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Chuanwen DONG

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Doctoral committee

Advisor:	
Prof. Dr. Robert Boute	*KU Leuven and Vlerick Business School*
Chair:	
Prof. Dr. Jan Vanthienen	*KU Leuven*
Members:	
Prof. Dr. Erik Demeulemeester	*KU Leuven*
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Prof. Dr. Sandra Transchel	*Kühne Logistics University*
Prof. Dr. Inneke Van Nieuwenhuyse	*KU Leuven*

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Dwell on the beauty of life. Watch the stars, and see yourself running with them.

- Marcus Aurelius (121-180).

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Chuanwen Dong September 2017.

Preface

Shifting freight traffic from road to rail and waterborne transportation can substantially improve the economic and environmental performance of logistics systems. Regrettably, even with technology and regulations developing over the last few decades, modal shifts have remained modest at best. Innovative approaches are urgently required to promote a greater use of more sustainable transportation modes.

Synchromodal transportation, or synchromodality, describes a structured and synchronized combination of different transportation modes serving for aggregated transportation demand, which entails a modal shift from road to the more sustainable transportation modes such as rail or waterway. However, rail or waterway transportation generally lack the flexibility in delivery quantity, frequency, schedule, etc., and result in larger inventory and/or longer periods between deliveries. Companies therefore often hesitate to implement synchromodality because of the presumption to trade higher inventory and/or lower service level for sustainability.

In this dissertation, we investigate synchromodality from a supply chain perspective (SSCP) to support shippers implement synchromodality and increase the share of intermodal transportation by quantifying the impact of synchromodality on companies' inventory and service levels. The distinct feature of this concept can be pinpointed in two aspects:

- Simultaneous use of more than one transportation mode in a single corridor. Whereas an inflexible, slow, but cheap transportation mode (e.g., intermodal rail) focuses on the sustainability of the transportation system, a flexible, fast, but more expensive transportation mode (e.g., direct trucking) guarantees adequate service levels. The parallel usage therefore captures both cost and responsiveness of the transportation system.

- Optimization of transportation problems from a supply chain perspective

> considering the inventory controls. Transportation decisions are, after all, part of companies' supply chain strategy and need to be jointly optimized with other activities of the supply chain. Technically speaking, the extension of transportation problem into a wider realm of supply chain management broadens the boundaries of the optimization problem and hence allows a new "global optimum".

The SSCP concept is illustrated by two quantitative modeling studies to support companies jointly manage their transportation and internal inventory controls. The first study captures the key drivers and characteristics of modal split via simple approximate analytical expressions. The second study uses stochastic dynamic programming to obtain the optimality of modal split decisions, including the optimal delivery quantity and frequency of rail transportation, and the optimal inventory controls at the distribution center. In addition to the conceptual and methodological contributions, a VBA-based Excel tool is presented to help managers implement synchromodality without necessarily understanding the mathematical details of the synchromodality models. The tool also allows the users to analyze the impact of synchromodality on other metrics of companies' supply chain, such as inventory management, production smoothing, and full container loading, etc.

A validation of our models using real data demonstrates that companies can jointly reduce cost and carbon emissions by applying synchromodality. Interestingly, companies could significantly increase their share in the sustainable intermodal rail transportation, with only a minor increase in inventory cost. The transportation cost savings obtained from a modal split will not only offset the extra spending in inventory, but also reduce the total costs of the supply chain without sacrificing the service level.

Our case studies suggest that the application of SSCP has the potential to substantially reduce CO_2 emissions through optimization of companies' "internal" supply chain, whereas the "external" interventions such as a carbon tax imposed by the government have only a minor incremental effect unless they are set at very high levels.

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Chapter 1

Introduction

Ceci n'est pas une pipe.[1]

– René Magritte (1898-1967), Belgium artist.

The objective of this dissertation is to support companies implement synchromodal transportation (synchromodality). In this introductory chapter, we motivate the research problem, define the research questions, and describe the outline of the thesis.

1.1 Research motivation and objective

Between now and 2050 we will have to reduce our greenhouse gas (GHG) emissions dramatically to keep our environment sustainable. According to calculations from the Intergovernmental Panel on Climate Change (IPCC), annual GHG emissions need to be reduced by $40 - 70\%$ between 2010 and 2050, for us to have 50% chance of keeping the increase in average global temperature staying within 2℃ by 2100 (IPCC, 2014). The Paris Accord, agreed at the COP21 conference in December 2015, committed the 195 participating countries to keeping this average

[1] Literally translated as "This is not a pipe.", it is a caption of a painting of a pipe. The contradiction is meant to intrigue and confound viewers.

temperature increase “well below 2℃ by 2100”, putting added pressure on them to cut GHG emissions (European Commission, 2015a).

All industrial sectors except transportation have been steadily reducing their GHG emissions. In the U.S., GHG emissions linked to transportation have increased by 17% since 1990 (U.S. Environmental Protection Agency, 2014). In the EU-28 (the 28 state members of the European Union), the transportation sector increased its relative share of total GHG emissions from 15% to 22% between 1990 and 2013 (EUROSTAT, 2015). The freight share of total transportation emissions is even expected to rise from 42% in 2010 to 60% in 2050 (OECD/ITF, 2015), making the freight transportation one of the hardest sectors to decarbonize (Guérin et al., 2014).

In addition to the environmental challenges, the transportation industry is also confronted with critical social issues. Statistics from European Commission (2016) demonstrate that the current road network has been over-utilized, which brings in extra “stress” to our society in terms of accidents, noises, air pollutions, etc. (Maibach et al., 2008). One intensively discussed social problem linked to transportation, among others, is congestion. European Commission (2012) finds that the total monetary cost of congestion mounts up to 134.3 billion euro in 2012, which is equivalent to about one percent of the total GDP of EU-28. It is even estimated that the congestion will be even more severe in the coming decades (Centre for Economics and Business Research, 2014). Another critical social challenge of the transportation industry is the truck driver shortage. According to American Trucking Associations (2015), the U.S. transportation industry faces a shortage of about 38,000 truck drivers in 2014, and this number is expected to grow to almost 175,000 by 2024. The driver shortage is also found in some of the emerging countries such as South Africa (FleetWatch, 2014) and India (The Times of India, 2011). The main reason for this shortage is that young generations are unwilling to work as truck drivers because of low wage rates, long periods away from home, poor working conditions, etc. (see, e.g., Bloomberg, 2013; Boston Consulting Group, 2015). A recent report from the McKinnon et al. (2017) states that “the shortage of truck drivers is currently the highest profile logistics skills issue in terms of company concerns, political lobbying, and media coverage”.

Finally, road transportation is costly. According to Boston Consulting Group (2015), freight costs are steadily rising, which reverses the effects of all supply chain cost-saving efforts. Road transportation is about five times more expensive than rail or waterway transportation per tonne-kilometer (TKM) of freight shipment (European Commission, 2016). This despite the fact that the profit margins of road transportation carriers are already very thin and further cost reductions are almost impossible (American Trucking Associations, 2014).

Clearly, the state-of-the-art freight system is not sustainable and urgently requires significant changes. One richly studied approach is the enforcement of a penalty cost for road transportation in the form of carbon taxes or toll charges by the policymakers (see, e.g., Tavasszy and van Meijeren, 2011; Fahimnia et al., 2015; European Commission, 2015b; European Court of Auditors, 2016). However, these approaches are practically not favored by companies, because they aim to improve the environmental impact of logistics systems by increasing companies' total spending. Companies incur higher cost in freight transportation due to extra spending on carbon taxes and/or toll charges, whereas the profit margin of freight transportation industry is nowadays already at a minor level. A study by the FTA and PricewaterhouseCoopers in 2013 has shown that the profit margin for the 100 biggest road transportation companies in the UK was only 1.0% in 2012, while the average over the 2008 to 2012 period was 2.4% (Freight Transport Association, 2013). A report on the European haulage market reveals that the profit margins of freight transportation ranging between −2.0% and +2.0% in France and 2.5% to 3.0% in Portugal (AECOM, 2014). On the other hand, the practical impact of a carbon tax on freight decarbonisation is being questioned. Proost and Van Dender (2001), for example, find that even though fuel is already heavily taxed in Europe, road transportation continues to grow rapidly. Cachon (2014) proposes a model to show that in a retailer store allocation problem, "a price on carbon is an ineffective mechanism for reducing emissions".

Another frequently mentioned approach is modal shift, i.e., transferring freight to "greener" transportation modes (Gota, 2016). According to European Environment Agency (2013), CO_2 emissions per tonne-kilometer from railways and inland waterways are about 3.5 and 5.0 times lower than those from road freight transportation. Shifting freight from road to these alternative modes can therefore be one of the most important means of decarbonizing logistics (see, e.g., Holguin-Veras et al., 2008; Winebrake et al., 2008; McKinnon, 2008; Hoen et al., 2013). However, in Europe, strenuous efforts over many years by national governments and the European Union (EU) to shift freight from road to rail and water have been unsuccessful. Between 1995 and 2013, road's share of total tonne-kms increased, rail's share declined and that of inland waterways remained fairly stable (Figure 1.1) (EUROSTAT, 2015). A recent report from the European Court of Auditors (2016) confirms that rail's share of the European freight market has declined since 2011 despite the fact that approximately 28 billion Euros of financial support was injected into railway projects across the EU over the period $2007 - 2013$. Therefore innovations are urgently needed to promote and revive modal shift as a freight policy option.

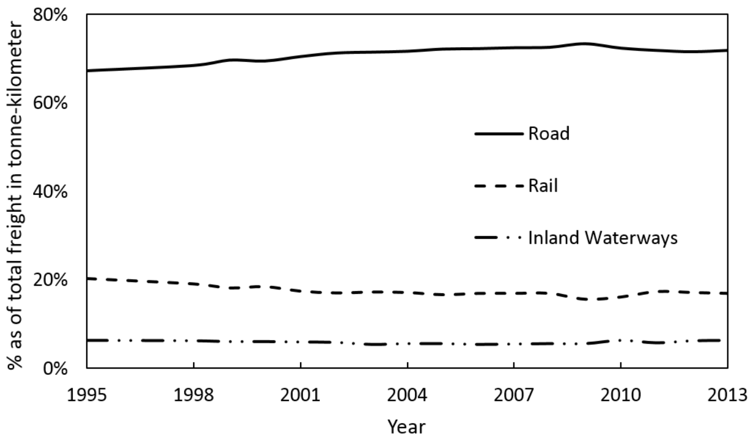

Figure 1.1: *The share of road transportation (tonne-kilometer) in EU-28 remains about* 70% *over the last decades, while the shares of the alternative, more sustainable transportation modes remain modest (EUROSTAT, 2015).*

Synchromodal transportation, or synchromodality, is regarded as an innovative approach to increase the sustainability of logistics systems (Verweij, 2011). It encourages companies to shift freight volumes from trucks to the more sustainable transportation modes such as trains or barges, and to synchronize the use of the transportation modes in a structured, integrated network. Distinct features of synchromodality include simultaneous use of more than one transportation modes in a single corridor so that to utilize the complementary nature of different transportation modes (Tavasszy et al., 2015; Behdani et al., 2016), and flexible, real-time shifts between different transportation modes in order to obtain highest modal split flexibility (Roth et al., 2013; Reis, 2015).

Synchromodality is a key building stone of the Physical Internet (PI, or π)(ALICE, 2014). The PI is an open global logistics system inspired by the information highway: Whereas the "digital" Internet transfers digital data smoothly among users, the "Physical" Internet moves physical objects seamlessly through an open and interconnected logistics network (Wible et al., 2014). The introduction of PI uncovers a paradigm-breaking logistics system that transforms the way physical objects are moved and aims to achieve a smart, efficient and sustainable future logistics system (Montreuil, 2011). Apparently, the seamless and efficient movements of physical objectives desire structured and synchronized transportation systems.

However, the current development of synchromodality is still in its early stage. The mainstream literature studies transportation problems with logistics service provider being the principal agent, and surprisingly little is known about shippers' (manufacturers) opportunities in synchromodality implementation and freight modal split. Compared to road, rail or waterway transportation generally lack the flexibility to vary carrying capacity and may hence result in unnecessary high inventory in the supply chain. They often operate following rigid, predesigned timetables and cannot efficiently respond to unexpected demand surges. Groothedde et al. (2005) describe that a typical industry practice is to ship the stable and well-predictable volume in the inflexible rail/water transportation and all the other variable volume in direct trucking. However, when the demand is volatile, the stable part is often marginal and restricted. The modest shares of rail and waterway transportation over decades in Figure 1.1 indirectly reflect companies' hesitation to encourage modal split.

In order to fill in the research gap, we partnered with companies to investigate shippers' challenges and opportunities in synchromodality. The research is inspired by industry practice, and the results of the research summarized in this dissertation have been used to guide companies implementing synchromodality. In this dissertation, we aim to contribute to synchromodality research by answering the following questions:

(i) How can a shipper implement synchromodality and shift freight to the "greener" transportation modes without increasing total supply chain costs or reducing service levels?

(ii) What is the impact of synchromodality on the shipper's supply chain metrics, such as inventory controls, carbon emission, production smoothing, etc.?

1.2 Outline of this dissertation

In Chapter 2 of this dissertation, we first review the recent literature stream from multimodal, intermodal, to synchromodal transportation to get a better understanding of the current state-of-the-art of the synchromodality studies. On the basis of the literature review, we propose a new concept called synchromodality from a supply chain perspective (SSCP), which broadens synchromodality from the transportation system to shipper's supply chain realm. This concept suggests shippers consider the total costs of the supply chain instead of focusing on the transportation part only. In addition to the conceptual analysis, we propose a first model to quantify the operationalization of SSCP in a case study suggested by a multinational company. This model differs from the current mainstream freight transportation models linked to inventory management (e.g., total logistics costs models) that it considers dynamic inventory replenishment policies under stochastic demand, rather than restrained with economic order quantity inventory models with deterministic demand. The case study demonstrates that it is possible to significantly increase the share of intermodal rail transportation within a corridor, without necessarily increasing total logistics costs or reducing the service level. In this way the total logistics costs and the CO_2 emissions can be jointly reduced. The analysis also suggests that when companies apply SSCP, an external carbon tax from the government would only entail marginal incremental savings in CO_2 emissions.

