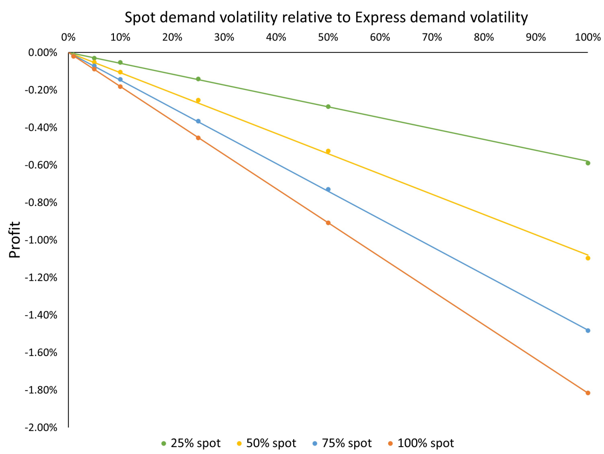


Figure 5.10: Profit given more uncertain spot market demand, with $D_E = \{8, 2\}$, $D_E = \{2, 8\}$, $r^E = 100$, $r^S = 80$, r^{spot}, and $p = 100$.

It turns out that the profit opportunity decreases when spot demand gets more uncertain. A contract portfolio that consists for 75% of Express shipments with 25% more volatile spot market results in equal expected profit as the portfolio with only Express shipments. That is, at this point the logistics service provider is indifferent between partly serving the spot market or only utilizing Express demand. Only serving Express demand is preferred as the spot volatility is more substantial than 25% compared to an allocation portfolio that consists for 25% of Express shipments. Furthermore, it turns out that a higher spot volatility is acceptable as the Express substitution rate increases. The penalty costs significantly influence the profit, which reflects that it is profitable to substitute Express shipments for spot demand because it reduces the expected excess shipments. Although, the exposure to spot demand volatility increases when relatively much capacity is reserved for spot sales, it is still profitable to substitute Express demand for spot demand. For example, it is profitable to substitute all Express demand for spot services as the spot market is 80% more volatile as contractual Express demand.

5.3.4 Stochastic spot freight rates

This section addresses the capacity allocation problem with stochastic spot freight rates. As discussed in Section 2.4, the stochastic spot rates exhibit a mean-reverting property, which is modeled by an Ornstein-Uhlenbeck process. To analyze the optimal allocation decision under stochastic spot freight rates, we alter the variance of the spot rates by varying the mean-reverting rate and the standard deviation.

Consider a capacity allocation problem with a fixed capacity of 50 TEU and 50 TEU demand for both Express and spot services, i.e., $\lambda_E = \lambda_{spot} = 50$, while there is no demand for Standard services, such that the service provider can solely focus on optimizing the capacity distribution to Express and spot market demand. This way, we exclude the shipment window complexity on the allocation decision. Moreover, in Section 5.3.3, we observed that it is only profitable to substitute Express demand with spot demand. We assume Normal distributed Express and spot demand, that approximate the Poisson distribution with mean λ and standard deviation $\sqrt{\lambda}$. Next, we assume that spot market demand is two times as volatile as Express demand, i.e., a standard deviation of $2\sqrt{\lambda}$, such that the benefits of serving the spot market are suspended, see Section 5.3.3. In other words, it is even profitable to serve the spot market as utilizing Express demand. Furthermore, we assume that there are no contractual volume restrictions, such that the service provider could determine the optimal cargo mix between Express and spot demand. The Express freight rates are deterministic and equal \$100. The spot freight rates are described by an Ornstein-Uhlenbeck process with the long-term mean freight rate θ of \$100, while we alter the standard deviation and mean-reverting rate of the freight rates to examine the sensitivity.

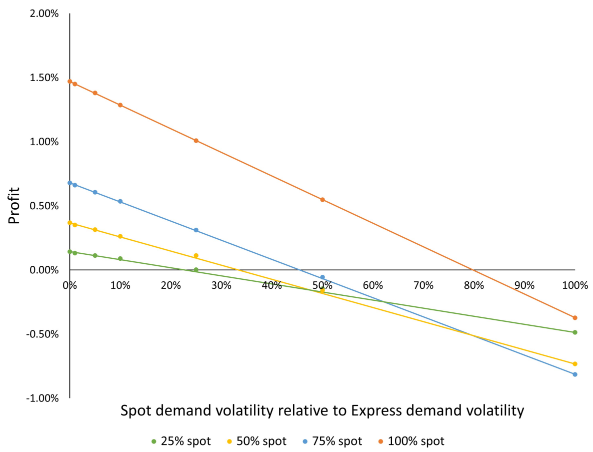


Figure 5.11: Simulation results of substituting Express demand with volatile spot demand relative to a portfolio that consists exclusively of Express demand, given an initial share spot orders.

We apply the simulation-based optimization model as in Section 3.3.1 and sample a spot price path in each simulation run via the OU-process, see Equation (3.27). We determine the expected profit of each allocation portfolio and identify the best performing allocation portfolio in each simulation run given the realized demand and spot freight rates. That is, we count the number of times that a portfolio resulted in the highest profit. Notice that we exclude the demand-supply mechanisms to reduce the complexity by assuming that the spot demand and freight rates are independent. All simulation results are subject to a 95%-confidence interval.

Figure 5.12 reflects the probability distribution that an allocation portfolio, indicated by the spot market booking limit, provides the highest profit, given stochastic demand and deterministic or stochastic spot freight rates. The probability distribution function is established based on the number of times that an allocation portfolio resulted in the highest profit. For example, given deterministic spot freight rates, there is a 10% probability that an allocation portfolio with a spot market booking limit of 30 shipments provides the maximum profit. In other words, allocating on average 22 Express shipments with a spot market booking limit of 30 shipments provided 505 times out of 5,000 simulations runs the highest profit.

It turns out that the optimal allocation portfolio that provides the highest expected profit is independent of the stochastic freight rate volatility because the optimal capacity allocation remains the same when the volatility increases, see Table 5.6. That is, the optimal allocation portfolio with n^*_{spot} does not significantly change when we increase the spot freight rate volatility, see Appendix F.3. More specific, the optimal allocation portfolio given deterministic and volatile spot freight rates includes a spot market booking limit of 30 shipments and 22 allocated Express shipment demand. A risk-neutral logistics service provider will commit to the allocation portfolio with the highest expected profit. Therefore, the optimal capacity distribution of the logistics service provider is insensitive to the spot freight rate volatility because the initial allocation portfolio provides the highest expected profit, even when the spot freight rate volatility surges.

Moreover, Table 5.6 provides the mean and the standard deviation of the optimal booking limit probability distribution. It turns out that increasing the spot freight rate volatility implies a reduced probability that the selected allocation portfolio provides the highest profit when the freight rates are realized in the booking horizon. In other words, increasing the variance of the spot freight rates results in a more substantial standard deviation of the optimal booking limit distribution, implying that we are less confident that the optimal allocation portfolio provides the maximum profit.

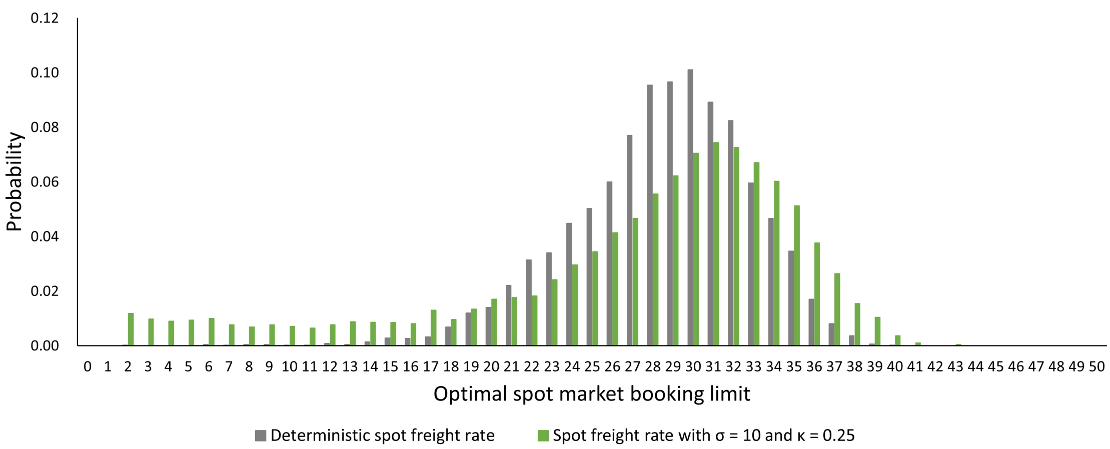


Figure 5.12: Probability mass distribution that the selected spot market booking limit results in the highest profit, given stochastic spot demand and deterministic or stochastic spot freight rates. Based on 5,000 simulations runs with $\theta = 100$, and $\kappa = 0.25$.

Table 5.6: Optimal capacity distribution to spot and Express demand given volatile spot market demand $\sigma_{spot} = 2\sqrt{\lambda}$, 50 TEU capacity, $r^E = 100$, $p = 150$, and the long-term mean spot rate $\theta = 100$

Spot freight rates			**Spot demand allocation**					
κ	σ_{rate}	Var	n^*_{spot}	Daily profit		$\mu_{booking\ limit}$	$\sigma_{booking\ limit}$	skewness
deterministic			30	4774.81	$\pm$1.78	28.46	4.37	-0.64
0.25	10	200	30	4753.54	$\pm$0.71	26.99	8.58	-0.78
0.25	20	800	30	4733.37	$\pm$3.75	25.46	12.11	-1.24

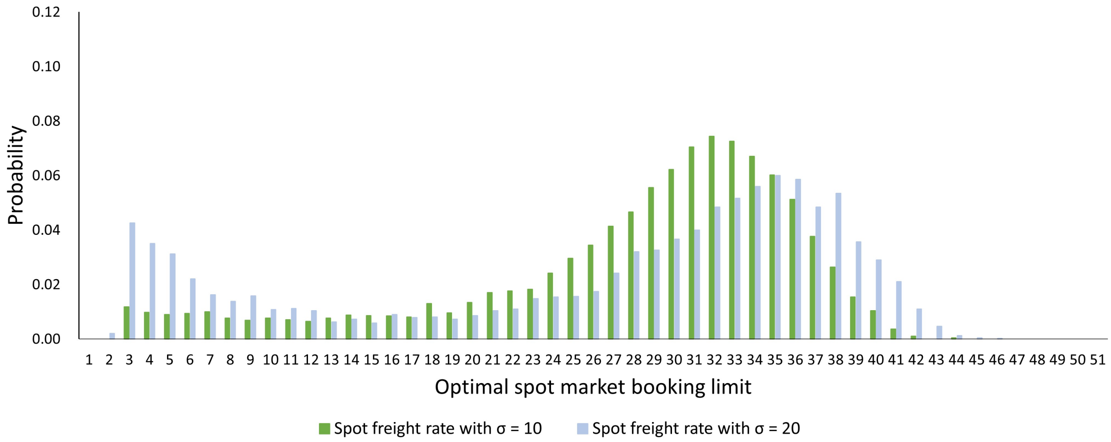


Figure 5.13: Probability mass distribution of that the selected spot market booking limit results in the highest profit, given stochastic spot demand and stochastic spot freight rates. Based on 5,000 simulations runs with $\theta = 100$, and $\kappa = 0.25$.

For example, consider the case in Figure 5.13, increasing the standard deviation from 10 to 20 reduces the probability that an allocation portfolio with 30 spot shipments is the optimal portfolio with 3%. That is, there is a 7% probability that a booking limit of 30 shipments with a standard deviation of 10 results in the highest profit, while this probability is only 4% when the standard deviation increases to 20. Notice, that the mean of the optimal booking limit distribution does not equal the allocation portfolio that provides on average the highest expected profit. The tails of the probability distribution increase with the stochastic spot freight rate volatility, which reduces the mean of the observations. However, increasing the spot rate volatility does not significantly affect the optimal capacity allocation to spot market demand.

Furthermore, it turns out that the optimal capacity allocation is moderately negatively skewed, which implies that the distribution has a relatively large lower tail compared to the upper tail, see Table 5.6. Again the optimal allocation portfolio with the highest expected profit remains equal when the volatility increases. Increasing the spot rate volatility results in a more significant lower tail of the optimal spot market booking limit relative to the upper tail. It follows that the service provider could hedge against the spot rate volatility by reducing the capacity reserved for spot sales. That is, the exposure to the spot freight rate uncertainty depends on the capacity size reserved for spot sales, implying that the exposure increases when the service provider allocates more capacity to spot market demand. The upper tail of the optimal allocation distribution is bounded by the spot demand size, which equals 50 shipments.

Another interesting observation from Figure 5.13 is that the probability of primarily serving Express demand, instead of spot demand, increases with the spot freight rate volatility. The Express freight rates provide security against the spot freight rate volatility, because the contractual freight rates are deterministic. As the spot freight rates have a negative trend, it becomes more profitable to serve Express demand since it has a higher revenue per shipment. However, if the spot freight rates have a positive trend, such that the spot prices exceeds the contractual prices, the logistics service provider could not profit of this opportunity when it allocates too few spot market demand. Therefore, the optimal allocation portfolio that results on average in the highest expected profit is independent of the spot freight volatility as it could have a positive or a negative trend, which is unknown at the moment of allocation.

Finally, we analyze the effects of the mean-reverting rate, which reflects the speed at which the spot freight rate reverts back to the long-term mean. To examine these effects, we alter the mean-reverting rate and the standard deviation such that it results in equal spot freight rate variance. It turns out that the standard deviation of the optimal capacity allocation distribution decreases when the mean-reverting rate increases, see Table 5.7. That is, if we increment the mean-reverting rate to 1, such that the prices tend to revert quicker back to the mean level, the standard deviation of the optimal allocation portfolio increases. Therefore, increasing the mean-reverting rate reduces the exposure to the spot freight rate volatility, because the prices revert earlier back to the mean-level, preventing 'extreme' freight rates.

Table 5.7: Optimal capacity distribution to spot and Express demand given volatile spot market demand $\sigma_{spot} = 2\sqrt{\lambda}$, 50 TEU capacity, $r^E = 100$, $p = 150$, and the long-term mean spot rate $\theta = 100$

Spot freight rates			**Spot demand allocation**		
κ	σ_{rate}	Var	n^*_{spot}	$\mu_{booking\ limit}$	$\sigma_{booking\ limit}$
0.25	20	800	30	25.46	12.11
0.50	28.28	800	30	26.63	10.35
1	40	800	30	27.97	8.28

5.3.5 Perfect-hindsight study

This study focuses on a static spot market booking limit, which indicates the maximum number of spot orders to accept, independent of available capacity and time. The service provider commits to allotment contracts before the start of the booking horizon and is obliged to serve all contractual demand, which holds that the service provider can only influence profit throughout the booking horizon by accepting and rejecting spot shipment requests. In order to quantify the performance of this static allocation strategy, we perform a simulation-based revenue-opportunity assessment.

The assessment compromises a perfect-hindsight approach that determines the optimal profit in case demand was perfectly known, see Talluri and Van Ryzin (2006). In retrospective, it is determined which spot requests should have been accepted given the actual realized contractual and spot market demand. The perfect-hindsight approach provides an upper bound to the expected profit, which we use to quantify the performance of the static allocation strategy. That is, we compare the profit obtained by a static booking limit strategy with the profit upper bound.

We analyze the profit of the optimal and static strategy in multiple scenarios in which we alter the utilization and the ratio of spot orders in total demand. We assume Poisson distributed Express, Standard and spot demand and fixed capacity. For simplicity, we assume equal freight rates for Express, Standard and spot shipments, penalty costs of 150% the freight rates, and a risk-free interest rate r_f of 1%. All simulations are subject to a 95%-confidence interval.

Given a 100% utilization, the assessment shows that the static strategy obtains on average 99.04% of the total profit that could have been acquired with the optimal strategy. In other words, the static allocation strategy results in 0.96% less profit compared to the profit upper bound. Adapting the allocation strategy could exploit this profit opportunity. It turns out that the revenue-opportunity grows proportionally with the ratio of spot sales to the total demand, especially in case of low and high utilization, see Figure 5.14.

There exist no revenue opportunities when the logistics service provider only serves contractual demand (0% spot) because the provider must accommodate this demand. On the other hand, only serving the spot market (100%) with an average asset utilization of 100% does also not provide revenue opportunities, because the booking limit equals the daily capacity, yielding no excess orders. Revenue-opportunities exist in all other cases, which could be exploited by accepting more or less spot shipment requests.

Considering a high asset utilization (110%), the service provider should reject spot shipments to prevent for excess orders, while it should accept more spot shipments in case of low asset utilization (90%). An asset utilization of 100% provides small revenue opportunities as the contractual demand, and the spot market sales are on average equal to the capacity. To exploit these revenue-opportunities, the service provider should reject spot shipment requests if they have more contractual sales on hand as expected and should accept requests if demand falls short. Notice that it is likely that the optimal solution to the capacity allocation problem has a utilization of about 100%, because overutilization results in penalty costs, while underutilization provides revenue opportunities.

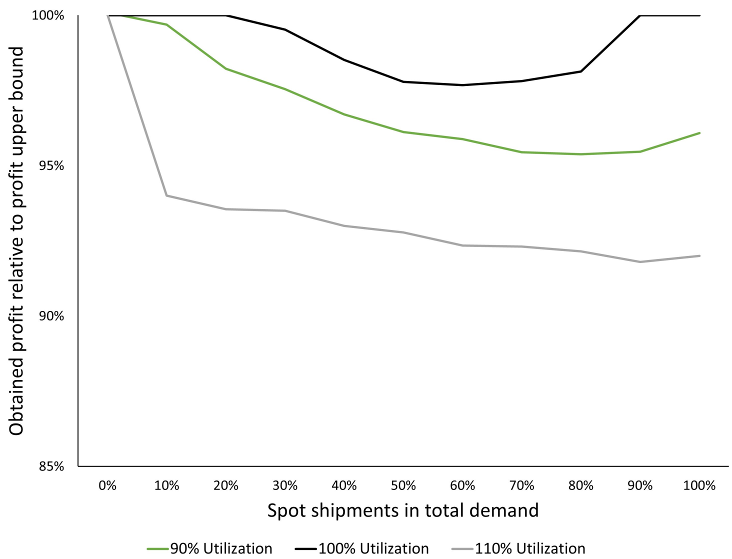


Figure 5.14: Profit opportunity assessment.