In Chapter 3 we provide an approximate closed-from solution that enables to determine the split in cargo volumes between a fast but expensive transportation mode (e.g., truck) and a slow but cheap transportation mode (e.g., train or barge). The objective of the model is to minimize long run average costs per period including transportation and inventory. The model is inspired by the classical Tailored Base-Surge (TBS) policy from dual-sourcing literature, where in every period, the slow mode delivers a constant quantity and the fast mode delivers under a base stock control. The closed-form solution provides structural insights on the trade-off between transportation cost savings and additional holding cost spending, which can be roughly captured by comparing two simple parameters: the unit transportation cost saving and the unit inventory holding cost. We validate our results and find that our analytic expressions of the modal split decision are close to optimality, with an approximation error of average cost per period up to 3%. The numerical test also shows that as much as 85% of the expected volume could be split into the more sustainable slow mode.

In Chapter 4 we generalize the inventory model discussed in the previous chapter by taking the fixed cost of the slow mode into account (aligned with the practical insights that rail transportation exhibits economies of scale), adding an extra decision in its delivery frequency, and releasing the assumption of the base stock policy of the fast mode. We show that, though the base stock policy is not imposed, the optimal replenishment decisions of the fast mode indeed have a base stock structure. In an infinite-horizon problem, the base stock levels in a cycle (a cycle accounts for the periods between two slow mode deliveries) converge. These structural properties allow us to obtain the optimal modal split using stochastic dynamic programming with acceptable computing effort. We determine the optimal controls of road and rail transportation and the corresponding inventory management, that minimize the long run average transportation and inventory costs per period. In a numerical study, we show how the optimal modal split decision is impacted by the various parameters of the supply chain.

In Chapter 5 we present a VBA-based Excel tool to support supply chain managers implement synchromodality without necessarily understanding the details of the mathematical models. By using the tool, we validate our synchromodality models presented in the previous chapters using real company data, and quantify the impact of synchromodality on the various supply chain metrics of the company. Interestingly, we find that with only a marginal increase in inventory, companies are able to increase the share of intermodal rail transportation for one of its fast-moving stock keeping units (SKU) [2] to about 67%. The implementation of synchromodality also reduces the total supply chain costs and smooths production without sacrificing service levels. For slow-moving SKUs with a high (larger than one) coefficient of variation (CV), the share of intermodal rail drops significantly. Longer inventory review periods are recommended to aggregate demand from several periods and reduce CV. As the synchromodality tool is based on the level of the SKU, we provide a binary programming model to aggregate the volume shifted to the slow mode from multiple SKUs to full container loads, such that the resulting total costs are minimized.

Synchromodality research is still in its early stage and this dissertation offers some first investigation of this interesting problem. In Chapter 6 we discuss the limitations of this dissertation as well as possible extensions of synchromodality research. One example is that the models proposed in this dissertation are all based on the stationary demand assumption. Non-stationary demand patterns, which might be practical more realistic, could be studied. Another example is that this dissertation is restricted to shippers' synchromodality problems and logistics service providers' perspective should be acknowledged, where freight can be flexibly shifted to different transportation modes when necessary. Possible extensions are discussed.

[2] A fast-moving SKU is a bestseller of the industry that generally has high demand mean and low demand variability.

Chapter 2

Synchromodality from a supply chain perspective

The real tragedy of the poor is the poverty of their aspirations.

- Adam Smith (1723-1790), Scottish economist.

Abstract

Despite the growing interest from manufacturers to implement synchromodality, most companies still rely heavily on road transportation, and modal shifts to rail and water have remained modest at best. In this chapter we argue that this is partly the result of a failure to take a holistic supply chain view of the modal shift process. On the basis of a literature review, we broaden the conventional focus of multimodal transportation to give it a supply chain dimension, and propose the concept of "Synchromodality from a Supply Chain Perspective" (SSCP). Using a case study we show that when the supply chain impacts are taken into account, it is possible to significantly increase the share of intermodal rail transportation within a corridor, without necessarily increasing total logistics costs or reducing the service level. In this way the environmental impact of freight activities can be significantly reduced.

2.1 Introduction

There is a mounting body of evidence justifying that we will have to make deep cuts in greenhouse gas (GHG) emissions from transportation in order to keep our environment sustainable. According to Schipper et al. (2000) and IPCC (2014), this will involve the application of a broad range of measures, falling into four categories: 1) activity (reducing the demand for transportation), 2) structure (shifting freight to lower carbon modes), 3) intensity (improving its energy efficiency) and 4) fuel (switching to lower carbon energy sources). By far the most frequently mentioned freight decarbonization measure in the Intended Nationally Determined Contribution (INDC) documents submitted to COP21 was modal shift, i.e. transferring freight to lower carbon transportation modes (Gota, 2016). According to European Environment Agency (2013), CO_2 emissions per tonne-kilometer from railways and inland waterways are about 3.5 and 5.0 times lower than those from road freight transportation. Shifting freight from road to these alternative modes can therefore be one of the most important means of decarbonizing logistics (Holguin-Veras et al., 2008; Winebrake et al., 2008; McKinnon, 2008; Hoen et al., 2013).

Modal shift has long been “seen by policy makers and politicians as the most promising way of easing the environmental and congestion problems associated with goods movement” (McKinnon, 2015). There has been over 50 years of research on the factors influencing companies’ choice of freight transportation mode (e.g., Bayliss and Edwards, 1970; Jeffs and Hills, 1990), and the use of public policy to alter the allocation of freight between modes. The case for government intervention has been underpinned by the belief that, at a macro-level, the freight modal split is economically and/or environmentally sub-optimal. This sub-optimality has resulted partly from a failure to internalize the environmental costs of freight transportation modes, but also from differences in the regulatory and pricing regimes of the various modes and deficiencies in corporate modal choice behavior. Much emphasis has been placed on the relative pricing of the alternative modes and numerous attempts have been made to quantify cross-modal price elasticities (De Jong et al., 2010; De Jong, 2013). Comparative freight rates, however, are only one of many factors influencing the freight modal split at both micro- and macro-levels. Other criteria, such as transit time, reliability, accessibility, flexibility, and security, are also important determinants of modal selection.

In Europe, strenuous efforts over many years by national governments and the EU to shift freight from road to rail and water have been unsuccessful. A recent report from the European Court of Auditors (2016) confirms that rail's share of the European freight market has declined since 2011 despite the fact that approximately 28 billion Euros of financial support was injected into railway projects across the EU over the period $2007 - 2013$. Therefore innovations are urgently needed to promote and revive modal shift as a freight policy option.

One of the reasons for the modal split being so difficult to change is that many stakeholders have not been taking adequate account of the overall supply chain impact of multimodal transportation. Trains or barges are in general cheaper and greener, but they lack flexibility in delivery quantity, frequency, and scheduling. As a consequence, logistics managers tend to perceive a straight shift from trucks to trains and barges as likely to have a negative impact on the supply chain. More specifically, in the absence of any associated adjustment to supply chain processes, a shift from trucks to trains and barges often leads to increases in inventory. As rail and inland waterway services are generally slower and less frequent than the equivalent road trips, in-transit inventories and stock levels might be higher at both ends of the journey. Trains and barges also require large and stable shipment volumes in order to be cost-efficient, making it difficult for them to cater for flows that are subject to widely fluctuating demand.

The end-to-end impact of the modal shift requires a change in the logistical decision-making process. Freight modal choice is, after all, a part of the supply chain strategy and needs to be jointly optimized with other supply chain activities, like inventory management and customer service levels. This involves the shipper more directly in the process and puts some onus to alter their schedules to accommodate changes in transportation mode.

Some researchers have already analyzed transportation as a part of the supply chain. Woodburn (2003) conducted a survey of 137 British shippers and observed that managers' perception of rail as possibly impairing supply chain performance is a barrier to this mode increasing its market share. Eng-Larsson and Kohn (2012) analyzed six case studies and found that shippers make modal shift decisions in a different way than Logistics Service Providers (LSPs) because they need to consider trade-offs and synergies across the supply chain as a whole. This previous research is mainly qualitative in nature and needs to be complemented by quantitative studies and best practices case studies.

In this chapter, we aim to fill this research gap and contribute to the existing literature on the following two points: First, this study broadens the focus of multimodal research from the transportation system to the supply chain. We review the development of multimodal transportation and the recent evolution of the so-called synchromodality concept. We argue that this concept needs to be more deeply embedded in supply chain management and propose the expression "Synchromodality from a Supply Chain Perspective" (SSCP) to reflect this. This is discussed in Section 2.2. Secondly, this study provides a quantitative demonstration using a company case study to show how modal shift can be enabled when the supply chain impact is taken into account. In Section 2.3 we show that by following an SSCP approach, a company can markedly increase the share of intermodal rail transportation within a particular transportation corridor without sacrificing either logistical efficiency or service quality. Section 2.3 also assesses the environmental impact of this modal shift using a case study of a company and discusses the role of a carbon tax herein. Section 2.4 summarizes the chapter and indicates further SSCP research opportunities.

2.2 The conceptual framework of SSCP

Companies adopting a multimodal strategy have to decide the optimum allocation of their freight among different modes. The development of intermodal transportation has expanded the range of modal options available. By allowing companies to combine different modes in various ways in the course of a single journey, it has further complicated the modal choice decision. The advent of synchromodality has made this decision even more complex, but also increased the potential for companies to make greater use of transportation modes besides road. The next section reviews the evolution of modal split research from multimodality and intermodality to synchromodality

2.2.1 Multimodal, intermodal, and synchromodal transportation

The general concept of combining the use of several modes for any shipment at strategic, tactical, or operational level is generally described as "multimodal transportation". Different modes can be used for various types of commodity, movements of distance, and requirements of services. A company's relative dependence on different modes can also vary significantly between countries reflecting, among other things, differences in the national freight market, the relative density of modal infrastructures and government transportation policy. Over the years numerous studies have been conducted on the topic and detailed literature reviews can be found in articles of McGinnis (1989), Meixell and Norbis (2008), Reis et al. (2013), SteadieSeifi et al. (2014), and Reis (2015).

Multimodality should be distinguished from “intermodality”. Although there is a lack of consensus on the definition of intermodality (Bontekoning et al., 2004), it is widely accepted that it refers to a sequence of different transportation modes used on a single journey, and very likely, a unitized module is used along this freight journey: For example, a container is “pre-hauled” by truck from the sender to an intermodal terminal, trunk-hauled by train or ship to another intermodal terminal, and then “post-hauled” by truck to the receiver. The same sealed, modular unit (e.g. a container) travels from origin to destination (Macharis and Bontekoning, 2004). Modular consignments are channeled through intermodal terminals where they are transshipped between modes in large numbers to exploit the scale economies of rail and water-borne transportation (European Commission, 1997). The literature on intermodality has been reviewed by, among others, Macharis and Bontekoning (2004), Bontekoning et al. (2004), Crainic and Kim (2007), SteadieSeifi et al. (2014), and Reis (2015).

Recently synchromodality (or “synchromodal transportation” has emerged as the next conceptual development linked to multimodal transportation (e.g., Verweij, 2011; Roth et al., 2013; Tavasszy et al., 2015). In one of its first explanations, Verweij (2011) characterized synchromodality as the ability to switch freely between transportation modes at particular times while a consignment is in transit. For example, a container that was originally planned to be shipped via intermodal rail transportation might be switched to direct trucking at certain terminals, because of real-time constraints or a desire to improve utilization/cut costs. The necessary level of flexibility for switching between different transportation modes requires efficient and responsive coordination of the schedules of the available transportation modes. In this way, synchromodality offers the potential to switch mode at several nodes on the route, while meeting cost and service level requirements.

Behdani et al. (2016) and Tavasszy et al. (2015) describe the distinctive feature of synchromodality as “horizontal integration” of freight transportation planning, which allows for parallel use of different transportation modes from the origin to the destination. Freight flows on a particular route, possibly satisfying the same order, are then split between different modes. This contrasts with “vertical integration” of different modes which is inherent in a door-to-door intermodal movement. Figure 2.1 illustrates both concepts. Intermodal transportation comprises sequential use of multiple transportation modes. synchromodal transportation, on the other hand, permits their simultaneous usage, and furthermore, one of these modes could be an intermodal service. Tavasszy et al., (2015) define synchromodality as “synchronized intermodality”. When Logistics Service Providers (LSPs) implement the horizontal integration of different transportation modes and internally synchronize flows, they can do so without consulting shippers. The shippers then make a-modal or “modal-free” bookings, giving LSPs discretion to use multiple modes on schedules that meet the shippers’ service level requirement at the agreed costs (Gorris et al., 2011).

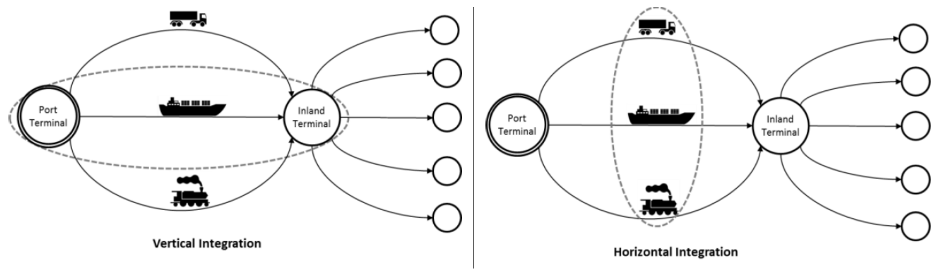

Figure 2.1: *The vertical and horizontal integration of freight transportation planning (Behdani et al., 2016; Tavasszy et al., 2015).*

Groothedde et al. (2005) show how this “horizontal integration” can be operationalized. In their case study, they model parallel usage of two transportation modes: a premium, fast and flexible transportation mode (direct trucking), and a relatively inexpensive, slow and inflexible transportation mode (intermodal). The two transportation modes are synchronized in such a way that the stable part of the freight demand is carried by intermodal transportation, and the variable peaks are accommodated by direct trucking.

2.2.2 Review of the current literature on synchromodality

While multimodal and intermodal transportation have been extensively reviewed in the literature, synchromodality is relatively new. We therefore reviewed the recent literature on synchromodality to get a better understanding of the current state-of-the-art. The keywords “synchromodality” and“synchromodal transportation” were inserted into the following databases: Emerald Insight, Google Scholar, IEEE Xplore, JSTOR, OECD (Organisation for Economic Co-operation and Development) library, Springer Link and Web of Science. In total 24 articles written in English were found that elaborate on the concept of synchromodality: nine journal articles, seven conference proceedings, three book chapters, four white papers and one working paper. We are aware that there may exist additional reports or articles in other languages. In Table 2.1 we list these 24 articles, together with their definition of the synchromodality concept and its advantages as described in their work.

Several key points emerged from the literature:

(i) Synchromodality research is still in its early stage. The number of publications, however, is growing as shown in Figure 2.2.

(ii) The majority of the studies are exploratory and qualitative in nature, which is not surprising for an emerging concept. The first quantitative study was found only in 2015. In 2016 three more quantitative studies were published. The emergence of quantitative studies indicates a deepening understanding of the concept and growing interest in its implementation.

(iii) Until now the synchromodality concept is largely defined in transportation terms and logistics service providers (LSPs) are its principal agents. Although in the original proposal of Verweij (2011) both the LSPs and the shippers were involved in its implementation, later research has generally focused on LSPs only. In the latter case, shippers simply leave the freight mode choice to the LSPs, thus making a "mode-free" booking.

(iv) The most quoted benefit of synchromodality lies in improved sustainability, both in economic and environmental terms. This accrues partly from increased probability of freight modal shift but also from greater flexibility in the real-time planning of transportation modes to adapt to variable demand.

(v) The relationship between synchromodality and the management of supply chain processes, particularly the management of inventory, has not yet been discussed in detail in the literature.

Table 2.1: *A view of current synchromodality literature up to 2015*

Author(year)	Principal	Explanation of Synchromodality
Verweij (2011)	LSP and shippers	Optimal operational alignment of shippers and carri- modes and infrastructure
Lu and Borbon-Galvez (2012)	LSP	An efficient, cost-effective and environmental friend-
Pleszko (2012)	LSP	Carriage of goods by using favorable and available
Roth et al. (2013)	LSP	MT that switches between different modes within mentally friendly distribution
Platform Synchro-modaliteit (2013)	LSP	MT that seamlessly switches between modes, consol- additional efficiency
SteadieSeifi et al. (2014)	LSP	A structured, efficient and synchronized combination
Lu (2014)	LSP	The use of alternative transportation modes in a circumstances as well as product and supply chain
Oonk (2014)	LSP	MT that cooperates within transport chains, aimed all times
ALICE (2014)	LSP and shippers	The service that, through informed and flexible plan- to make mode and routing decisions at the individual
Hofman (2014)	LSP	N.A.
Singh (2014)	LSP	MT that efficiently plans and optimizes the utiliza-
Reis (2015)	LSP and Shippers	MT that adds adaptive mode choice based on real transport system
Van Riessen et al.(2015a,2015b,2015c)	LSP	MT that optimizes all transportation in an integrally
Singh and Van Sinderen (2015)	LSP	MT that allows LSPs to have the freedom in trans- quanlity requirements
Xu et al. (2015)	LSP	A structured, efficient and synchronized combination
Tavasszy et al. (2015)	LSP	A network of well-synchronized and interconnected cater for the aggregate transportation demand
Putz et al. (2015)	LSP	MT network that the modes are operated in parallel
DINALOG (2015)	LSP	A shipper agrees with an LSP on the delivery of sustainability but gives the LSPs the freedom to these specifications
Prandtstetter et al. (2016)	LSP	MT consisting of at least two modes and supporting based on optimized mode choice decisions
Mes and Iacob (2016)	LSP	MT in which the best possible combination of trans- transportation order
Zhang and Pel (2016)	LSP	The same as DINALOG (2015)
Behdani et al. (2016)	LSP	An integrated transportation service by looking at transportation modes

	Advantages of Synchromodality
ers in their choice of transportation	An flexible, efficient and sustainable transport strategy
ly multimodal transportation (MT) strategy	The optimal flexibility and sustainability
transport modes	Flexible and sustainable utilization of transport resources
a more timely, efficient and environ-	Flexible, sustainable transport process with lower cost and higher service level
idate consignments and achieve	A sustainable and flexible transport strategy
of two or more transport modes	A flexible (real-time) transportation process
flexible way, depending on temporary characteristics	An efficient, sustainable, and reliable transportation network
at using the right transport modes at	Alternatives and options for flexibility and responsiveness
ning, booking and management, allows shipment level as late as possible	An transportation network that reduces costs and saves both time and energy
	Real time design and coordination of value chains in the transport system
tion of different transport modes	Flexibility in changing different modes, emission reduction
time information and situation of the	Efficient transport service based on real time information
operated network	Efficient and sustainable transportation plan for all orders
portation modes to fulfill timing and	Higher flexibility, lower GHG emissions, and lower costs
of two or more transportation modes	Optimized transportation profit
transportation modes, which together	Flexible and sustainable transportation chain with higher service
and interconnected with each other	Flexible transportation network with sustainably use of transportation resources
products at specified costs, quality, and decide on how to deliver according to	Speed, cost reduction and sustainability
real-time switching among these modes	Flexible and environment friendly transportation service
portation mode is selected for every	Minimization of cost, delay, and emissions
	Cost and emission reduction without sacrificing the service level
the complementary nature of available	Improve service and cost by optimally use of all transportation modes

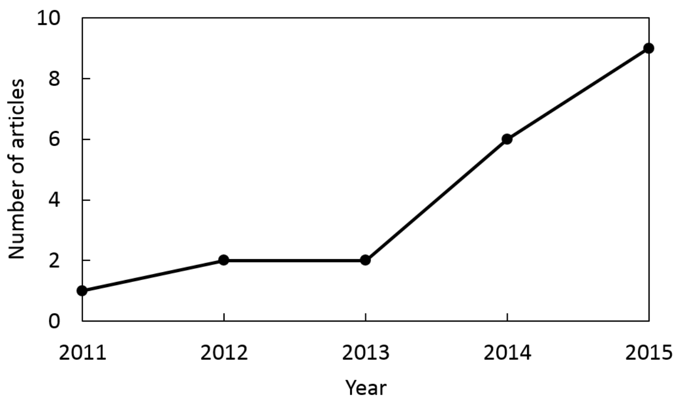

Figure 2.2: *The number of published articles on synchromodality up to 2015*

2.2.3 Synchromodality from a supply chain perspective

While synchromodality adds the synchronization of the transportation modes to the conventional intermodality problem, the SSCP concept further extends synchromodality from being a transportation concept to a principle impacting more widely on supply chain decision-making.

Figure 2.3 illustrates intermodal transportation, synchromodal transportation and SSCP. Synchromodal transportation (Figure 2.3b) extends the one-dimensional freight pathway of intermodal transportation (Figure 2.3a) to a two-dimensional freight flow network involving simultaneous use of different modal pathways in the same corridor. One of these pathways could be intermodal transportation. In SSCP, the transportation decision, after all, is only one building block in the overall optimization of a supply chain (see Figure 2.3c). The meaning of "synchro" in synchromodality needs to be broadened from the synchronization (and scheduling) of the different transportation modes towards the synchronization (and scheduling) of transportation with other supply chain activities such as inventory management and the setting of service levels.

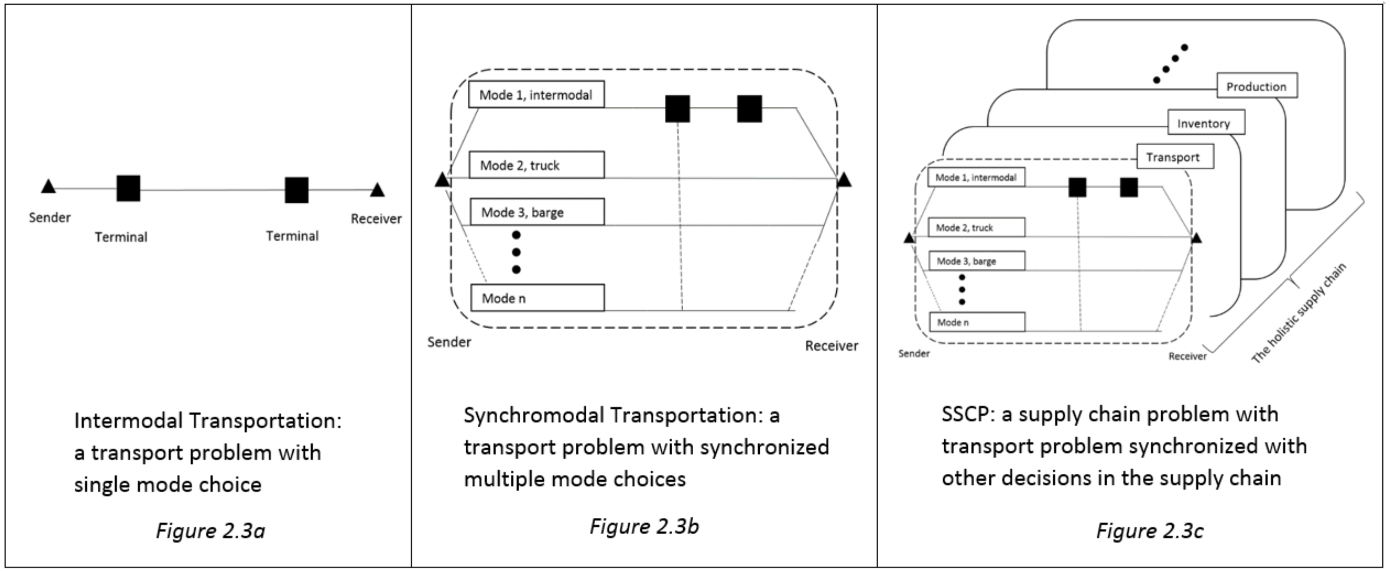

Figure 2.3: *A comparison between intermodality, synchromodality and SSCP*

In Groothedde et al. (2005) the synchronized parallel usage of direct trucking and intermodal transportation is discussed, thereby operationalizing synchromodality from an LSP's perspective. We suggest that, when a shipper wants to implement synchromodality, it needs to evaluate the transportation decisions from an overall supply chain perspective. For example, intermodal transportation may lack the flexibility to vary carrying capacity and may result in unnecessarily high inventory in the supply chain. It also requires a long lead time and therefore may not satisfy demand surges at short notice. As a consequence more sophisticated supply chain models in which transportation decisions are synchronized with other decisions within the supply chain, such as dynamic inventory management and service level controls, are required.

The SSCP approach entails a more holistic view of the supply chain incentives that the shippers may have when they make synchromodal decisions, instead of simply outsourcing the transportation decision to the LSPs and leaving them to optimize the transportation operation. Even where shippers contract out their transportation, they can still exert control over the choice of mode and carrier through a "control tower". According to a survey by Boston Consulting Group (2015) with 40 international corporations, up to 59% of the surveyed shippers now manage transportation in-house, as they believe that they can have a "better control of their service levels". A broader third-party logistics study by CapGemini (2016) reports that although shippers in general continue to rely heavily on LSPs, about 35% of them are insourcing more control of their logistics activities. The reasons offered for this include misalignment of logistics goals and objectives, lack of transparency and effective communications, lack of IT capabilities among LSPs, etc.

Naturally, LSPs and shippers have different business models and operational strategies. The LSPs that explore synchromodality as a business model tend only to consider how it affects their own transportation operations. Shippers, on the other hand, are also interested in its wider impacts on endogenous elements in the production and distribution systems, such as inventories and production schedules. As a consequence, the shipper-based, supply chain perspective on synchromodality is much broader than that of an LSP. The differences are summarized in Table 2.2.

Synchromodality from a Supply Chain Perspective is defined as:

A multimodal strategy that incorporates the flexible choice of freight transportation modes into shippers' management of supply chain processes.

Table 2.2: *Different perspectives of synchromodality*

	Transportation perspective	Supply chain perspective
Organization	mainly LSPs	Shippers
Scope	A transportation network	End-to-end supply chain
Complexity	Network extent and intermodal connections	Supply chain trade-offs and synergies
Objective	A flexible transportation network, where all transportation modes are efficiently utilized and modal shift facilitated	A optimized supply chain, where inventory-transportation trade-offs are recalibrated to exploit multimodal flexibility
Quantitative Research Method	Transportation planning algorithms, e.g., the multi-objective k-shortest path problem used by Mes and Iacob (2016)	Supply chain optimization, e.g., modals integrating transportation and inventory decisions

This perspective redefines the modal choice decision and encourages shippers to re-examine their transportation strategies from a holistic supply chain perspective. Synchromodality requires the active involvement of shippers in modal split decisions to align mode choice with production and inventory management and to accommodate transportation changes into their end-to-end supply chains. Shipper's responsibility and effort are acknowledged, in order to improve the performance of the supply chain.

2.2.4 SSCP and the total logistics costs approach

Whereas synchromodality allows for parallel usage of different transportation modes from the origin to the destination, SSCP aims to determine the optimal allocation of freight between the transportation modes that optimizes the total supply chain performance. This is closely related to the literature applying a total logistics costs (TLC) approach to optimize freight modal choice and inventory decisions, which is already extensively discussed in the literature. The general problem setting is proposed by Baumol and Vinod (1970), who develop a total logistics costs model (they define it an "inventory-theoretic model") to analyze the trade-off between transportation and inventory costs. When companies use a slow rather than a fast transportation mode, it will increase the inventory holding costs.

Baumol and Vinod's TLC model is extended in various ways, e.g., by considering demand variability Das (1974), inventory backorder costs Constable and Whybark (1978), capacity and service level constraints Sheffi et al. (1988), production set-up costs Blumenfeld et al. (1991), to multi-products with different value and transportation schedules Speranza and Ukovich (1994), in a multi-echelon inventory setting Miller and Matta (2003), in a transportation network allowing for freight consolidation in specific nodes in the network De Jong and Ben-Akiva (2007), lead time variability Dullaert and Zamparini (2013), etc. All these models aim to support companies' decisions in freight mode choice and inventory controls. Lloret-Battle and Combes (2013), Combes (2013), and Combes and Tavasszy (2016) provide empirical justification of the inventory-theoretic model, and show that shippers significantly increase their freight mode decisions when incorporating inventory controls. We refer to Winston (1983), Min and Zhou (2002), Meixell and Norbis (2008), and Tavasszy et al. (2012) as extensive literature reviews on studies applying a total logistics costs approach.

Although there is a substantial body of literature on the application of the TLC approach, Groothedde et al. (2005) is one of the few studies that incorporates simultaneous usage of more than one transportation mode. In their model, the more stable part of the freight demand that can be more accurately predicted is allocated to an intermodal transportation service, while the more variable part is delivered by truck. Our research relaxes the limiting assumption made by Groothedde et al. (2005) that only stable, predictable flows are shifted to intermodal services. This should permit greater use of slower, greener intermodal services. Rather than restrict the use of these services to a particular category of demand, our model allocates freight in relation to TLC measured on a supply chain basis from the shipper's perspective allowing for dynamic inventory management and stochastic customer demand. Application of our model should therefore enable shippers to exploit synchromodality more fully and increase their usage of intermodal transportation.