5.3.6 Penalty costs

Penalty costs constraint the service provider in its allocation decision. Naturally, increasing the penalty costs reduces the demand allocation to prevent excess shipments, see Table 5.8. More specifically, the results in Table 5.8 reflect that the spot booking limit decreases when the penalty costs increase. The saved penalty costs outweigh the additional revenue obtained by allocating extra spot shipments. Hence, the optimal capacity allocation is a trade-off between revenue and penalty costs. Consequently, the logistics service provider should temper the demand allocation as the penalty costs increase.

Table 5.8: *Penalty costs analysis. Poisson distributed Express, Standard and spot demand, with $\lambda_E = \{8, 2\}$, $\lambda_S = \{2, 8\}$, $\lambda_{spot} = 13$, $r^E = 100$, $r^S = 80$, $r^{spot} = 120$, and $p = 150$.*

Penalty costs	**Contracts**	n_{spot}	**Profit**	**Utilization** [%]	**Excess** [orders]
120	[0,1]	13	2028	95.7	2.43
150	[0,1]	12	1982	99.1	1.21
200	[0,1]	11	1946	98.4	0.70
300	[0,1]	10	1910	96.7	0.29

5.3.7 Shipment window

In this study, we assumed a 1- and 2-day shipment window for Express and Standard services respectively. This section evaluates the effects of increasing the Standard shipment window relative to the Express window on the allocation decision and the on performance regarding profit, revenue, and penalty costs.

Table 5.9 displays the expected profit given the shipment window policy. It turns out that extending the shipment window, while keeping the same allocation, results in additional profit. That is, extending the shipment window to a 3-day policy yields 2.7% more profit, due to penalty cost savings, see Table 5.10. This finding is in line with the work of Van Riessen et al. (2017) that show that increasing the Standard shipment window results in costs savings.

Furthermore, extending the shipment window provides the opportunity to accept more demand. A 3-day policy allows incrementing the booking limit with one spot order, yielding 3.4% more profit. The additional shipment day hedges against demand uncertainties as demand fluctuations are absorbed. Extending the shipment window to a 4-day policy allows to increment the booking limit with another additional shipment and surges the profit with 5.9% compared to the 2-day policy.

It is plausible to assume that the customer will only agree to extended shipment windows if it is reflected by the freight rates. Therefore, the logistics service provider should transfer part of the financial benefits that follow from extending the shipment window to the customer. For example, extending the shipment window from a 2-day to a 3-day policy results in \$50 (=\$1993-\$1883) additional profit, provided that the allocation not changes. This extended window allows the service provider to reduce the Standard shipment freight rate with \$7.14 (= \$50/7), given an expected demand of 7 Standard shipments, such that the expected profit of the 2-day policy equals the 3-day policy profit. Consequently, the logistics service provider charges \$72.86 per Standard shipment instead of \$80.00. Notice that we assumed in this example that the shipment demand is independent of the freight rate, i.e., demand does not inflate due to the reduced prices.

Table 5.9: *Simulation results of extending shipment window of Standard services, based on 10,000 runs of 252 days. 20 TEU capacity, and Poisson distributed Express, Standard and spot demand, with $\lambda_E = \{7, 3\}$, $\lambda_S = \{3, 7\}$, $\lambda_{spot} = 10$, $r^E = \{100, 100\}$, $r^S = \{80, 80\}$, $r^{spot} = 120$, $p = 200$.*

Allocation			**Average Daily Profit**					
x_1	x_2	n_{spot}	2-day policy		3-day policy		4-day policy	
0	1	11	**1883 ± 0.1**		1933 ± 0.1	(+2.7%)	1951 ± 0.2	(+3.6%)
0	1	12	1878 ± 0.2	(-0.3%)	**1942 ± 0.1**	**(+3.4%)**	1972 ± 0.2	(+5.0%)
0	1	13	1867 ± 0.3	(-0.8%)	1939 ± 0.2	(+3.9%)	**1977 ± 0.2**	**(+5.9%)**

Table 5.10: Standard shipment profit for 2 and 3-day policy with contract portfolio [0,1] and a booking limit of 11 shipments.

Policy	Revenue	Penalty	Profit
2-day	1960	77	1883
3-day	1960	27	1933
	[0%]	[-65%]	[+3%]

5.3.8 Forecast reliability

The allotment bid specifies the expected daily number of shipments per service type that the freight forwarder expects to ship. This suggests that the service provider should optimize its allocation portfolio based on demand forecasts that are provided by the freight forwarders. In this section, we evaluate the effects of the forecast reliability on service provider's expected profit. We define the forecast reliability as the variance of the demand distribution, i.e., it indicates the spread of the random demand variables from the mean. Accordingly, a high forecast accuracy implies a low variance. To assess the forecast reliability effects on the profit, we assume that demand is Normal distributed and alter the standard deviation as in Section 5.3.3. The reference case follows a Normal distribution with a standard deviation of $\sqrt{\lambda}$ and approximates the Poisson distribution for $\lambda > 10$.

Table 5.11 provides a summary of the expected profit given the forecast reliability. It turns out that the profit increases with the forecast reliability, insinuating that the service provider should prefer customers with reliable forecasts, provided that the freight rates of less reliable customers do not compensate the profit loss. Contracts with reliable forecasts are profitable because there is a lower probability that the capacity is exceeded, yielding reduced penalty costs. Next, a lower standard deviation implies that the realized shipments are closer to the mean, which positively effects operations as the probability of 'extreme' shipment volumes decreases.

Reliable contracts are preferred in situations with normal asset utilization (1.00), high asset utilization (1.10), low asset utilization (0.90), and in case of only Express demand. However, it turns out that the forecast reliability does not affect the profitability in case of only Standard orders because the 2-day shipment window of the Standard services hedges against demand uncertainty. That is, Standard shipments are postponed to the next day in case of high demand, which is not allowed for Express and spot shipments. The shipment window of Standard services absorbs demand fluctuations and is thus less sensitive to the forecast reliability.

Table 5.11: Simulation results of the allotment contract's forecast reliability without spot market demand. 95%-confidence interval based on 10,000 simulation runs.

Capacity	**Demand**	**Freight Rates**	**Standard Deviation**			
	(exp/std)	*(exp/std)*	$0.5\sqrt{\lambda}$	$\sqrt{\lambda}$	$2\sqrt{\lambda}$	$3\sqrt{\lambda}$
200	100/100	100/80	**17068** (±1)	17005 (±1)	16744 (±2)	16341 (±4)
180	100/100	100/80	**12441** (±6)	12429 (±6)	12356 (±7)	12203 (±9)
220	100/100	100/80	**17996** (±2)	17987 (±2)	17956 (±1)	17838 (±3)
100	100/0	100/0	**9445** (±2)	8887 (±1)	7772 (±2)	6658 (±3)
100	0/100	0/80	**7087** (±3)	**7089** (±3)	**7087** (±3)	**7088** (±3)

Chapter 6

Conclusions

This project presented a single-leg cargo revenue management model to determine the optimal cargo capacity distribution that maximizes the expected profit. In this chapter, we answer the research question, reflect upon the scientific contribution, formulate practical recommendations, and provide directions for future research. The research question that guided this research was formulated as:

How can the introduction of a revenue management model that optimizes the capacity allocation to allotment contracts and spot market demand support EGS's performance in terms of profit and asset utilization?

A synchromodal logistics service provider offers two mode-free transportation services: Express and Standard with a 1- and 2-day shipment window respectively. The logistics service provides faces a capacity allocation problem, which is an economic trade-off between guaranteeing that capacity is utilized by committing to allotment contracts and reserving capacity for spot market sales, with the objective to maximize the expected profit, while coping with the shipment windows, limited capacity, stochastic demand, and (optionally) stochastic spot freight rates.

Two optimization models are defined to the cargo capacity allocation problem that acknowledge the stochastics and constraints. First, a stochastic integer program is defined to determine the capacity distribution that maximizes the expected profit, given deterministic spot freight rates. In the second, we formulated a simulation-based optimization model that incorporates stochastic spot freight rates, which exhibit mean-revering characteristics and are modeled by an Ornstein-Uhlenbeck process. The optimal allocation portfolio suggests which contracts to accept, which to reject and includes a spot market booking limit, which indicates the maximum number of spot orders to accept on a day. Next, the models provide the expected profit, asset utilization and excess shipments of the allocation portfolio.

Furthermore, we presented a method to determine the minimum bid-price of contracts that are rejected due to other more profitable business opportunities. The minimum bid-price indicates the required freight rate of a contract such that it offsets the profit opportunities. In other words, it specifies the floor price from which the contract is profitable to grant.