2.3 A case study of SSCP

In this section, we present the findings of a real world research project, which examined the potential for increasing a large shipper's relative use of intermodal rail transportation by using SSCP. In order to preserve commercial confidentiality, it is not possible to reveal the company data used in this case study. Instead, the values declared for key parameters are realistic industry-level figures and not specific to any particular company. We show that by applying SSCP with industry level parameters, the company can increase its modal split of currently 30% of the freight volume shipped via intermodal rail in one specific corridor, to as much as 70% consigned on intermodal rail transportation in the same corridor. The environmental impact of this modal shift involves a reduction of CO_2 emissions with 30% on this specific transportation lane.

Whereas the SSCP concept involves the integration of the flexible choice of freight mode into a shipper's supply chain strategy, including transportation, inventory, production, etc., in this case study we restrict to the modal split between two transportation modes, intermodal rail and truck, and focus on the essential transportation-inventory trade-off in managing supply chains. As flexible mode shifts are practically infeasible in this corridor, we did not take that attribute of synchromodality into account.

2.3.1 Current baseline situation in the literature

A shipper operates a distribution center (D), which is replenished from its plant (P). The replenishment orders are measured in the standard unit of Full Container Load (FCL). An FCL accounts for the volume loaded in a standard 45-foot container. Replenishment orders vary over time, and we assume that the replenishment order follows a gamma distribution and normalize its mean to be 100. Note, because the objective of companies is to increase the *ratio* of intermodal rail transportation, the normalization of the numbers will not affect the outcome. Due to the nature of the products, replenishment orders are highly volatile. Standard deviation is assumed to be 60, indicating that the coefficient of variation of the freight volume is 60%.

The road corridor connecting plant P and distribution center D is 500 kilometers. There is no direct rail connection between P and D, but there is an intermodal rail corridor that consists of a rail leg of 500 kilometers and a road leg of 50 kilometers. The distance of this corridor is larger than 300 kilometers, which is long enough to use intermodal rail transportation as suggested by European Commission (2011). Intermodal rail transportation is assumed to has a lower cost than road transportation per unit of delivery. However, despite its cost advantage, intermodal rail transportation has inflexibilities in delivery quantity and schedule: Because of the rigidity of the train schedule and its transportation capacity, intermodal rail transportation requires shippers to commit stable volumes over a long planning horizon. This stability is essential to make intermodal rail economically viable. The shipper needs to decide the constant volume consigned on intermodal rail transportation on a daily base.

For the shipper, it is not feasible to put all its freight orders on intermodal rail. Given the rigidity of rail transportation, such a level strategy with constant deliveries equal to the average demand each period, leads to an unstable inventory process which increases in variability over time (Boute et al., 2007; Boute and Van Mieghem, 2015). To limit the resulting inventory increase at the distribution center D, the shipper therefore only consigns the stable part of its freight volumes onto intermodal rail, and the volatile part of its freight volumes on trucks to satisfy the service levels. The stable part coincides with the lower bound of the demand volumes (see Figure 2.4). The share of freight moved by intermodal rail is thus calculated as:

$$Share\ of\ intermodal\ rail\ transportation = \frac{minimum\ replenishment\ order}{mean\ replenishment\ order} \tag{2.1}$$

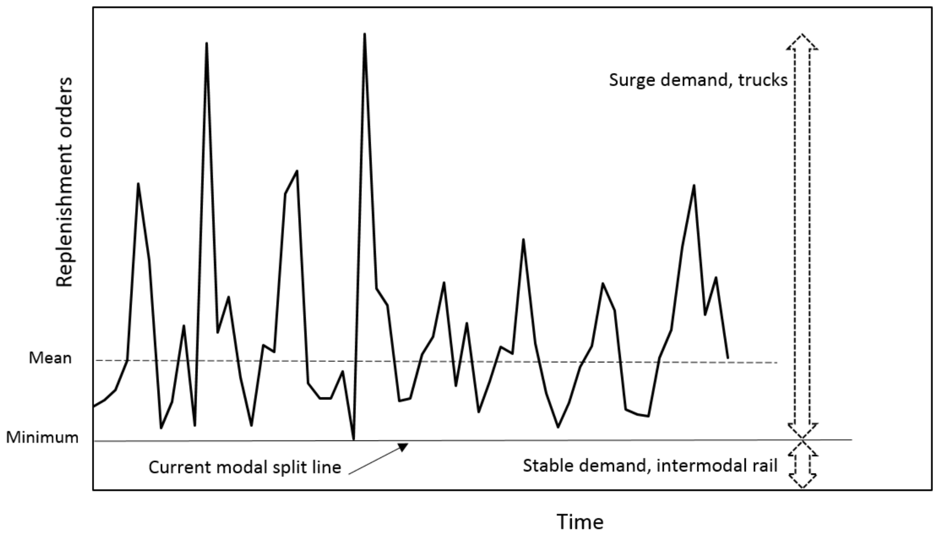

Figure 2.4: *In the current practice, only the stable part of the replenishment order is shifted to the more sustainable intermodal rail transportation. The majority of the volume remains on trucks.*

This approach is standard practice in industry (see, e.g., Groothedde et al., 2005). However, when the replenishment orders are volatile, as in Figure 2.4, the stable part of the replenishment order is often minimal, which discourages a high usage of intermodal rail transportation. In our case study, the ratio of intermodal rail is about 30% of total freight movement on the particular route, i.e., $\frac{minimum\ replenishment\ order}{mean\ replenishment\ order} = 0.3$, which indicates that as much as 70% of total volume still needs to be transported via road transportation. We acknowledge that in practice, companies can move the current modal split line slightly above to gain more opportunities in intermodal rail transportation. Nevertheless, the intermodal rail ratio remains at roughly 30%.

Obviously, this ratio varies widely among companies. The chemical industry for example traditionally faces a more stable demand, where the ratio in expression (2.1) is much higher. This is a major reason why the chemical industry has a much higher utilization of intermodal rail, e.g., BASF (2012).

2.3.2 Increasing the share of intermodal rail transportation by applying SSCP

The operational inflexibility of intermodal rail transportation, in terms of volume, delivery frequency and schedule, etc., does not fit the volatile nature of freight volume, and hence discourages a high ratio of modal split in intermodal rail transportation in the current baseline situation. The SSCP approach allows companies to have more flexibility by exploiting a flexible usage of different transportation modes, as well as capturing the wider trade-off inside the supply chain.

The current modal split ratio as described above is based on the assumption learnt from standard industry practice (Groothedde et al., 2005) that only the stable part of the replenishment order (defined by its minimum) is transported by intermodal rail, because managers tend to perceive that a straight shift from trucks to trains and barges is likely to have a negative impact on the supply chain, especially an increase of inventory in both ends of the journey. No account is taken of shipper's total logistics costs. Instead, it is presumed that the use of intermodal services will incur higher inventory costs thereby discouraging the use of these services by all but stable, predictable flows.

We argue that a proportion of the less stable flows can also be transported by intermodal rail, if the modal split ratio is optimized concerning the shipper's transportation and inventory costs. When the transportation cost reduction resulting from the increased share of intermodal rail exceeds the corresponding inventory costs increase, it makes sense to do so from a total supply chain cost perspective. SSCP therefore looks at the synchromodal decision from the total supply chain perspective, rather than only looking at it in transportation terms.

Notation

t	Time period index, $t = 1 \dots T$
c^{TR}	Unit transportation cost via truck
c^{RA}	Unit transshipment cost via intermodal rail
e^{TR}	Unit carbon emission via truck
e^{RA}	Unit carbon emission via intermodal rail
l^{TR}	Lead time of truck
l^{RA}	Lead time of intermodal rail
h	Unit inventory holding cost
k	Unit cost of capital
b	Unit inventory backorder cost
ξ_t	Demand in period t, following a non-negative i.i.d. distribution
μ	Mean of demand
x_t	Starting inventory position at the beginning of period t
q	The constant delivery quantity via intermodal rail, *decision variable*
S	The order-up-to level of the inventory policy, *decision variable*
z_t	The delivery quantity via truck placed in period t
C_t	The total logistics costs in period t
$\bar{C}$	The average of C_t. *This is the objective to be minimized*
$\bar{e}$	The average emissions per period

Model

A company ships its replenishment orders from P to D by a simultaneous usage of two transportation modes: intermodal rail, and truck. From a modeling point of view, "intermodal rail" can be read as "rail transportation" and this change will not affect the setting and analysis of the model. We use "intermodal rail" because in our specific case study, the connection is an intermodal rail instead of a direct train. Similar to the standard approach described in Groothedde et al. (2005), our model assumes that intermodal rail always delivers a constant shipment quantity q from P to D for every period. This quantity q is a decision variable. Because a constant quantity is shipped and delivered during every period, the lead time of intermodal rail transportation can be ignored (Baumol and Vinod, 1970). However, the pipeline inventory incurs a financial cost, i.e., the opportunity cost of the capital invested in inventory within the transportation system.

Another decision is the volume simultaneously shipped by truck z_t in period t linked to the inventory replenishment policy. The current mainstream freight transportation models linked to inventory management are formed on the basis of the classical Economic Order Quantity (EOQ) model (e.g., Combes, 2013). However, EOQ models are built on a strong assumption that the demand of the model is deterministic, i.e., the demand remains the same in all periods. In order to analyze the volatile demand, we implement the base-stock inventory replenishment policy as suggested widely in the inventory literature, e.g., Arrow et al. (1958), Zipkin (2000), and Porteus (2002).

The base-stock policy works as follows: At the beginning of t the company has x_t inventory in D, then the truck transportation delivers $z_{t-l^{TR}}$ (Truck transportation has a lead time of l^{TR} periods so that the replenishment orders from $t - l^{TR}$ period arrives in period t) and intermodal rail transportation delivers q, and the company thus has an inventory level of $x_t + z_{t-l^{TR}} + q$. If this inventory level is below the base-stock level S, then $z_t = (S - q - z_{t-l^{TR}} - x_t)$ units are to be replenished and delivered via truck. Otherwise no delivery is made. Hence, $z_t = (S - q - z_{t-l^{TR}} - x_t)^+$, with $(\ )^+$ defined as the positive part of a real-valued function in the brackets. After that, demand ξ_t is realized. Note, ξ_t is a non-deterministic variable. Because of the uncertainty in ξ_t, at the end of every period two mismatch-scenarios could happen: 1) If the on-hand inventory in D, denoted as $x_t + z_{t-l^{TR}} + q$, is larger than ξ_t, the remaining inventory will be stored to the next period at a unit holding cost h. 2) If the on-hand inventory is less than ξ_t, the unmet demand will be back-ordered to the next period with a unit penalty cost b. Denote c^{RA} the unit transportation cost with intermodal rail and c^{TR} the unit transportation cost with truck, the total costs in period t is then:

$$\begin{aligned} C_t = & c^{RA}q + c^{TR}z_{t-l^{TR}} + h(x_t + q + z_{t-l^{TR}} - \xi_t)^+ \\ & + b(\xi_t - x_t - q - z_{t-l^{TR}})^+ + k(l^{RA}q + z_{t-1} + \ldots + z_{t-l^{TR}}), \end{aligned} \tag{2.2}$$

where $c^{RA}q$ represents the transportation cost of the freight volume received by intermodal rail, $c^{TR}z_{t-l^{TR}}$ the transportation cost of the volumes received by truck, $h(x_t + q + z_{t-l^{TR}} - \xi_t)^+$ the inventory holding cost in period t, $b(\xi_t - x_t - q - z_{t-l^{TR}})^+$ the inventory backorder cost which is incurred in case the demand exceeds the total supply, and $k(l^{RA}q + z_{t-1} + \ldots + z_{t-l^{TR}})$ the cost of capital linked to the in-pipeline inventory on both transportation modes at a rate of k. Although we acknowledge that the cost structure of an intermodal rail operator is typically lumpy (we refer to European Intermodal Association (2012) for the detailed cost structure of rail operation), we use a linear approximation because the cost structure for a shipper, i.e., the transportation cost paid by the shipper to the carrier, is close to a linear function.

The decision variables are q and S and the objective is to minimize the average total logistics costs per period, including transportation (intermodal rail

+ truck) and inventory mismatch (holding + backorder) costs:

$$\bar{C} = \frac{1}{T}\sum_{t=1}^{T} C_t. \tag{2.3}$$

Parameters (normalized)

The inventory holding costs from companies' perspective do not only consist of warehouse storage and handling cost, but also include the cost of capital linked to the inventory. It is usually assumed that, the annual rate of cost of capital is 10% and the annual inventory holding cost of a product is equivalent to 25% of its value. The average value of the cargo in an FCL is assumed to be 100,000 EUR. The average cost of capital per day: $k = 100,000\frac{10\%}{365} = 27$, and the average inventory holding cost per FCL per day is therefore calculated as: $h = 100,000\frac{25\%}{365} = 68$. The inventory backorder penalty cost b can be calculated indirectly via the customer service level, which is assumed to be 95%. In a base-stock inventory setting, the customer service level is given by the critical fractile $b/(b+h)$(Zipkin, 2000, p.215). As a result, we obtain $b = 1292$. To transport one FCL from P to D via road transportation is assumed to cost 600 EUR, i.e., $c^{TR} = 600$, and to transport the same FCL via intermodal rail costs $c^{RA} = 550$. The lead time of road transportation is one day, i.e., $l^{TR} = 1$, and the lead time of intermodal rail is two days, i.e., $l^{RA} = 2$. Table 2.3 summarizes the parameters values.

Table 2.3: *The parameters used in the SSCP model (normalized)*

Notation	Description	Value	Unit
μ	Mean of demand	100	Full container load (FCL)
σ	Standard deviation of demand	60	FCL
c^{TR}	Unit transportation cost by truck	600	EUR per FCL
c^{RA}	Unit transportation cost by intermodal rail	550	EUR per FCL
l^{TR}	Lead time of truck	1	Day
l^{RA}	Lead time of intermodal rail	2	Day
h	Unit inventory holding cost per period	68	EUR per FCL per day
k	Unit cost of capital per period	27	EUR per FCL per day
b	Unit inventory backorder cost per period	1292	EUR per FCL per day

Results

Although the problem structure is straightforward, the model is unfortunately analytically intractable. The characterization of the inventory process as a result of the dual-sourcing inventory policy (a simultaneous usage of both transportation modes) makes it impossible to solve the model analytically: because the intermodal rail transportation always delivers a constant quantity into the distribution center, it is possible that it delivers more than needed and shoots the inventory over the base stock control level, and this excessive inventory cannot be obtained in explicit form. We refer to Rosenshine and Obee (1976), Allon and Van Mieghem (2010), and Janakiraman et al. (2014) for more detailed analysis on the characterizations of the inventory process. To the best of our knowledge, Combes (2011) and Dong et al. (2017a) are the only studies that solve similar transportation problems with inventory considerations. However, they both use an approximation approach and do not show the optimal solutions. Our simulation approach is straightforward and obtains optimal solutions.

We solve the model optimally via simulation-based optimization through a search for all possible combinations of q and S over a simulation time horizon T. Because both q and S are integers, the computing effort is moderate.

The ratio $\frac{q}{\mu}$ represents the share of the intermodal rail transportation. As described in Section 2.3.1, the company currently operates with intermodal rail share of 30%, given by expression (2.1). The company wants to reduce the environmental impact by shifting more volume from trucks to intermodal rail (i.e., increasing the value of q), without increasing its total supply chains costs. We examine how the expected total cost per period behaves as a function of the intermodal rail share, i.e., we observe how $\bar{C}$ changes when q varies from its lower-bound zero (intermodal rail share of 0%) to its upper-bound [1] (100% intermodal rail share), and depict the results in Figure 2.5. The solid curve represents $\bar{C}$, the expected total logistics costs per period, and the two dotted curves represent the breakdown of the total cost $\bar{C}$ into transportation and inventory costs. For confidentiality reasons, the exact numbers in the y-axis are not reported. In fact, we are interested in increasing the share of intermodal rail transportation and the exact value of $\bar{C}$ is out of scope of this research. Figure 2.5 shows that as the intermodal rail share goes up, the total transportation costs go down linearly, but inventory costs increase in a convex manner. Specifically, when the share of the intermodal rail approaches to 100% (point F), almost all volumes are shipped via intermodal rail, the SSCP model loses all flexibility, resulting in excessive inventory holding costs. As a comparison, at point E the company has all volume transported via road and the inventory is minimized.

In Figure 2.5, point A represents the current baseline situation, where about

[1] q should not exceed μ, otherwise the expected supply will be larger than the expected demand and the inventory will continuously build up.

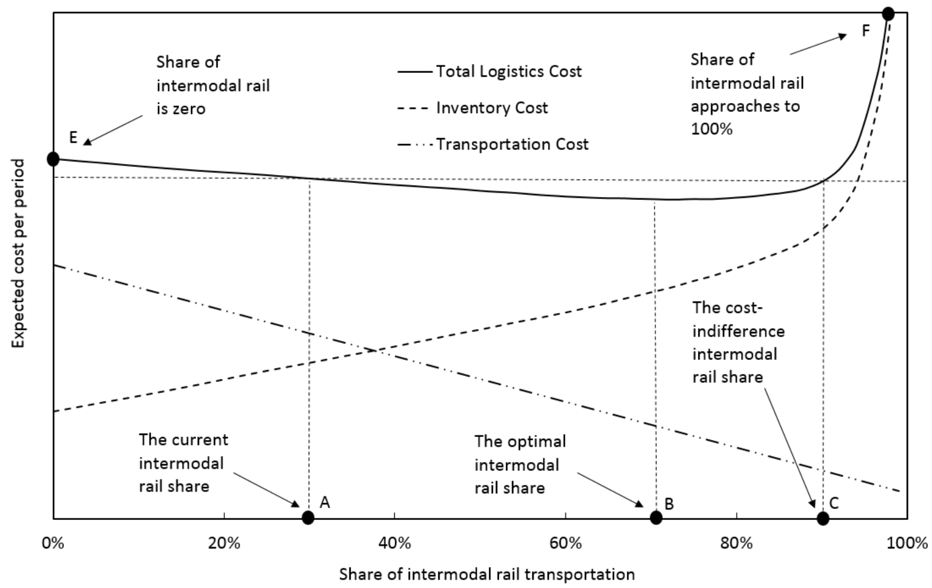

Figure 2.5: *By applying SSCP, the company incurs higher inventory cost and lower transportation cost. The total logistics costs is minimized at point B, where about* 70% *of the total volume is shifted to intermodal rail.*

30% of the volume is shipped by intermodal rail in the specific corridor from P to D. When optimizing the modal split taking its impact on both transportation and inventory costs into account, we find that the total logistics costs can be further reduced by increasing the intermodal rail share to point B, where about 70% of the freight is shipped using intermodal rail on this specific intermodal rail corridor. This is a considerably higher modal share than in the current situation and is achieved without increasing the total logistics costs or reducing the customer service level. The move from point A to point B represents a redefinition of the synchromodality problem. Point A corresponds to the current practice of modal split as defined among others by Groothedde et al. (2005), in which the company optimizes its mode choice as a pure transportation problem, and ships the stable, well-predictable flow using intermodal rail and accommodates the unpredictable flow by direct trucking. Using this approach intermodal rail is assigned 30% of the freight. Moving the optimum to Point B effectively extends the boundary of the optimization problem into the supply chain realm. This can raise the intermodal rail share to 70% and shows how combined modeling transportation and inventory variables allows synchromodality to achieve a more radical reallocation of freight between modes. Point A can be considered a sub-optimal modal split based on transportation parameters only while point B a new global supply chain optimum.

From point A to B, the company obtains more transportation cost savings than extra inventory cost spending. From point B to point F, the total logistics costs increase mainly due to an excessive increase in inventory holding costs. Point C is another interesting point. It represents a cost indifference point where the shipper remains at the same total logistics costs as its current situation, which is represented by point A. It indicates that the company could theoretically shift about 90% of its volume on a particular corridor onto intermodal rail, without compromising total logistics costs. Although this would indicate a major reduction in its environmental impact, this point will in practice be hard to attain because, without external stimulations from governmental policy or customer requirements, most companies will prioritize costs over emissions, and therefore stay at Point B. Still, Point C indicates that SSCP still offers further theoretical potential for environmental improvement at a supply chain level.

2.3.3 The environmental impact of SSCP

In this section we illustrate the environmental impact of SSCP by analyzing the corresponding savings in carbon dioxide (CO_2). We use the standard emission factor from European Environment Agency (2013): road transportation discharges in average 75 grams CO_2 per tonne-kilometer (TKM), and rail transportation in average 21 grams CO_2 per TKM. An FCL has an average payload of 24 tons so that to ship one FCL from P to D (distance of 500kms) by road transportation emits on average $75 \times 24 \times 500 = 900,000$ grams, or 0.9 tons of CO_2. We obtain $e^{TR} = 0.9$. The intermodal journey has a rail trunk haul of about 500 kilometers with combined road feeder distances of 50 kilometers. To transport one FCL from P to D using the intermodal service emits $(75\times24\times50)+(21\times24\times500) = 342,000$ grams, or 0.342 tons of CO_2. We set $e^{RA} = 0.342$. The average CO_2 emission per period is then presented as:

$$\bar{e} = \frac{1}{T}\sum_{t=1}^{T}(e^{RA}q + e^{TR}z_{t-l^{TR}}). \tag{2.4}$$

We do not consider GHG emissions caused by holding inventory. According to the World Economic Forum (2009), "logistics buildings", comprising freight terminals, warehouses and depots, account for approximately 10% of total GHG emissions from logistics. The storage-related emissions would represent only a fraction of this 10% and be relatively fixed in the short- to medium-term regardless of the amount of inventory. A further reason for excluding inventory-related emissions from the analysis is that the products did not require temperature control. No refrigerant gases were emitted from this supply chain nor CO_2 emissions associated with the cooling of warehousing or vehicles.

Because the unit emission from intermodal rail transportation is smaller than that from road transportation, i.e., $e^{RA} < e^{TR}$, to shift freight from road to intermodal rail transportation linearly decreases total emission $\bar{e}$. In theory, the company could minimize $\bar{e}$ in (4) by maximizing q, i.e., shifting all freight to intermodal rail transportation. This is not a feasible solution, however, because the company would then incur a significant increase in inventory costs as shown in point F in Figure 2.5.

We illustrate in Figure 2.6 the trade-off between total logistics costs and emissions when the company increases its dependence on intermodal transportation. The current situation is denoted as Point A as the basis for comparison (30% intermodal rail share). Point E indicates total reliance on road transportation, which causes emissions and costs to be, respectively, 9% and 5% higher than at present. Point F corresponds to a scenario in which the share in intermodal rail transportation approaches to 100%. Although F is the “greenest” solution in this plot with about 45% CO_2 emission savings compared to the baseline situation, it would inflate total logistics costs by roughly 40% as a result of higher inventories accumulating in the distribution center. Points B and C remain the same as in Figure 2.5. At point C, the company can save about 40% of total CO_2 emission without incurring extra costs. The most realistic result of SSCP is point B, where the company could obtain logistics cost savings of about 6% as well as emissions savings of about 30%, compared to the current situation at point A. This would represent a win-win option yielding economic and environmental benefit.

Hoen et al. (2013) have discussed a trade-off between cost and emissions. They find that “intermodal transportation, which is typically less carbon emitting, is more expensive (in terms of total logistic cost) than road transportation for 63% of the customer lanes”. On the basis of this observation, they demonstrate that companies in general need to trade higher cost for an emission reduction. In contrast to their study, our model assumes that the greener intermodal alternative is also cheaper compared to road transportation (see, e.g., EUROSTAT, 2015; Floden and Williamsson, 2015). Greater use of intermodal transportation can therefore lead to both cost and emission reductions.

If the current choice is to regard the choice of transportation mode as purely

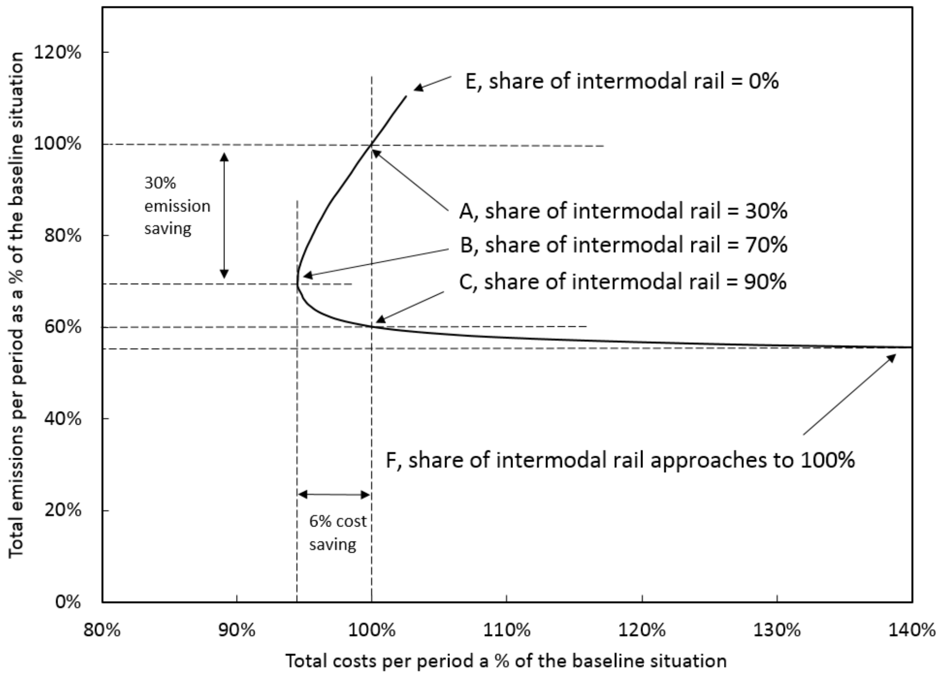

Figure 2.6: *By applying SSCP in the specific corridor, the company is able to jointly reduce cost and emissions by moving from point A to B. When it moves from B to F, it has to trade higher cost for additional emissions reductions.*

a transportation problem, companies stay at point A. The analysis indicates that by applying SSCP and optimizing modal choice at a supply chain rather than transportation level, companies will be able to further exploit both the economic and environmental benefits of intermodal rail transportation. From points B to F, the company would have to trade-off higher logistics costs for emission reductions. It would have to be incentivized to make such a trade-off by exogenous pressures, such as the imposition of a carbon tax, greater willingness of customers to pay for low-carbon products, or steep increases in fossil fuel prices.

The introduction of a carbon tax would encourage companies to shift freight to lower carbon modes. We have used our SSCP model to assess the impact on carbon emissions and logistics costs of setting carbon taxes at different levels.

Denoting β as the carbon tax per ton, the company needs to minimize the total costs of transportation, inventory, and carbon tax payments. The total costs per period in the presence of a carbon tax is then:

$$\hat{C}_t = c^{RA}q + c^{TR}z_{t-l^{TR}} + h(x_t + q + z_{t-l^{TR}} - \xi_t)^+ + b(\xi_t - x_t - q - z_{t-l^{TR}})^+ \\ + k(l^{RA}q + z_{t-1} + \ldots + z_{t-l^{TR}}) + \beta(e^{RA}q + e^{TR}z_{t-l^{TR}}). \quad (2.5)$$

The objective is to minimize the average of $\hat{C}_t$.

We follow Fahimnia et al. (2015) and set the value of β to 0, 21, 42, 104 and 208 EUR per ton[2]. The resulting cost and emission trade-off curves are plotted in Figure 2.7.

The curve with $\beta = 0$, i.e., no carbon tax, is equivalent to the single curve shown in Figure 2.6. However, now the benchmark is changed from point A to B, because the impact of the carbon tax is evaluated against the optimum. When the value of β increases, the trade-off curve moves to the right, indicating that the total costs are inflated by the addition of the carbon tax payments.

Point B in Figure 2.7 minimizes the average total costs $\hat{C}_t$ when there is no carbon tax, and point H minimizes the total costs in the high carbon tax scenario of $\beta = 208$ EUR per ton. In the high carbon tax scenario (point H), the company needs to trade 17% more total logistics costs for 9% fewer emissions. The cost increase is significantly larger than the emission reduction. In the absence of carbon tax, the use of SSCP allows the company to optimize synchromodality in a broader supply chain context and obtain a 42% emission reduction (from A to B). However, when the supply chain of the company is optimized by using SSCP (at point B), the incremental effect of a carbon tax on CO_2 emission reductions is relatively small (only 9% represented by the move from B to H). This suggests that the application of SSCP has the potential to substantially reduce CO_2 emissions (from point A to B) through optimization of the company's "internal" supply chain, whereas the "external" interventions such as a carbon tax imposed by the government have only a minor incremental effect (moving from point B to H), unless they are set at very high levels.