We solved the capacity allocation problem optimally for small-sized numerical problems, conducted a case study and performed a sensitivity analysis to extend our insight on the allocation dynamics. The numerical analysis revealed that the profit function is concave in the capacity since the profit increases when additional demand is allocated to underutilized capacity, while it decreases as capacity is overutilized due to penalty costs owing to excess shipments. The case study showed that the optimization algorithm results on average in 3.68% more profit compared to the allocation decisions taken by experienced sales representatives.

The sensitivity analysis illustrated that the optimal cargo allocation distribution depends on the capacity, contractual and spot demand, the corresponding freight rates, the transportation services, and on the spot market demand volatility.

Moreover, the analysis revealed that the optimal distribution between Express and Standard services depends on the shipment windows and the freight rate spread. It is shown that it is profitable to include Standard shipments in the allocation portfolio provided that the freight rate spread is at most 30%, because the extra shipment day of the Standard service hedges against demand uncertainty, which in turn positively contributes to the profit. The smaller the freight rate spread, the more profitable to include Standard services.

Furthermore, the sensitivity analysis showed that extending the shipment window of the Standard service yields additional profit due to penalty cost savings, and allows to allocate more demand. The logistics service provider could use the additional profit to compensate the customer for the extended shipment window.

Besides, we addressed the customer's demand forecast reliability, which indicates the demand volatility. The lower the reliability, the more substantial the demand deviations. Reliable forecasts positively contribute to the profit, while the expected profit reduces with the reliability. It follows that the freight rates charged to unreliable customers should compensate the profit loss. Besides, the service provider should prevent excess shipments as the penalty costs increase.

Numerical experiments showed that it is profitable to substitute Express shipments with spot shipments, while it is only profitable to substitute Standard shipments if the spot freight rate compensates the profit loss due to reduced planning flexibility. Serving the spot market exposures the logistics service provider to the risk of underutilized capacity, because the realized shipment request could fall short. It turned out that the optimal capacity allocation to Express, Standard and spot market demand depends on the freight rates and the spot demand volatility.

Moreover, we showed that the optimal capacity allocation of a risk-neutral logistics service provider is independent of the spot freight rate volatility, because increasing the spot price volatility results in exactly the same capacity allocation. However, the probability of selecting the optimal capacity allocation decreases as the spot freight rate becomes more volatile since there is more uncertainty in the realized spot freight rates. Additionally, the exposure to spot price volatility increases as more capacity is reserved for spot sales.

To improve the practicability of the optimization models, we developed a genetic algorithm as a heuristic to the capacity allocation problem. Computational results showed that the proposed algorithm provides (near-) optimal solutions within a reasonable computation time, with a reported average error term of 0.08%, and average time savings of 60%.

The conducted research provides the foundation to answer the research question. As stated in the problem statement, the company's current sales strategy focuses on maximizing the asset utilization, without accounting for stochastic demand and the transportation services' shipment windows. The introduction of a revenue management model that optimizes the capacity distribution to allotment contracts and spot market demand, and copes with fixed capacity, stochastic demand, freight rates, and stochastic spot freight rates provides the opportunity to improve the company's profit. That is, numerical experiments and the sensitivity analysis showed the dependency of the optimal allocation on the demand, shipment windows and freight rate characteristics. The optimal asset utilization depends on the allocation portfolio that maximizes profit. Consequently, maximizing the profit may not imply maximized asset utilization. Furthermore, this study showed that performance improvement is possible by reserving capacity for spot market sales. Quantifying the profit opportunity was not possible, due to a lack of available company data.

By addressing the cargo revenue management problem for synchromodal service providers, we contribute to the limited literature on revenue management for synchromodal transportation and cargo capacity allocation problems in general. We showed that the shipment windows affect the optimal cargo distribution. Furthermore, we contribute to literature by showing that it is profitable to substitute advanced capacity sales with spot market demand. Finally, this paper contributes to current cargo revenue management literature by studying the capacity allocation problem with stochastic spot freight rates, by modeling it as a Ornstein-Uhlenbeck process.

6.1 Recommendations

Based on the conclusions drawn, we formulate the following practical recommendations.

Focus on profit maximization

From the conclusion drawn in the previous section, it follows that the logistics service provider can maximize its profit by optimizing the capacity distribution to multiple freight forwarders and spot market demand, while coping with stochastic demand, freight rates, spot demand volatility and customer reliability. Therefore, it is recommended to shift from a maximizing asset utilization strategy to a strategy that focuses on maximizing profit by accounting for stochastic demand, freight rates, spot demand volatility and customer reliability in the capacity allocation process.

Reserve capacity for spot market demand

In this study, we showed that serving the spot market provides an opportunity to improve the profit. Spot market shipment requests provide an option on demand because the service provider is allowed to reject incoming shipment requests. While demand from the allotment contracts must be accommodated, spot shipment requests could be rejected. Case in point, if the carrier has sufficient capacity available, spot requests would be accepted and rejected if capacity is insufficient. The sensitivity analysis revealed that substituting Express shipments with spot shipments yields additional profit, while substituting Standard shipments is only profitable if the spot freight rate compensates the reduced planning flexibility. Serving the spot market exposures the logistics service provider to the risk of underutilized capacity, because the realized shipment requests could fall short. The results of this study indicate that less capacity should be reserved for spot market sales as the demand volatility increases. In short, it is recommended to reserve capacity for spot market sales, while coping with the stochastic spot demand and freight rates.

It should be noted that this study did not analyze the actual spot market demand and freight rates, due to unavailable data. Therefore, we recommend that ECT and EGS should survey the spot market characteristics.

Include Standard services in the allocation portfolio

Given a 1- and 2-day shipment window for Express and Standard services, respectively, and a 10% freight rate spread between the services, the capacity allocation distribution that would maximize the expected profit consists for 18% of Standard shipments and 82% of Express services, provided that spot market demand is not utilized.

In this study, we showed that the optimal capacity distribution to the transportation services depends on the shipment windows and the freight rate spread. It turned out that it is profitable to include Standard services in the allocation portfolio provided that the freight rate spread is at most 30%. The additional shipment day of the Standard transportation service provides extra planning flexibility, and reduces the probability of excess orders, yielding lower penalty costs that offset the revenue loss of selling Express services. Consequently, a higher profit may be obtained with a lower revenue. Therefore, it is recommended to focus on selling Express services, but account for planning flexibility by including Standard services in the portfolio.

Measure and incorporate the customer's forecast reliability

Currently, EGS does not measure and incorporate the customer's forecast reliability in its capacity allocation decision process. This study showed that the forecast reliability affects the expected profit from the allocation portfolio. It turned out that the Express services are especially sensitive to the forecast reliability. As the shipment window of the Standard services hedges against the demand uncertainties, it is less sensitive to demand fluctuations. Therefore, it is recommended to incorporate the customer's demand reliability in the allocation decision process, especially if the service provider sells mainly Express services. Next, it is recommended to reflect the customer's reliability in the freight rates, such that unreliable customers compensate the service provider for the demand uncertainty. To incorporate the forecast reliability, the company should start measuring the reliability of its current customers, such that this information could be exploited in the next allocation process.

6.2 Limitations

We identify the following limitations of our research:

- No empirical demand and freight rate data is used in the simulations. The input parameter values are guessed based on previous work and recommendations of sales representatives. Due to a lack of data, it was impossible to test the proposed model based on actual information. Consequently, there is a discrepancy between the current situation and the simulations, yielding results that may deviate from the real-world situation. Nevertheless, the simulations provided insights into the mechanisms of the proposed model.
- We assumed Poisson distributed demand. Again, empirical data was unavailable which makes fitting a theoretical distribution impossible. To deal with other theoretical distributions model adoptions are required. Notice that the proposed simulation-based optimization model fits all theoretical distributions.
- A fixed capacity is assumed but, in reality, capacity could be flexible.
- A deterministic lead time of each modality is assumed.

6.3 Future research

This section derives suggestions for future research.

Network revenue management

In our study, the capacity allocation problem was solved optimally for a single corridor, i.e., a single-leg revenue management problem. In reality, most carriers operate a network of connections. Maximizing the profit of a single corridor might not yield an overall maximized network-wide profit. Including multiple corridors introduces extra complexities since a freight forwarder might, for example, wants a contract that covers the whole network, while another carrier has only demand for a single corridor. Therefore, it would be interesting to study the multi-leg cargo capacity management problem of a synchromodal service provider.

Overbooking

We neglected the effects of no-shows and cancellations on the allocation decision in this study. Although various studies focused on the overbooking concept, it is not studied in a business context with multiple transportation services. It is therefore interesting to examine the overbooking effects in future research.

Booking control

In this study, we presented a capacity allocation model with a static booking limit, which indicates the maximum daily number of spot shipments to accept. In reality, the service provider could exploit the latest information available in its spot request acceptance decision. The complexity is that the carrier should decide whether to accept the spot order when the actual demand at departure is unknown. Accounting for delayed demand or demand that does not show up makes the problem even more complicated. Accordingly, the carrier faces a booking control problem, which requires a booking policy that determines if a spot request should be accepted in order to maximize profit. In Section 5.3.5 we showed that profit opportunities exist by optimizing the spot request allocation decision. For future research, it is therefore interesting to study the booking control problem given multiple transportation services.

Booking control models have been studied by Amaruchkul, Cooper and Gupta (2007); Levin et al. (2012) and Moussawi-Haidar (2014), but all focus on a single transportation service. The booking control problem is a dynamic process as the spot acceptance decisions are time-dependent. Therefore, the mechanisms of the problem can be modeled by a Markov Decision Process, where the state variable represents the current inventory on hand. The objective of the problem is to accept the optimal amount of spot shipment requests such that profit is maximized. The optimal acceptance decision depends on the current orders on hand, the expected demand, the expected cancellations, and the show-up probability. The complexity of the booking control problem for the synchromodal service provider is that Standard orders could be postponed to the next day. Modeling this problem as a Markov Decision Process results in an infinite Markov Chain because postponing shipments influence the bookings on hand of the next day and the days after that, e.g., a spot order is accepted if there is room to postpone a Standard shipment to the next day and tomorrow's Standard shipment to the day after. This also holds that the MDP state variables should be formulated such that both Express and standard Shipments on hand are tracked.

Extending transportation services

In our study, we assumed that there are only two transportation services with fixed shipment windows. Accordingly, the proposed stochastic integer model is bounded by the number of services and the corresponding shipment windows. It would be interesting to study the effects of relaxing these assumptions.

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Appendix A

Company background

Table A.1: Key Figures European Gateway Services

Number of TEU	800.000
Number of employees	230
Number of ports	2
Number of hinterland terminals	17
Barge	6
Rail	4
Barge and Rail	7
Number of countries	5

Figure A.1: European Gateway Services network

Appendix B

Formulation optimization models

B.1 Stochastic Integer Problem with deterministic freight rates

$$\max_{\vec{x}, n_{spot}} \quad \sum_{i \in B} x_i \left(\lambda_i^E r_i^E + \lambda_i^S r_i^S\right) + r^{spot} \mathbb{E}(X_{spot}|n_{spot}) - p\mathbb{E}(E_s)$$

where

$$\begin{aligned}
\mathbb{E}\big(X_{spot}|n_{spot}\big) &= \sum_{k=1}^{n_{spot}-1} kP(X_s = k) + n_{spot}[1 - F(n_{spot})] \\
\mathbb{E}(E_S) &= \sum_{m=1}^{\alpha+\beta+n_{spot}} m \sum_{z=0}^{n_{spot}} \sum_{q=1}^{\beta} P(D_E = c + m - z - q) P(D_{spot}) \pi_q \\
D_E &= \sum_{i=1}^{n} x_i \lambda_i^E \sim Poisson(\lambda_1^E, \ldots, \lambda_n^E) \\
D_S &= \sum_{i=1}^{n} x_i \lambda_i^S \sim Poisson(\lambda_1^S, \ldots, \lambda_n^S) \\
D_{spot} &= \min\big(X_{spot}, n_{spot}\big)
\end{aligned}$$

subject to

$$\begin{aligned}
& n_{spot} \leq C \\
& \pi_j = \sum_i \pi_i p(i,j) \\
& \sum_i \pi_i = 1
\end{aligned}$$

$$\pi_{(i,j)} = \begin{cases} P(D_S = 0) \sum_{z=0}^{n_{spot}} P(D_E > C - i - z) P(D_{spot} = z) \\ \quad + \sum_{s=0}^{C-i} \sum_{z=0}^{n_{spot}} P(D_E = C - i - z - s) P(D_{spot} = z) P(D_S \leq s) & \text{if } j = 0, \\ \\ P(D_S = j) \sum_{z=0}^{n_{spot}} P(D_E > C - i - z) P(D_{spot} = z) \\ \quad + \sum_{s=0}^{C-i} \sum_{z=0}^{n_{spot}} P(D_E = C - i - z - s) P(D_{spot} = z) P(D_S = s + j) & \text{if } j > 0. \end{cases}$$

$$\begin{aligned}
& \pi_j \geq 0 && \forall j \\
& x_i \in \{0, 1\} && \forall x \in B \\
& n_{spot} \in \mathbb{N}
\end{aligned}$$

B.2 Simulation-based optimization model with stochastic freight rates

$$\max_{\vec{x}, n_{spot}} NPV_{allotment} + NPV_{spot} - NPV_{excess}$$

where

$$NPV_{allotments} = \sum_{t \in T} \sum_{i \in B} x_i (r_{E,i} D_{E,i}^t + r_{S,i} D_{S,i}^t) e^{-\frac{r_f t}{252}}$$

$$NPV_{spot} = \sum_{t \in T} S^t D_{spot}^t e^{-\frac{r_f t}{252}}$$

$$NPV_{spot} = NPV_{excess} = \sum_{t \in T} p^t \max\Big(\sum_{i \in B} D_{E,i}^t + D_{spot}^t + R_S^{t-1} - C, 0 \Big) e^{-\frac{r_f t}{252}}$$

$$dS_t = \kappa(\mu - S_t)dt + \sigma dW_t$$

$$S_{t+1} = S_i e^{-\kappa t} + \mu(1 - e^{-\kappa t}) + \sigma \sqrt{\frac{1 - e^{-2\kappa t}}{2\kappa}} N_{0,1}$$

$$R_S^t = \sum_{i \in B} D_{S,i}^t - \max\Big(C - R_S^{t-1} - \sum_{i \in B} D_{E,i}^t - D_{spot}^t, 0 \Big)$$

$$r_{max} = \max_{i \in B}(r_{E,i})$$

$$p^t = \min(r_{max}, S^t) * (1 + premium)$$

subject to

$$x_i \in \{0, 1\} \qquad \forall x \in B$$

$$n_{spot} \in \mathbb{N}$$

Appendix C

Genetic algorithm

C.1 Pseudocode

Algorithm 1 Genetic Algorithm to the Capacity Allocation Problem

GA(N, p_s, p_m, C, T)
$N \leftarrow$ population size
$P^k \leftarrow$ generation k with n individuals
$X_i^k \leftarrow$ Chromosome of individual i of generation k
$x_i^g \leftarrow$ Gene g of individual i
$p_s \leftarrow$ Selection probability
$p_m \leftarrow$ Mutation probability
$C \leftarrow$ Number of children
$T \leftarrow$ Termination criteria: maximum number of generations

Initialize generation P^0 with N random individuals:
while $< N$:
    generate *individual* X_i^0
Evaluate individuals in P^0:
compute fitness for all $X_i^0 \in P^0$
while maximum generation not reached $(k < T)$ **do**:
//Create generation $k + 1$:
//Selection
    Create $\frac{N}{2}$ tournaments
    for Each Tournament **do**
        if $P^k \neq \emptyset$ **do**
            Select and remove randomly two individuals X_i from P^k
            if $fitness(X_1) \leq fitness(X_2)$ **do**
                insert X_1 into mating pool with probability p_s
                insert X_2 into mating pool with probability $1 - p_s$
            else
                insert X_1 into mating pool with probability $1 - p_s$
                insert X_2 into mating pool with probability p_s
            end if
        else
            Replace all individuals in P^k
        end if
    end for

▷ continues on next page

//**Crossover**
while population $< N$ **do**
    Create C couples of parents from the mating pool
    for Each Couple **do**
        for Each $x^g \in X$ **do**

$$X^g_{Child} = \begin{cases} x^g_{Parent1}, & \text{with probability } 0.5 \\ x^g_{Parent2}, & \text{otherwise.} \end{cases}$$

        end for
    end for
//**Mutation**
for Each Individual $X^k_i \in P^k$ **do**
    for Each gene of individual X^k_i **do**
        if random number $\leq p_m$ **do**
            Flip value of gene x^g_i into opposite value
        end if
    end for
end for
//**Evaluate** individuals in P^k
compute fitness for all $X^k_i \in P^k$
//**Increment**
k: k+1
end while
//**Improve**
Select best fit individual from all generations P
Increase booking limit of best individual with +1
Evaluate fitness(i+1)
while $fitness(i+1) \geq fitness(i)$ **do**
    Increase booking limit of individual i with +1
    Evaluate $fitness(i+1)$
end while $fitness(i+1)$
Decrease booking limit of best individual with -1
Evaluate fitness(i+1)
while $fitness(i+1) \geq fitness(i)$ **do**
    Decrease booking limit of individual i with -1
    Evaluate $fitness(i+1)$
end while $fitness(i+1)$
//**Solution**
Return fittest individual

C.2 Parameter analysis

This appendix presents an analysis of the Number of Generations input parameter of the Genetic Algorithm. Two parameter settings are analyzed: a fixed parameter value and a parameter value that depends on the CAP problem size. It turns out that the error term reduces when the number of generations increases and that the optimal number of generations depends on the problem size. A recommendation for the optimal parameter value as a function of the problem size is provided, given that all other parameter values are set as stated in Section 4.2.

Evaluation criteria

The main evaluation criteria of the GA is the profit error term between the solution found and the optimal solution. The error term is defined as the percental difference between the revenue of the best solution found by the GA and the revenue of the optimal solution, which is found by exactly solving the CAP. The second evaluation criteria is the accuracy of the algorithm, which is defined as the number of times that the algorithm was able to find the optimal solution.