2.3.4 Discussion

Although this case study is analyzed on the basis of one set of parameters, several general insights can be found to support companies reduce their environmental impact in freight movement in any industry. This case study shows that when

[2] The prices are originally quoted in USD in Fahimnia et al. (2015), and in our case study changed into EUR on the basis of the exchange rate on July, 1st, 2015: 1 USD = 0.9054 EUR.

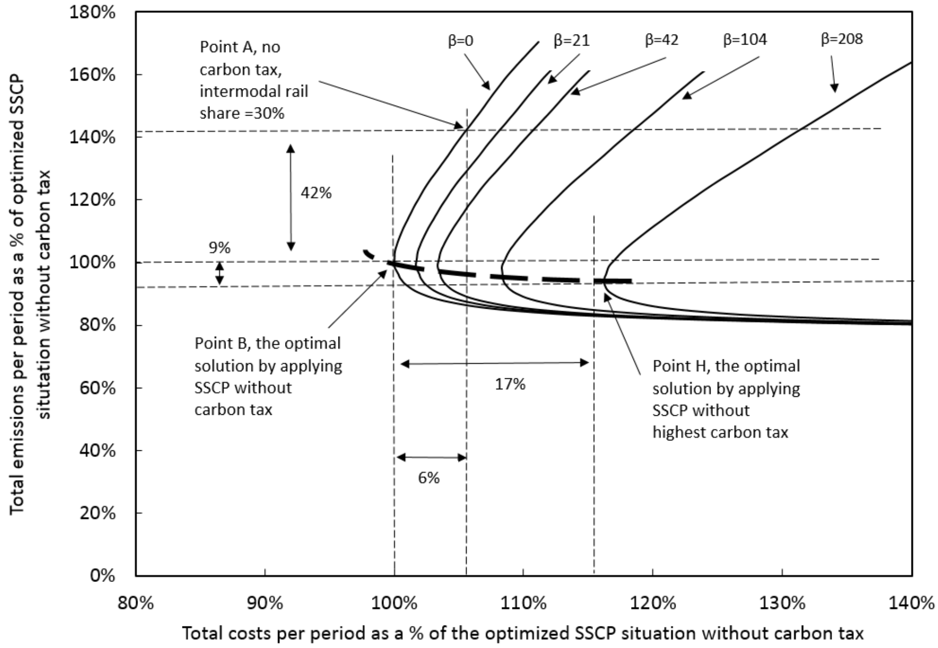

Figure 2.7: *An installment of carbon tax inflates the total logistics costs and enforces companies to reduce emissions. However, when companies already implements SSCP, the incremental carbon reduction driven by carbon tax is modest.*

current standard practice in industry is applied, with only the stable freight volumes transported by intermodal rail transportation (Groothedde et al., 2005), the share of intermodal rail is only moderate in case freight volumes are highly volatile. In order to increase the ratio in intermodal rail transportation, more flexibility can be introduced into the freight system by the following two aspects: i) the simultaneous usage of two transportation modes and, ii) the incorporation of the consequential transportation-inventory trade-off of the supply chain. These two aspects are the major features that we exploit in our SSCP concept discussed in Section 2.2. By following the SSCP approach, we show that it is possible to substantially reduce the total logistics costs and emissions at the same time.

We are aware that the case study does not fully reflect all attributes of SSCP as discussed in Section 2.2. Additionally, synchromodality allows switching freely between transportation modes at particular times while a consignment is in transit Verweij (2011). In the case study presented in this chapter, freight can practically not be shifted from road to intermodal rail during the journey, and vice versa. The lack of this flexibility might prevent our models from obtaining even higher costs savings and emission reductions. Nevertheless, even without this extra flexibility, our model has already demonstrated substantial improvement of the economic and environmental impact of the transportation system.

As this case study is specific, it would clearly be unwise to apply the same modal split ratios for any practical scenarios. Our results are illustrative for this case study, which should not necessarily be representative of all industries as a whole. Depending on the company's freight volume volatility, unit transportation cost of intermodal rail versus road, and the cost of holding excess inventories, the optimal modal split ratio and its corresponding cost savings and emission reductions may be different.

We have subjected our results to a sensitivity analysis to test its robustness in different environments. In the current case study, intermodal rail costs about eight percent less per unit than trucking and captures about 70% of the freight. If the cost differential between both transportation modes goes down, intermodal rail's share will be reduced. However, even if intermodal rail is only one percent cheaper than trucking, it retains around 60% of the traffic. We also tested the impact of the demand variability: when the demand is more volatile, trucking services that can handle variable delivery quantities will be favored. A numerical test shows that when the demand standard deviation increases from 60 to 200, the optimal modal share for intermodal rail drops from 70% to about 30%. Although this is a substantial reduction, 30% is still significantly higher than the baseline share, where the lower-bound of the demand and the corresponding modal split were close to zero.

Finally, when the shipper applies our concept of SSCP, the LSP will have a different use of its transportation modes, and most likely more freight shipped via (intermodal) rail and less volume via road transportation. This is not per se negative for the LSP, even on the contrary. By increasing the volume in its rail freight transportation, it could enable a higher asset utilization of its rail infrastructure. However, that relies on many assumptions - a detailed quantification of its impact is therefore beyond the scope of this chapter, but it is an interesting future research avenue.

2.4 Conclusion

Despite the efforts of policy-makers, particularly in Europe, to shift freight traffic from road to rail and waterborne transportation, the road-rail modal split has changed little over the past two decades. Innovations are urgently required in order to promote a substantial modal shift to alternative, more-environmental modes. This chapter suggests that Synchromodality from a Supply Chain Perspective (SSCP) is such an innovation. It extends the original concept of synchromodality into the wider realm of supply chain management and shows how by adjusting their "internal" inventory management shippers can more effectively exploit the greater modal flexibility which the "external" synchromodality offers. A case study has been used to illustrate this approach and show how a shipper can increase the modal share of intermodal rail and road from 30% to 70% in one intermodal rail corridor, resulting in a 6% total logistics costs saving and 30% emissions saving.

This study shows how the scope of the conventional multimodal transportation can be enlarged by including inventory management into the modeling of freight modal options. Further extensions of this work could incorporate other supply chain decisions relating production scheduling and service level constraints, or across the bounds of a single company's supply chain to a wider network involving more parties, e.g., under vertical collaboration, shippers and LSPs could coordinate their separate synchromodality decisions and achieve win-win solutions. The growth of horizontal collaboration among groups of companies is "bundling" freight along particular corridors to more viable train loads (Sanchez-Rodrigues et al., 2015). If these companies collectively apply the SSCP principle, the potential impact of synchromodality on the freight modal split would be substantially reinforced. For example, if one shipper had a slump in demand, the others might still have sufficient volume to maintain adequate capacity utilization of the train. The aggregated demand of all the collaborating shippers drives a pooling effect and therefore reduces the risk to system viability posed by the variability of any single shipper's freight demand. This stabilization of total demand should further increase of intermodal rail's share and improve the environmental impact of freight transportation.

Chapter 3

An inventory control model for synchromodality: A tailored base-surge approximation approach

Wer immer strebend sich bemüht, den können wir erlösen. [1]
– Johann Wolfgang von Goethe (1749-1831), German writer.

Abstract

This chapter aims to support companies implement synchromodality by providing a quantitative analysis on its relevant challenges and opportunities. We develop a stochastic modal split transportation model with two transportation modes: the fast mode (e.g., direct trucking) with flexible delivery quantity, high delivery frequency, short lead time but high transportation cost, and a slow mode (e.g., intermodal rail) with fixed delivery quantity, low delivery frequency, long lead time but low transportation cost. Following the supply chain perspective of synchromodality proposed in Chapter 2,

[1] Whoever exerts himself in constant striving, Him we can save. in *Fraust Part II.*

the objective of the model is to minimize the long-run expected total costs of transportation, inventory holding, and backlogging. The model is a generalization of the classical tailored base-surge (TBS) policy known from the dual-sourcing literature with non-identical delivery frequencies of the two transportation modes. By analyzing the model, we find that a major challenge to implement synchromodality and shift volume from the fast to the slow mode lies in determining companies' inventory level at the delivery destination: A special phenomenon called inventory "overshoot" is observed, which is analytically not tractable.

We propose a novel approach to analytically approximate overshoot and obtain closed-form solutions of the modal split decision. The solution provides an easy-to-implement solution tool for practitioners. The results provide structural insights regarding the trade-off between transportation cost savings and holding cost spending and reveal a high utilization of the slow mode. A numerical performance study shows that our approximation is reasonably accurate, with an error of less than 3% compared to the optimal results. The result indicates the potential opportunity of implementing synchromodality: As much as 85% of the expected volume of a pilot, fast-moving SKU could be split into the slow mode.

3.1 Introduction

An operationalization of the synchromodality concept proposed in Chapter 2 can be described as a modal split transportation (MST) problem: to optimize the allocation of cargo into more than one transportation mode. Rather than shipping all the cargo by truck, there is an increasing interest in moving transportation volumes to trains or barges. There are numerous reasons for this prospective paradigm shift. First, road transportation is generally more expensive per unit of cargo shipped, and its cost is still forced upward by factors such as congestion and empty running (American Transportation Research Institute, 2014; McKinnon and Ge, 2006). Second, the shortage of truck drivers is limiting the supply of truck capacity and causing structural fleet management issues (Boston Consulting Group, 2015; Sheffi, 2015). Third, companies' sustainability agendas and carbon reduction targets facilitate the shift to "greener" transportation modes that favor trains or ships over trucks (Dey et al., 2011; Dekker et al., 2012).

Despite the increasing emphasis that MST receives, shifting volume away from the road remains challenging. Statistics demonstrate that since 1995, there has been no significant change in modal split ratios among road, rail, and waterway in the EU-28 zone (EUROSTAT, 2015). In contrast, rail transportation on certain routes had to be closed after several years of operation because the rigid schedule could not cope with the practical demand changes (Lammgård, 2012). Shippers hesitate to implement train transportation due to the concern that there will not be sufficient volume to secure a cheap price (Pallme et al., 2014). The timetable of rail or barge is rigid, and it is therefore almost impossible to send an extra train when demand surges (Reis et al., 2013). Compared to other transportation modes, truck transportation is still the most flexible mode in terms of delivery time, routes, and quantity.

To obtain further insights into the challenges of MST, we partnered with companies that further inspired our research. The companies currently consign almost all of the transportation volume into trucks. On a daily basis, the distribution centers (DC) order inventory from the plant and expect instant deliveries within a short lead time. Such a "pull" inventory system allows the DCs' to easily adapt their orders from day to day in line with demand; however, this creates high fluctuations in shipment volume. The company is interested in shifting more transportation volume from trucks to trains or barges with the intent of saving cost and operating more sustainably. From interviews with managers, a practical challenge with the implementation of MST is to synchronize the more rigid slow transportation modes with the more flexible fast transportation mode without harming service levels or increasing inventories.

More specifically, train or barge operations are subject to restrained schedules and often have lower delivery frequencies than trucks. These schedules generally remain fixed over a long period (e.g., half of a year to one year), and companies are required to commit a fixed loading quantity over the period in advance to obtain a low transportation cost. For example, a shipper needs to fix ten containers on the train from Antwerp (Belgium) to Hamburg (Germany) every Monday for the entire calendar year. Therefore moving from truck transportation to MST also implies a change in the inventory control policy from a pure "pull" strategy to a hybrid "push-pull" strategy. Due to the long-term commitment, the slow mode shipments can be viewed as the inventory that is pushed to the DCs, while the more flexible fast mode shipments contain inventory that is pulled by the DCs. Against this background, we develop an MST policy that should consider the simultaneous usage of both modes, i.e., trucks and trains/barges in a single transportation corridor, and incorporate the costs of inventory management. Although transportation and inventory decisions require an integrated approach, practitioners often struggle to holistically implement the required policies. The fundamental objective of this research is to develop an insightful and easy-to-implement modal split policy to guide practitioners in real-world MST problems.

In this chapter, we develop a single-product-single-corridor stochastic MST model with two transportation modes considering a hybrid push-pull inventory policy. The model covers the following setting. A company delivers a product from a plant to a DC and has to decide how to split the delivery quantity into two transportation modes: a slow mode that is rather rigid in terms of time and delivery quantity, i.e., the company has to commit to a fixed quantity to be shipped at specific time points, and a fast mode that operates every period and has full flexibility in terms of delivery quantity but also at higher transportation cost than the slow mode. Whereas the "fast mode" in our research clearly indicates truck, the "slow mode" is not necessarily a certain mode but can also mean a mixed strategy using trucks and trains/barges. The company aims to minimize the expected transportation- and inventory-related costs by optimizing the fixed slow mode quantity that is committed in advance (push) and the delivery policy for the more flexible fast mode (pull).

Our MST model has a structural form comparable to the tailored base-surge (TBS) model studied in the dual-sourcing literature where companies split their orders into a fixed "base" quantity ordered from a cheap oversea supply source and a flexible "surge" quantity ordered from a more expensive but fast supply source (Allon and Van Mieghem, 2010).

The primary difference between our MST model and the classical TBS model is that the TBS model assumes that both slow mode and fast mode orders have identical delivery frequencies. Our MST model considers different delivery frequencies of the two modes based on the fact that trains/barges operate less frequently than trucks. Therefore, our MST model is a generalization of the classical TBS model. To the best of our knowledge, this is the first study that makes this generalizing assumption.

However, previous studies have shown that the TBS model is not amenable to exact analysis, mainly due to the tractability of the expected overshoot analysis (e.g., Janssen and de Kok, 1999; Allon and Van Mieghem, 2010; Janakiraman et al., 2014; Boute and Van Mieghem, 2015). The authors exclusively rely on a "heavy traffic" analysis in a GI/G/1 queue to derive a closed-form expression for the expected overshoot. Unfortunately, this "heavy traffic" phenomenon cannot be guaranteed in our MST model since slow mode deliveries are less frequent than fast mode deliveries. The different delivery frequencies result in all periods within a cycle (the time between two slow mode deliveries) being structurally different in a steady state. Therefore, the approximations of the classical TBS problem do not successfully work for the more general MST problem.