Test environment

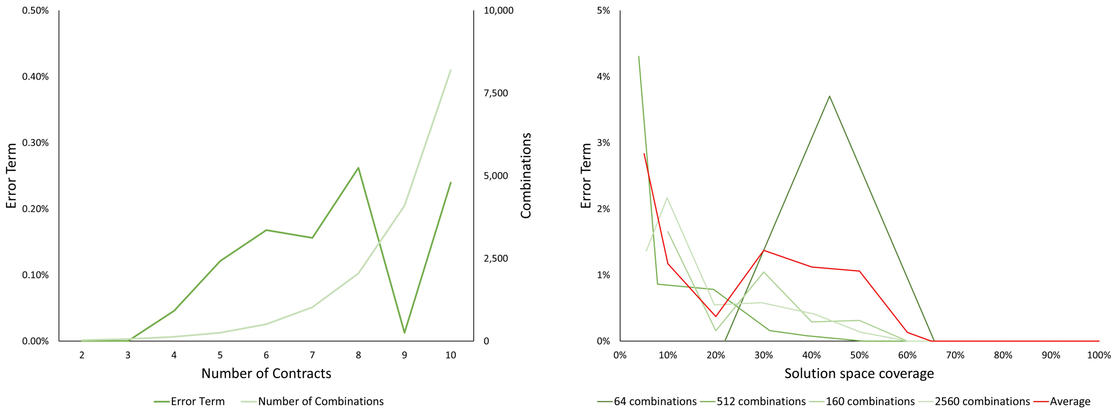
The two parameter value strategies are evaluated based on the same scenarios. The strategies are tested in multiple scenarios where the number of contracts, i.e. the problem size, increases while keeping all other problem input values (capacity, revenue per shipment etc.) and the GA process parameters equal. Each scenario consists of x contracts and an expected spot market demand of 2 shipments. The demand to capacity ratio is set to 1.8, which holds that the contractual and spot market demand is 180% the size of the available capacity. Furthermore, the problem size of a scenario, i.e. all possible candidate solutions, is $2^k\gamma$, where k are the number of contracts and γ the spot market booking limit upper bound. Next, the GA parameters, except the Number of Generations parameter, are determined according to the basic settings, see Section 4.2. An overview of the parameter settings for each scenario can be found in Table C.1. For each case, i.e., a scenario with a specific parameter value, five GA runs are executed to ensure consistency among scenarios. This way, the randomness effects on the GA performance are reduced. The average performance of the five GA runs is calculated.

Table C.1: Scenario and corresponding parameter values

Scenario	#Contracts (k)	λ_{spot}	Problem Size	Population Size	#Children	#Parents	p_m	p_s
1	2	2	32	12	2	6	0.167	0.800
2	3	2	64	14	2	7	0.143	0.800
3	4	2	128	16	2	8	0.125	0.800
4	5	2	256	18	2	9	0.111	0.800
5	6	2	512	20	2	10	0.100	0.800
6	7	2	1024	22	2	11	0.091	0.800
7	8	2	2048	24	2	12	0.083	0.800
8	9	2	4096	26	2	13	0.077	0.800
9	10	2	8192	28	2	14	0.071	0.800

Fixed parameter value

The fixed parameter value strategy holds that the number of generations is fixed, independent of the problem size, and independent of the other parameters. That is, the GA is terminated after x generations. Figure C.1a presents the results of a scenario where the number of contracts increases, while the parameter value is fixed to 8 generations. The results indicate that the error term increases with the problem size (number of contracts), except for one outlier (9 contracts). Multiple fixed Number of Generations parameter values were tested and all results indicate that the error term increases in the problem size.



(a) Fixed number of generations termination criteria.

(b) Problem size dependent termination criteria.

Figure C.1: Error term.

The increasing error term is explained by the fact that the GA examines a fixed number of candidate solutions since the Number of Generations parameter and all other parameters are fixed. While increasing the problem size and keeping the number of generations fixed, the number of candidate solutions examined relative to the population size decreases. This holds that the probability of selecting the candidate solution with the highest revenue decreases. It should be noted that increasing the number of generations while keeping the problem size fixed reduces the error term.

Problem size dependent parameter value

The results of the fixed parameter strategy indicate that there is a relation between the optimal number of generations and the problem size. Therefore, the relation between the problem size and the number of generations is analyzed with the goal to identify the optimal problem size coverage. Multiple Number of Generations parameter values are tested. For each value, the percental coverage of the solution space is calculated, by multiplying the number of generations G with the population size S and dividing it by the problem size, see Equation (C.1). It should be noted that this does not imply that $x\%$ of the solution space is actually examined. A single solution could be examined multiple times due to the randomness of the evolution operators. Accordingly, the coverage rate only indicates the total number of individuals in all populations examined and not the unique ones. Next, only 4 different scenarios with varying amounts of candidate solutions are examined, due to computation time limitations.

$$Coverage = \frac{S * G}{k + n} \tag{C.1}$$

It turns out that increasing the solution space coverage reduces the error term, see Figure C.1b. By classifying the coverage space of the multiple scenarios into intervals it is tried to determine the average of all error terms. The error term results indicate that an coverage of 66% of the solution space results in optimal GA performance, i.e. with an error term of 0%. Leaving out the scenario with the smallest solution space (64 combinations) indicates that a coverage of 60% is sufficient. Due to the low number of combinations of the 64 combination scenario the coverage step size is 33%.

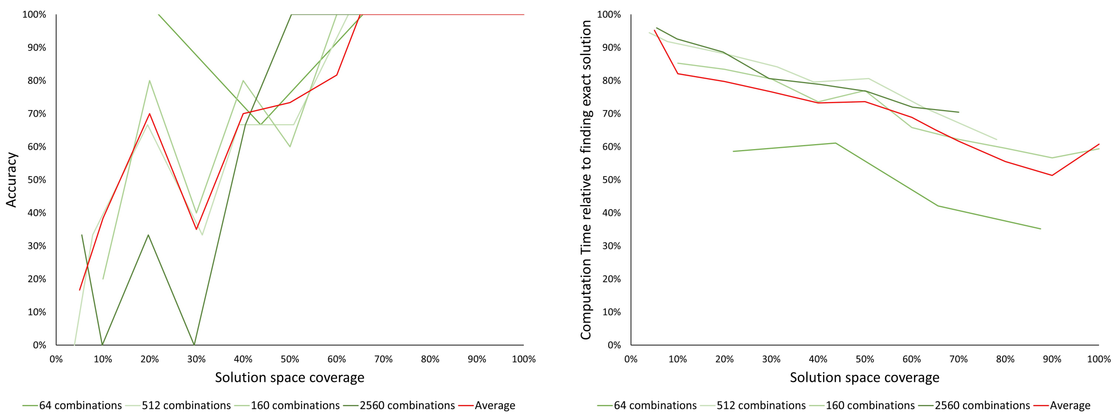
Clearly, there is a relation between the performance and the solution space coverage, and thus the number of generations since the population size is fixed. In addition, a high coverage of the solution space results in a high accuracy of the GA, Figure C.2a. A coverage of more than 66% (60% without the smallest scenario) results in an accuracy of 100%, which implies that the algorithm was able to find the optimal solution in each trial run. Finally, increasing the number of generations negatively affects computation time since more candidate solutions are examined, figure Figure C.2b.

Parameter analysis results

Analyzing the two-parameter strategies shows that the optimal number of generations depends on the number of candidate solutions in the solution space. A fixed number of generations, while keeping all other parameters fixed, results in an error term that increases with the problem size. It is therefore recommended to determine the optimal number of generations based on the problem size. It turned out that a 60% coverage rate is sufficient such that the GA performs optimal, i.e., with a 0.00% error term and a 100.00% accuracy. Therefore, the number of generations should be set such that 60% of the solution space is covered. More specific, the optimal number of generations G is a function of the problem size and the population size S, Equation (C.2).

It should be noticed that an optimal GA performance, i.e. with a 0.00% error term, is not guaranteed with this parameter function. Although that the probability of finding the optimal solution increases with increasing the number of generations, the GA evolution process still contains randomness, which could influence the performance both positively and negatively. In addition, it should be noticed that only a few scenarios are examined, yet as already stated, the main focus of the GA development is to show its effectiveness and not the best algorithm.

$$G_{opt}(S, k, \gamma) = \left\lceil \frac{2^k \gamma * 60\%}{S} \right\rceil \tag{C.2}$$



(a) Accuracy.

(b) Computation time.

Figure C.2: Problem size dependent termination criteria.

C.3 Performance analysis scenarios and results

Table C.2: Scenario 1 - Problem size

#Contract	Capacity	Ratio Demand/Capacity	λ_{spot}	#Generations	Population Size	#Children	#Parents	p_m	p_s
2	25	1.8	2	2	12	2	6	0.167	0.800
3	25	1.8	2	3	14	2	7	0.143	0.800
4	25	1.8	2	5	16	2	8	0.125	0.800
5	25	1.8	2	9	18	2	9	0.111	0.800
6	25	1.8	2	16	20	2	10	0.100	0.800
7	25	1.8	2	28	22	2	11	0.091	0.800
8	25	1.8	1	35	22	2	11	0.091	0.800
9	25	1.8	1	55	24	2	12	0.071	0.800
10	25	1.8	1	120	15	2	13	0.077	0.800

Table C.3: Scenario 2 - Capacity

#Contract	Capacity	Ratio Demand/Capacity	λ_{spot}	#Generations	Population Size	#Children	#Parents	p_m	p_s
5	5	1.8	1	5	20	2	10	0.100	0.800
5	10	1.8	1	5	20	2	10	0.100	0.800
5	15	1.8	1	5	20	2	10	0.100	0.800
5	20	1.8	1	5	20	2	10	0.100	0.800
5	25	1.8	1	5	20	2	10	0.100	0.800
5	30	1.8	1	5	20	2	10	0.100	0.800
5	35	1.8	1	5	20	2	10	0.100	0.800
5	40	1.8	1	5	20	2	10	0.100	0.800
5	45	1.8	1	5	20	2	10	0.100	0.800
5	50	1.8	1	5	20	2	10	0.100	0.800
5	60	1.8	1	5	20	2	10	0.100	0.800
5	70	1.8	1	5	20	2	10	0.100	0.800
5	80	1.8	1	5	20	2	10	0.100	0.800

Table C.4: Results scenario 1 - Problem size

#Contracts	Error Term	Exact Profit	Average GA Profit	Run 1	Run 2	Run 3	Run 4	Run 5
2	0.00	2471.56	2471.56	2471.56	2471.56	2471.56	2471.56	2471.56
3	0.00	2433.32	2433.32	2433.32	2433.32	2433.32	2433.32	2433.32
4	0.00	2398.23	2398.23	2398.23	2398.23	2398.23	2398.23	2398.23
5	0.02	2561.62	2561.13	2559.12	2561.62	2561.62	2561.62	2561.62
6	0.05	2514.33	2513.13	2514.33	2514.33	2508.32	2514.33	2514.33
7	0.16	2603.88	2599.81	2583.54	2603.88	2603.88	2603.88	2603.88
8	0.09	2553.77	2551.37	2553.77	2553.77	2553.77	2553.77	2547.77
9	0.01	2497.46	2497.16	2497.46	2497.46	2497.46	2497.46	2495.94
10	0.01	2613.77	2613.51	2613.77	2613.77	2612.46	2613.77	2613.77

Table C.5: Results scenario 2 - Capacity

Capacity	Error Term	Exact Profit	Average GA Profit	Run 1	Run 2	Run 3	Run 4	Run 5
5	0.00	430.66	430.66	430.66	430.66	430.66	430.66	430.66
10	0.17	945.13	943.53	945.13	945.13	945.13	945.13	937.13
15	0.16	1473.51	1471.11	1461.51	1473.51	1473.51	1473.51	1473.51
20	0.32	2005.04	1998.65	2005.04	2005.04	2005.04	1973.07	2005.04
25	0.16	2537.36	2533.46	2517.36	2537.36	2537.36	2537.36	2537.36
30	0.16	3070.15	3065.35	3070.15	3070.15	3046.16	3070.15	3070.15
35	0.00	3603.36	3603.36	3603.36	3603.36	3603.36	3603.36	3603.36
40	0.00	4136.96	4136.96	4136.96	4136.96	4136.96	4136.96	4136.96
45	0.00	4671.22	4671.22	4671.22	4671.22	4671.22	4671.22	4671.22
50	0.15	5205.45	5197.52	5165.52	5205.45	5205.45	5205.45	5205.45
60	0.00	6275.69	6275.45	6275.69	6275.69	6275.10	6275.69	6275.69
70	0.30	7348.66	7326.26	7292.66	7348.66	7292.66	7348.66	7348.66
80	0.00	8424.40	8424.40	8424.40	8424.40	8424.40	8424.40	8424.40

Appendix D

Case study

D.1 Case description

Table D.1: Relation between demand and revenue parameters for each scenario.

Demand \ Revenue	Express = Standard	Express > Standard	Express >> Standard
Express = Standard	1	2	3
Express > Standard	4	5	6
Express >> Standard	7	8	9
Express < Standard	10	11	12
Express << Standard	13	14	15

Table D.2: Case study contract terms, with 200 TEU capacity, $\lambda_{spot} = 4$, $r^{spot} = 150$, and $p = 200$.

Contract	**Demand**		**Freight rate**	
	Express	Standard	Express	Standard
1	8	0	112	100
2	25	20	96	96
3	16	16	128	76
4	21	16	134	52
5	3	12	111	94
6	9	3	105	105
7	12	10	114	82
8	10	10	102	102
9	13	22	134	67
10	22	16	112	76
11	10	13	102	102
12	8	10	97	97
13	8	8	122	65
14	14	21	115	78
15	0	9	141	92

D.2 Case results

Table D.3: Results of case study.

Case	Allocation	Spot limit	#Contracts	$\mathbb{E}(D_E)$	$\mathbb{E}(D_S)$	$\mathbb{E}(D_{spot})$	$\mathbb{E}(E_S)$	Profit	ΔProfit	Revenue	Penalty	Utilization
Optimal	[1,1,1,0,1,1,1,1,0,0,1,1,0,0,0]	10	9	101	94	4	0.9	19990		20012	178	99.1%
1	[1,1,1,1,0,0,0,0,0,1,0,0,0,1,0]	5	6	106	89	3.6	0.6	19373	-3.1%	19485	112	99.0%
2	[1,0,1,0,1,1,1,1,1,1,1,0,0,0,0]	5	9	103	102	3.6	9.1	18958	-5.2%	20782	1824	99.7%
3	[1,1,0,0,1,0,1,1,1,1,1,1,0,0,0]	5	9	111	113	3.6	23.1	17700	-11.5%	22324	4624	102.2%
4	[1,1,1,0,1,1,1,1,0,0,1,1,0,0,0]	5	9	101	94	3.6	0.5	19848	-0.7%	19952	104	99.0%
5	[0,1,0,1,1,0,1,1,1,0,0,1,0,0,1]	5	8	92	109	3.6	5.1	18853	-5.7%	19876	1023	99.7%
6	[1,1,1,0,1,0,0,0,1,1,1,0,0,0,0]	4	7	97	99	3.2	0.5	19465	-2.6%	19569	104	99.4%

Appendix E

Capacity and demand size

E.1 Scenario

Table E.1: Scenario 1: Two allotment contracts with opposite demand for Express and Standard services, and spot market demand $\left(=\frac{2}{3}capacity\right)$. $r^E = 100$, $r^S = 80$, $r^{spot} = 120$.

Scenario	**Capacity**	**Demand**		
x times scaled		Contract 1 *(exp/std)*	Contract 2 *(exp/std)*	Spot
1	20	7/3	3/7	13
2	40	14/6	6/14	26
3	60	21/9	9/21	39

E.2 Scaling demand and capacity size

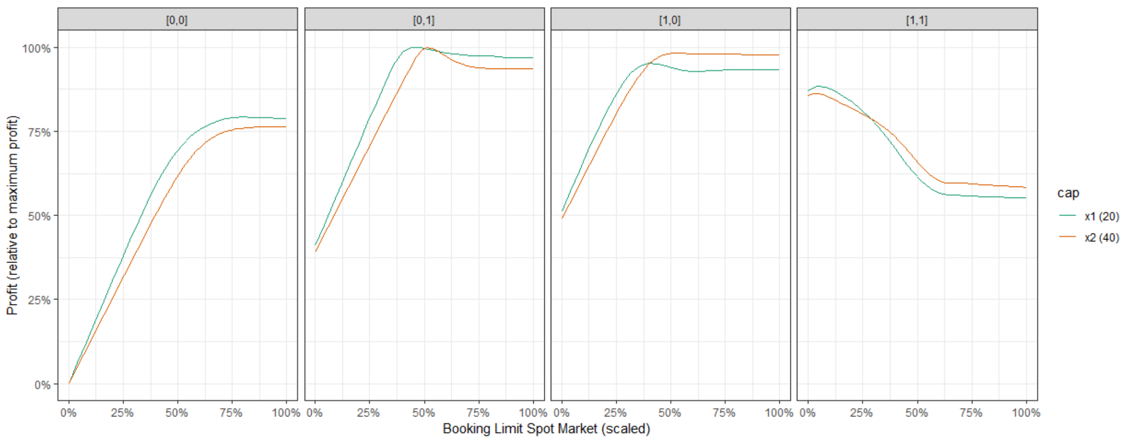


Figure E.1: Model behavior of scaling capacity and demand proportionally with only Express or Standard services