To obtain an analytical solution that is applicable in a practical environment, we use the deterministic benchmark (i.e., demand is perfectly known) as a starting point to identify key drivers and determinants of the volume allocation between the two transportation modes. Based on these findings, we propose different tailored approximations of the cost function for different ranges of cost parameters (mainly with respect to transportation cost savings and inventory holding cost). These approximations allow us to derive closed-form expressions for the modal split policy, i.e., a fixed shipment quantity allocated to the slow mode and a base stock policy for the fast mode, which is an easy-to-implement tool for supply chain managers.

A numerical performance study with a wide range of parameters reveals that our approximation has sufficient accuracy compared to optimal solutions calculated using a complete enumeration. On the test bed, the approximation error is less than 3%, and the computing time is only a fraction of the complete enumeration.

The analytic characterizations of our results capture the key trade-off of the MST problem: a *commitment effect* and a *cycle stock effect*. The commitment effect refers to the long-term commitment of the constant quantity in the slow mode enabling the reduction of transportation cost compared to the fast made. The cycle stock effect refers to the higher shipping quantity in the slow mode that potentially increases the inventory holding cost. Interestingly, the marginal effects can be simply determined by two parameters that frame the solution for the MST problems. We characterize these key drivers of volume allocation in the slow mode as follows: (i) the unit transportation cost savings of the slow mode compared to the fast mode and (ii) the volatility of the stochastic demand. This appears counterintuitive to many supply chain managers' beliefs: they often assume that the size of this fixed volume should not exceed the lower bound of the demand over the entire period when committing a constant volume in the slow mode in the long run. The presumption is that the volume that is delivered in the slow mode should always be consumed before the next slow mode delivery arrives. This is a major disadvantage of the practitioners who only treat MST as a pure transportation problem.

Further insights from the numerical study reveal that for typical fast-moving products with high expected demand and low demand variability (Relph and Milner, 2015), the optimal volume allocated to the slow mode could be as high as 85%

of the expected demand. This surprisingly high ratio supports our findings and indicates that a holistic approach to jointly decide on inventory and transportation mode is essential.

The remainder of this chapter is organized as follows. In Section 3.2, we review the relevant literature. Next, we formulate the MST model in Section 3.3. In Section 3.4, we analyze the MST policy and derive approximate analytic solutions. In Section 3.5, we provide numerical results that highlight the error of our approximation and the potential volume split for both modes. We also present a model extension that considers volume-dependent transportation cost. In Section 3.6, we summarize our research and discuss further avenues of MST.

3.2 Relevant literature

Our research is built on two streams of literature: (i) the freight mode choice literature, which studies problems in a context similar to ours, and (ii) the dual-sourcing literature, which studies a different sourcing model with multiple suppliers but has a similar mathematical structure as ours.

The freight mode choice literature analyzes the selection and usage of different transportation modes in certain freight corridors or networks. It can be characterized in two categories: freight mode choice with multimodal transportation, which focuses on the trade-off of the characteristics of different transportation modes, e.g., cost, capacity, and lead time, and decides on how to simultaneously use them in a given freight network, and freight mode choice of alternative single transportation mode, which studies the trade-off between inventory and transportation costs and proposes alternative decisions in fast or slow mode.

Studies involving multimodal transportation generally focus on transportation issues only and disregard stochastic inventory decisions. For example, Verma and Verter (2010) study how to choose between road and rail transportation modes in a certain transportation network by minimizing the total transportation costs of the two modes and subject to a set of pre-specified lead time constraints. Interested readers are referred to Bontekoning et al. (2004), Crainic and Kim (2007), and most recently, SteadieSeifi et al. (2014), for an extend literature review.

Studies that incorporate inventory decisions focus mainly on alternative single transportation modes. Baumol and Vinod (1970) are one of the first to raise the idea that the transportation mode choice needs to be made with inventory considerations. They develop a so-called “inventory-theoretic” model, and illustrate that a change in usage from a fast to a slow transportation mode will theoretically increase a company's inventory costs. Larson (1988) studies the same model and determines the optimal delivery quantity by minimizing the joint cost of transportation and inventory. Speranza and Ukovich (1994) consider how to minimize the sum of transportation and inventory costs in a multi-product setting with the freight mode choice between full and partial truckload. They find that when multiple products are consolidated, companies might take advantage of economies of scale and change from partial truckload to full truckload. Kutanoglu and Lohiya (2008) study a model with freight mode choice, inventory decisions, and service-level constraints with the objective of minimizing total inventory and transportation costs. They find that this problem is an NP-hard problem and develop feasible heuristics. They show that the company can save total costs by making alternative decisions in fast, medium, and slow modes. Lloret–Battle and Combes (2013) empirically examine companies' freight mode choice decisions based on a French shipper survey dataset including more than $10,000$ shipments, and they find that by incorporating inventory costs, companies improve their decisions in freight mode choice.

Our research differs from this stream of literature by studying a freight transportation problem with a simultaneous use of two modes (multimodal) and incorporating inventory decisions with stochastic demand. We consider a model that minimizes the long-run average total costs, including transportation cost, inventory holding, and backorder cost under stochastic demand, by jointly making decisions on the inventory policy and optimal split between the two transportation modes. This setting is mathematically similar to the classical dual-sourcing inventory model, where a company simultaneously orders from two sources (e.g., suppliers) in which one source provides a cheaper product with a longer lead time and the other source offers a higher price but with a shorter lead time. Previous studies in this field are numerous.

The first dual-sourcing model dates back to Barankin (1961), who analyzes this problem in a single-period case. Whittemore and Saunders (1977) find that the optimal policy is complex and that analytic solutions can only be found when the lead time difference is one. A detailed review of dual-sourcing is summarized by Minner (2003). Recent dual-sourcing research mainly focuses on approximations or heuristics of practical policies, e.g., the dual index policy (DIP) and tailored base-surge (TBS) policy. In both policies, a special phenomenon of "overshoot" is observed, which leads to a complication of the problems. An overshoot occurs when the inventory position exceeds the base stock levels. DIP policies allow both sources to replenish following base stock policies and typically obtain overshoots via simulations. We refer to Veeraraghavan and Scheller–Wolf (2008), Sheopuri et al. (2010), Arts et al. (2011), and Arts and Kiesmüller (2013).

In the TBS model, a company periodically orders a fixed quantity from the cheap but slow source, whereas the fast but expensive source orders follow a base stock policy. Janssen and de Kok (1999) study a similar policy by modeling the inventory system in a GI/G/1 queue. They solve the model using simulations. Allon and Van Mieghem (2010) optimize the TBS analytically and find that "the economic optimization naturally brings the system into a parameter regime called heavy traffic", where the GI/G/1 queue is always busy with waiting customers. This key finding allows for the utilization of Kingman's bound (Kingman, 1970) in heavy traffic analysis and further obtains an approximate analytic solution of the "base" volume. Klosterhalfen et al. (2011) use the term "constant order policy" rather than TBS to describe the same inventory control policy. They compare the policy with DIP numerically and find that either can outperform the other under some parameter settings. Boute and Van Mieghem (2015) make use of linear control theory for analytic solutions without relying on heavy traffic analysis. They find that TBS and other dual-sourcing policies smooth orders when capacity cost, inflexibility, or longer lead time difference is considered. Janakiraman et al. (2014) analyze TBS in a discrete-time model and approximate the "base" volume in a closed form by using an upper bound for the cost function. They further numerically examine the accuracy of their approximation with different parameter settings.

Our study differs from the existing dual-sourcing literature by incorporating different delivery frequencies of the two sources/modes. Our model reflects the practical characteristics that in the transportation world, trains or barges deliver less frequently than trucks. To the best of our knowledge, our model is the first dual-sourcing model that considers different delivery frequencies of the two modes/sources.

3.3 Model formulation

In this section, we formulate the model that is used for our analysis. The notation is summarized in Table 3.1.

We consider a distribution center D of a company that periodically orders from its manufacturing plant P with unlimited capacity. The demand per period at D is denoted by the random variable ξ and is independently and identically

Table 3.1: *A list of the parameters in the model.*

ξ	Demand per period (an i.i.d random variable)
μ	Mean of ξ
σ	Standard deviation of ξ
$\Phi(\cdot)/\phi(\cdot)$	CDF/PDF of ξ
c^s	Shipment cost per unit of the slow mode
c^f	Shipment cost per unit of the fast mode
Δ	Cost savings per unit of the modal shift, $\Delta = c^f - c^s$
h	Holding cost per unit per period
b	Penalty cost per unit per period
$S^{\mathcal{B}}$	Optimal base stock level when only the fast mode is utilized
t	Index of time, $t = 1, 2, ...T$
i	Index of period in a steady state cycle, $i = 1, 2$
$\mathcal{B}$	Symbol of the optimal base stock policy with fast mode only
$\mathcal{D}$	Symbol of the model split policy with both modes
$C^{\mathcal{B}}$	Expected total cost of two periods (a cycle) following policy $\mathcal{B}$
$C^{\mathcal{D}}$	Expected total cost of two periods (a cycle) following policy $\mathcal{D}$
Π	Cost savings of policy $\mathcal{D}$ over $\mathcal{B}$, i.e., $\Pi = C^{\mathcal{B}} - C^{\mathcal{D}}$
O_t	Overshoot in period t
$O_{\infty,i}$	Steady state overshoot in period i of a cycle
L	Expected mismatch cost
q	Fixed delivery quantity of slow mode in each cycle (decision variable)
S_i	Base stock level in period i of a steady state cycle (decision variable)

distributed (i.i.d.) with mean μ and standard deviation σ. The cumulative distribution function (CDF) and probability density function (PDF) of ξ are $\Phi(\cdot)$ and $\phi(\cdot)$ respectively.

We consider a baseline model in which every period D places an order at P and ships this order via the *fast mode* at a unit delivery cost c^f. The plant P has sufficient capacity to fulfill every order with an overnight shipment, which implies a zero lead time with the fast mode transportation. The inventory level at the end of each period is charged a holding cost of h per unit, and any unmet demand is backlogged at a unit cost of b. Furthermore, we assume that $b > c^f$, indicating that a pure accumulation of backorders without any deliveries is not the optimal solution. The distribution center needs to decide on the order/delivery quantities that minimize the expected total cost in transportation and inventory mismatch.

It is already proven by Karlin (1960) that a base stock policy with an order-up-to level of $S^B = \Phi^{-1}\left(\frac{b}{b+h}\right)$ is optimal for such a system. We denote the optimal fast-mode-only policy as baseline policy $\mathcal{B}$. The expected total cost for a cycle of two periods is then

$$C^{\mathcal{B}} = 2(c^f\mu + L(S^B)), \tag{3.1}$$

where $2c^f\mu$ represents the expected transportation cost and $2L(S^B)$ represents the expected inventory mismatch cost for the two periods of the cycle with $L(S^B) = h\int_0^{S^B}(S^B - \xi)\phi(\xi)d\xi + b\int_{S^B}^{\infty}(\xi - S^B)\phi(\xi)d\xi$. Note that $C^{\mathcal{B}}$ remains constant in the baseline model.

Given that an additional slow mode option exists, companies wants to implement a *modal split transportation (MST)* policy (denoted as $\mathcal{D}$) in the following way: the company has an offer from a *logistics service provider (LSP)* to regularly ship a constant quantity of q items via the *slow mode* at a unit delivery cost c^s with a cost savings $\Delta = c^f - c^s > 0$ per unit shipped. The parameter c^s includes transportation cost and all other incremental costs associated with slow mode shipment, e.g., higher working capital costs for additional in-transit inventories or higher handling costs. Although the slow mode has a lower total landed unit cost, it is not available every period and only operates at a lower delivery frequency. Whereas the fast mode can be used every period, we assume that the slow mode is only available every other period. We define the time interval between two consecutive slow mode shipments as a delivery *cycle*. The slow mode shipment can be viewed as a form of a *commitment* for the company in a way that every other period, the company ships a constant quantity of q units from P to D via the slow mode. Because a constant q is shipped and also received at a fixed delivery frequency, the lead time of the slow mode can be neglected. In addition to the slow mode shipments, D can still place flexible orders via the fast mode in every period following a base stock policy. The company's objective is to determine the optimal slow mode quantity and the optimal base stock policy to minimize the expected total costs, consisting of the expected transportation cost (slow mode and fast mode) and inventory mismatch cost. The difference in terms of the fast-mode-only policy is that we have to consider the expected cost during a cycle because the two periods within a cycle are not identical.

The aforementioned problem is structurally similar to the TBS policy in the dual-sourcing literature (see, e.g., Janssen and de Kok, 1999; Allon and Van Mieghem, 2010; Klosterhalfen et al., 2011; Janakiraman et al., 2014). The TBS policy is specified by two parameters: a constant order quantity q that is placed with a cheap supplier with a long lead time (comparable to our slow mode) and a base stock level S that determines the flexible order policy from a more expensive supplier with a lower lead time (comparable to our fast mode). In all the TBS models discussed thus far, the order frequencies of the two source modes are assumed to be identical, i.e., the fast mode and the slow mode are available every period, which is not the case in our problem. In the MST problem, the slow mode deliveries are available less frequently compared to the fast mode. Therefore, we cannot simply minimize the expected cost per period but have to consider a cycle structure where for every period in that cycle, the base stock levels for using the fast mode could be different. In the following, the index i denotes the period of a cycle, i.e., $i = 1$ is the first period of the cycle where the slow mode delivery arrives, and $i = 2$ defines the second period of a cycle where only the fast mode ordering is available. With an ongoing numbering, every "odd" period is a period with a slow mode delivery, while in every "even" period, only the fast mode is available. Since fast mode orders are available every period following a base stock policy, we denote $S_i, i \in \{1, 2\}$ as the base stock levels in period i of a steady state cycle. Thus, our MST policy is addressed by three parameters: q, S_1, and S_2.