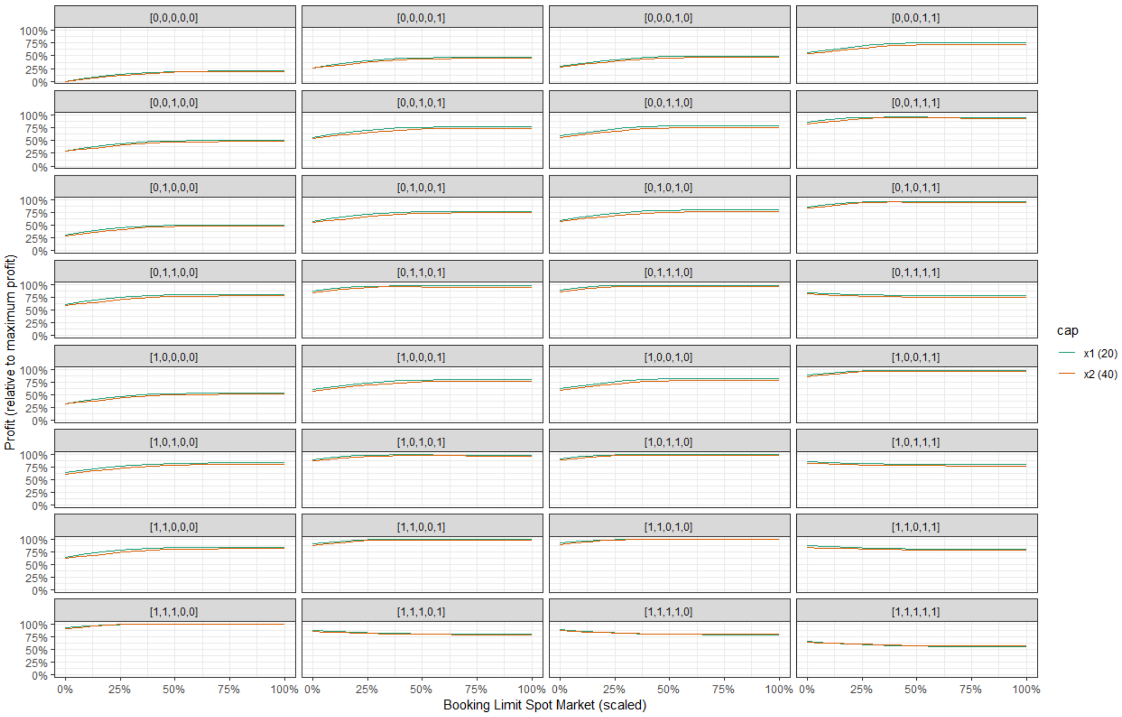


Figure E.2: Model behavior of scaling capacity and demand proportionally with five contracts

Appendix F

Stochastic freight rates

F.1 Freight rate evolution

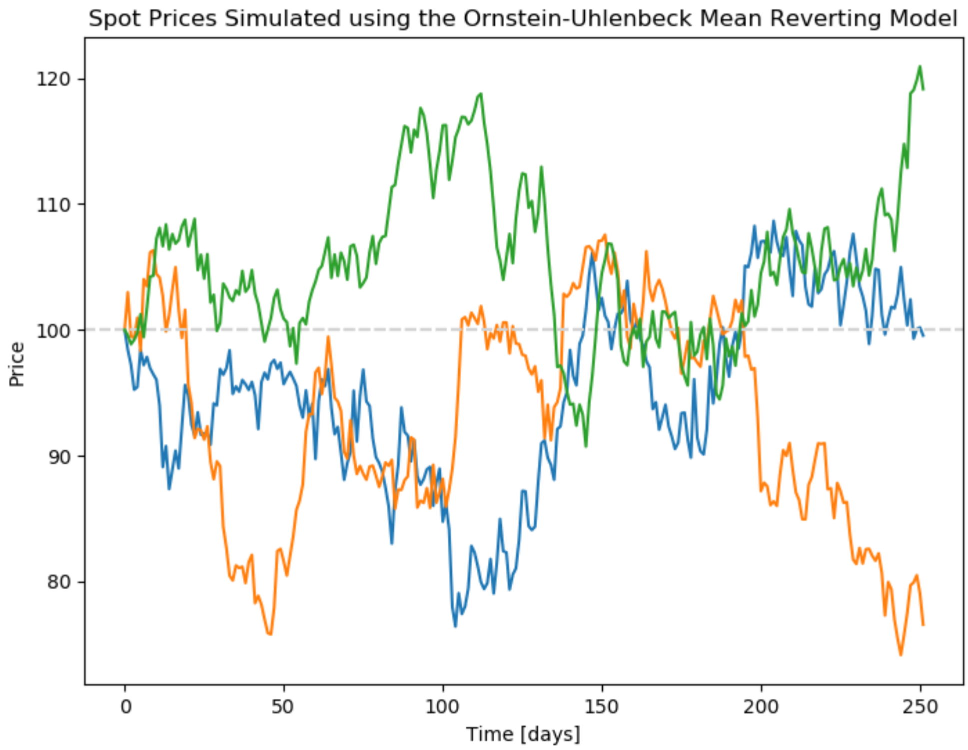


Figure F.1: Three possible spot price paths in a year. Simulated using the Ornstein-Uhlenbeck Mean Reverting Model with $\theta = 100$, $\sigma = 2$, $\kappa = 0.01$ and $T = 252$ days.

F.2 Mathematical derivation

$$S_{t+1} = S_t e^{-\kappa t} + \theta(1 - e^{-\kappa t}) + \sigma \int_0^T e^{-\kappa(T-t} dW_s$$

$$\begin{aligned}
E[S_t] &= S_t e^{-\kappa t} + \theta(1 - e^{-\kappa t}) \\
\lim_{T\to\infty} e^{-T} &= 0 \\
\lim_{T\to\infty} E[S_t] &= \lim_{T\to\infty} \big(S_0 e^{-\kappa T} + \theta(1 - e^{-\kappa T})\big) \\
&= S_0 \lim_{T\to\infty} e^{-kT} + \theta\big(1 - \lim_{T\to\infty} e^{-kT}\big) = \theta
\end{aligned}$$

$$\begin{aligned}
V[S_t] &= \frac{\sigma^2}{2\kappa}(1 - e^{-2\kappa T}) \\
\lim_{T\to\infty} V[S_t] &= \lim_{T\to\infty} \big(\frac{\sigma^2}{2\kappa}(1 - e^{-2\kappa T})\big) \\
&= \frac{\sigma^2}{2\kappa}\big(1 - \lim_{T\to\infty} e^{-2\kappa T}\big) \quad = \frac{\sigma^2}{2\kappa}
\end{aligned}$$

F.3 Analysis

Table F.1: Simulation results to determine the optimal capacity distribution to spot and Express demand given volatile spot market demand with $\sigma_{spotdemand} = 2\sqrt{\lambda}$, 50 TEU capacity, $r^E = 100$, $p = 150$, and deterministic spot freight rates with mean spot rate $\theta = 100$. Top 10 observations of 5000 simulation runs with a 95%-confidence interval.

n^*_{spot}	λ_E	Daily Profit		#Observed optimum	Probability optimal allocation
30	22	4774.81	(±1.78)	505	0.10
31	21	4774.75	(±1.79)	446	0.09
29	23	4774.23	(±1.79)	483	0.10
32	20	4773.89	(±1.78)	412	0.08
28	24	4773.86	(±1.79)	477	0.10
27	25	4771.63	(±1.79)	385	0.08
33	19	4771.42	(±1.78)	298	0.06
26	26	4770.30	(±1.80)	300	0.06
34	18	4768.95	(±1.77)	233	0.05
25	27	4767.46	(±1.79)	251	0.05
35	17	4765.27	(±1.76)	173	0.03

Table F.2: Simulation results to determine the optimal capacity distribution to spot and Express demand given volatile spot market demand with $\sigma_{spotdemand} = 2\sqrt{\lambda}$, 50 TEU capacity, $r^E = 100$, $p = 150$, and spot freight rates with mean spot rate $\theta = 100$, rate $\kappa = 0.25$ and standard deviation $\sigma = 10$. Top 10 observations of 5000 simulation runs with a 95%-confidence interval.

n^*_{spot}	λ_E	Daily Profit		#Observed optimum	Probability optimal allocation
30	22	4753.54	(±0.71)	352	0.07
31	21	4753.53	(±0.86)	372	0.07
29	23	4752.61	(±0.45)	311	0.06
32	20	4752.57	(±1.05)	363	0.07
33	19	4751.64	(±1.16)	363	0.07
28	24	4750.95	(±0.17)	277	0.06
34	18	4749.49	(±1.26)	301	0.06
27	25	4748.86	(±0.48)	233	0.05
26	26	4747.02	(±0.66)	207	0.04
35	17	4746.14	(±1.39)	256	0.05
25	27	4744.18	(±0.83)	172	0.03

Table F.3: Simulation results to determine the optimal capacity distribution to spot and Express demand given volatile spot market demand with $\sigma_{spotdemand} = 2\sqrt{\lambda}$, 50 TEU capacity, $r^E = 100$, $p = 150$, and spot freight rates with mean spot rate $\theta = 100$, rate $\kappa = 0.25$ and standard deviation $\sigma = 20$. Top 10 observations of 5000 simulation runs with a 95%-confidence interval.

n^*_{spot}	λ_E	Daily Profit		#Observed optimum	Probability optimal allocation
32	20	4733.38	(±3.75)	251	0.05
31	21	4733.09	(±3.60)	236	0.05
33	19	4732.55	(±3.89)	271	0.05
30	22	4732.45	(±3.45)	198	0.04
29	23	4731.24	(±3.32)	181	0.04
34	18	4730.39	(±4.03)	292	0.06
28	24	4729.21	(±3.16)	159	0.03
35	17	4727.59	(±4.17)	288	0.06
27	25	4726.84	(±3.00)	159	0.03
31	20	4724.96	(±3.66)	6	0.00
32	19	4724.62	(±3.80)	7	0.00