Similar to the classical TBS policy, a special phenomenon of our MST policy is the *overshoot*. The overshoot in an inventory system is defined as the amount by which the inventory position exceeds the base stock levels (Allon and Van Mieghem, 2010). We use O_t, $(t = 1, 2, ..., \infty)$, to denote the overshoot in t, which describes a stochastic process. It is well known that in an inventory system following a base stock policy, orders are placed to bring the current inventory positions up to the predefined base stock levels. This is why a base stock policy is also called an "order-up-to" policy. In an MST system, however, a constant quantity q is cyclically pushed into the system regardless of the levels of the inventory positions and might shoot the inventory position "over" the base stock levels. Figure 3.1 shows an example of how overshoots behave depending on the pre-assumed q, S_1, S_2, and the starting inventory I_1 in period 1. In periods 1 and 2, orders are placed in the fast mode, $z_1 > 0, z_2 > 0$, to bring the inventory positions up to S_1 and S_2, respectively, which is similar to the situation in the baseline models. However, in period 3, the arrival of q shoots the inventory position over S_1, and overshoot $O_3 > 0$ is observed. Although q only arrives in the odd periods, it might also indirectly drive the overshoot in the even periods, as shown in period 4 of the example. Still, the overshoots in odd and even periods are structurally different from each other because q only arrives in the odd periods and its impact on the even periods is indirect.

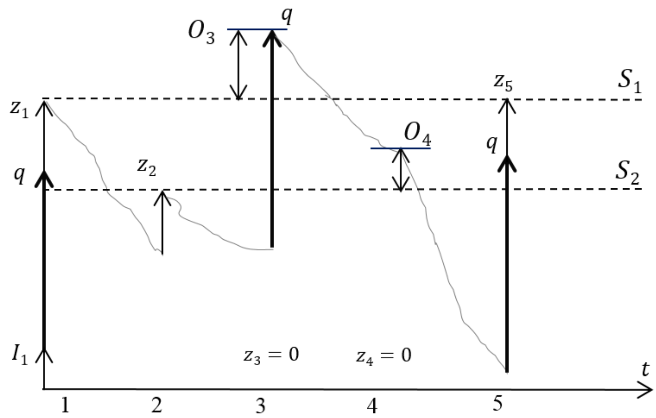

Figure 3.1: *An example of the overshoots*

If t is an odd period (i.e., period $t = 1, 3, 5, ...$), then the inventory position at the end of this period can be written as a function of O_t, $S_1 + O_t - \xi$; if t is an even period (i.e., period $t = 2, 4, 6, ...$), then the inventory position at the end of t is $S_2 + O_t - \xi$. Therefore, the overshoot in period $t + 1$, O_{t+1}, is the excessive amount (if any) over S_2 (when t is odd) or S_1 (when t is even) and can be recursively written as:

$$O_{t+1} = \begin{cases} (O_t + S_1 - \xi - S_2)^+ & \text{when } t \text{ is odd,} \\ (O_t + S_2 + q - \xi - S_1)^+ & \text{when } t \text{ is even,} \end{cases} \tag{3.2}$$

where $()^+$ denotes the positive part of a real number. As a comparison, the classical TBS policy from the dual-sourcing literature does not consider different delivery frequencies of the two modes, and it therefore only optimizes a single base stock level. Consequently, the recursion of the overshoot in a TBS policy has a simpler form as described in (1) of Janakiraman et al. (2014), and its calculation should be reasonably easier compared to the overshoot in our MST problem.

We assume that $q < 2\mu$, indicating that the supply from the slow mode should not exceed the expected demand[2]. Because the company will adjust fast mode deliveries based on overshoots, it will not accumulate overshoots infinitely,

[2] If $q > 2\mu$, the system diverges with infinite inventory because there is more supply than demand. If $q = 2\mu$, the system is in the state of "unstable equilibrium", where any deviation from the uncertainty of random demand will bring the system into a state of chaos.

and the magnitudes of the overshoots are therefore bounded. Denote $O_{\infty,1}$ and $O_{\infty,2}$ as the overshoots in periods one and two of a steady state cycle, and both $E[O_{\infty,1}]$ and $E[O_{\infty,2}]$ are hence non-negative and finite. Let i denote the index of the period within a cycle, i.e., $i = 1$ is the first period of the cycle where the slow mode delivery arrives and $i = 2$ is the second period of the cycle with fast mode order only. In period i, $i \in \{1, 2\}$ of the steady state cycle, the expected inventory position before demand realization is $S_i + E[O_{\infty,i}]$. Note that because of the overshoots, the expected inventory positions are "over" S_i. Given the stochastic demand ξ, the expected mismatch cost L_i is:

$$L_i(S_i + E[O_{\infty,i}]) = hE\left[(S_i + E[O_{\infty,i}] - \xi)^+\right] + bE\left[(\xi - S_i - E[O_{\infty,i}])^+\right]. \quad (3.3)$$

The company aims to find the optimal combination of (q^*, S_1^*, S_2^*) to minimize the total expected cost of a steady state cycle, formalized as:

$$C^{\mathcal{D}} = c^s q + c^f(2\mu - q) + \sum_{i=1}^{2} L_i(S_i + E[O_{\infty,i}]), \quad (3.4)$$

where $c^s q$ is the (expected) transportation cost via the slow mode, $c^f(2\mu - q)$ is the expected transportation cost via the fast mode, and $\sum_{i=1}^{2} L_i(S_i + E[O_{\infty,i}])$ is the expected total mismatch cost over the entire cycle. Comparing the cost savings of the MST policy to the baseline policy, i.e., $\Pi = C^{\mathcal{B}} - C^{\mathcal{D}}$, optimizing the MST policy is equivalent to maximizing the cost savings:

$$\Pi = C^{\mathcal{B}} - C^{\mathcal{D}} = \Delta q + 2L(S^B) - \sum_{i=1}^{2} L_i(S_i + E[O_{\infty,i}]). \quad (3.5)$$

Equation (3.5) captures the trade-off of the MST problem: Δq is the transportation cost savings from the slow mode, and $2L(S^B) - \sum_{i=1}^{2} L_i(S_i + E[O_{\infty,i}])$ is the expected net effect from the inventory cost. The holistic supply chain is optimized by trading off transportation and inventory decisions.

3.4 Model analysis

The difficulty in the model analysis lies in finding analytic expressions for the stationary expected overshoot $E[O_{\infty,i}]$ for $i = 1, 2$. Analyzing the overshoot is already challenging in the classical TBS policy where slow mode and fast mode orders have the same delivery frequency. Janssen and de Kok (1999) use an approximation based on the equivalence of the overshoot to the waiting time in a GI/G/1 queuing model. Allon and Van Mieghem (2010) evaluate the system using a GI/G/1 queue and find that the optimization of the TBS policy naturally brings the queue into a “heavy traffic” state, where the slow mode is heavily utilized (q close to its upper bound μ). The authors further show that analytic closed-form expressions are not tractable. To solve the problem, the authors perform an asymptotic analysis and use one of Kingman’s bounds (Kingman, 1970) to bound the expected steady state overshoot. Klosterhalfen et al. (2011) pursue an exact approach by modeling the overshoot as a Markov chain with an infinite state space. Boute and Van Mieghem (2015) state that the evaluation of a GI/G/1 queue in TBS is required; otherwise, a simulation analysis needs to be used. Janakiraman et al. (2014) also use Kingman’s bound to bound the expected steady state overshoot and thus the average cost per period to analyze the effectiveness of the best TBS policy relative to the optimal policy over all feasible policies. To the best of our knowledge, the heavy traffic analysis is currently the only method mentioned in the literature for approximating and characterizing an exact TBS analysis.

As a generalized TBS problem, the MST system unfortunately cannot guarantee the heavy traffic phenomenon. First, because the slow mode delivery q arrives only once every two periods due to the different delivery frequencies, it may induce a “cycle inventory”, i.e., inventory that is stocked to exploit lower transportation costs at the beginning of the first period. It is difficult to analytically distinguish between the cycle stock and overshoot. Second, the steady state overshoot in the even periods is structurally different from the overshoot in odd periods and thus requires different treatments. Third, if the transportation cost savings Δ are much smaller than the additional holding cost h, the company tends to commit a smaller q for the slow mode to reduce the overshoot risk in the second period in (3.2) and the consequential inventory holding cost in (3.5); therefore, a slow mode cannot be heavily utilized. From a practical perspective, a small Δ is not a rare event. Many sites do not have a direct connection with trains or barges and thus require a multimodal transportation mode, e.g., truck-train-truck, which requires additional costs for extra handling, waiting, and detour, among others, and offsets or sometimes even outweigh the cost savings from the utilization of a slow mode. Macharis et al. (2010) support this observation based on academic research. Therefore, a new methodology is required to characterize the generalized TBS problem.

3.4.1 Deterministic demand

We first restrict our attention to MST under deterministic demand, i.e., $\sigma = 0$, and capture the trade-off effects. The optimal solution clearly has a bang-bang structure. If the savings by using slow mode transportation cost are greater than the additional holding cost during a cycle, i.e., $\Delta > h$, then the company ships the demand of both periods via the slow mode, i.e., $q^* = 2\mu$. The consequence is an additional holding cost for an inventory level of μ at the end of the first period (cycle inventory). If the transportation cost savings are less than the additional holding cost, i.e., $\Delta < h$, then the company only ships the demand of the first period via the slow mode, i.e., $q^* = \mu$, and the fast mode shipment at the beginning of the second period equals the demand of the second period μ. If $\Delta = h$, the company is indifferent in terms of the two options. Figure 3.2 illustrates the optimal slow mode order q^* and the profit Π^*. The question arises as to how q^* changes when the demand is stochastic and additional inventory is required to buffer uncertainty.

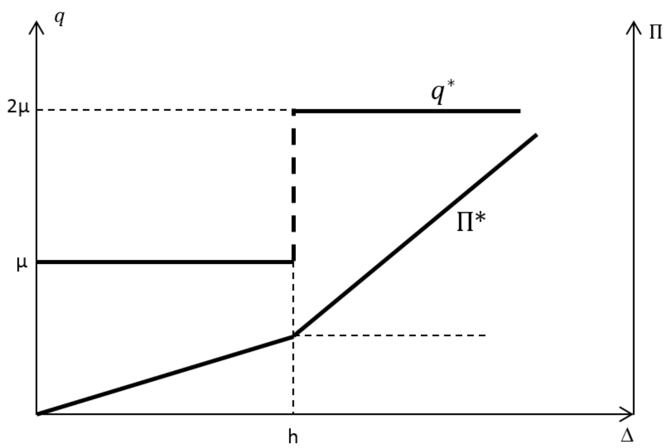

Figure 3.2: q^* *and* Π^* *for deterministic demand*

An additional insight from the deterministic case is that the profit function is not continuously differentiable in the decision variable q, which needs to be considered in the stochastic case when $\sigma \longrightarrow 0$.

3.4.2 Stochastic demand

When demand is stochastic, i.e., $\sigma > 0$, there is an additional uncertainty of not meeting the demand in a period. Hence, inventory at the end of a period can have two functions: (i) it may serve as safety stock to buffer against demand uncertainty, and (ii) it serves as cycle stock to exploit lower transportation cost from the slow mode, which runs every other period. We will utilize the results of the deterministic case to solve the stochastic version of the problem. For the solution, we distinguish three scenarios A, B, and C that differ based on the relationship between h and Δ.

Scenario A: $\Delta > h$

If $\Delta > h$, i.e., the unit savings in the transportation cost from the slow mode are higher than the unit holding cost per period. Intuitively, the company is inclined to commit to a larger q shipped via the slow mode. “Large” here means that after the delivery of q, the inventory on hand is expected to satisfy not only the demand in the first period but also part[3] of the demand in the second period of the cycle despite extra inventory holding costs at the end of the first period. Hence, the probability of using the fast mode transportation and/or running out of stock at the end of the first period of a cycle tends to be zero. Consequently, we eliminate the decision variable S_1 and assume no fast mode ordering in period one. We replace the expected mismatch cost at the end of the first period by $h\,(S_2 + E[O_{\infty,2}] + q - 2\mu)$ (no backorders occur at the end of the first period). The expected mismatch cost at the end of the first period is approximated as $L_1(S_1 + E[O_{\infty,1}]) = h(I_1 + q - \mu)$, where I_1 is the expected starting inventory in period one and $I_1 = S_2 + E[O_{\infty,2}] - \mu$. Thus, the cost savings of $C^{\mathcal{D}}$ over $C^{\mathcal{B}^*}$, derived from (3.5), can be approximated as:

$$\hat{\Pi} = \Delta q + 2L(S^B) - h\,(S_2 + E[O_{\infty,2}] + q - 2\mu) - L_2\,(S_2 + E[O_{\infty,2}])\,, \qquad (3.6)$$

and the long-run policy can be reduced to two decision variables, q and S_2.

Because we do not consider fast mode ordering in the first period and thus no S_1 and $E[O_{\infty,1}]$, S_2 only depends on the slow mode quantity q, such that $S_2(q)$

[3] The constant delivery quantity q via the slow mode is not expected to satisfy the demand in both periods, i.e., $q < 2\mu$. If $q > 2\mu$, the system diverges because there is more supply than demand; if $q = 2\mu$, the system is in the state of “unstable equilibrium”, where any deviation from the uncertainty of random demand will bring the system into a state of chaos.

is the solution to the newsvendor formula of $\frac{dL_2(S_2+E[O_{\infty,2}])}{dS_2} = 0$, which yields:

$$S_2 = \Phi^{-1}\left(\frac{b}{b+h}\right) - E[O_{\infty,2}], \tag{3.7}$$

where $E[O_{\infty,2}]$ is a function of q. Modeling the cyclic inventory system as a GI/D/1 queue, we can show that the expected overshoot $E[O_{\infty,2}]$ does not depend on S_2 and can be approximated with Proposition 3.4.1 (the proofs of all propositions can be found in the appendix).

Proposition 3.4.1. *The expected overshoot in the second period of a steady state cycle is independent of the base stock level S_2 and can be bounded by:*

$$E[O_{\infty,2}] \leqslant \frac{\sigma^2}{2\mu - q}. \tag{3.8}$$

To determine the optimal slow mode level q, we use the upper bound approximation by Janakiraman et al. (2014): For any (x, y) for which $y \geqslant 0$, it follows that $(x+y)^+ \leqslant x^+ + y$ and $(x+y)^- \leqslant x^-$. Therefore, we obtain an upper bound for the expected mismatch cost of the second period as $L_2(S_2+E[O_{\infty,2}]) = hE\left[(S_2 + E[O_{\infty,2}] - \xi)^+\right] + bE\left[(S_2 + E[O_{\infty,2}] - \xi)^-\right] \leqslant hE\left[(S_2 - \xi)^+\right] + hE[O_{\infty,2}] + bE\left[(S_2 - \xi)^-\right] = L_2(S_2) + hE[O_{\infty,2}]$, which implies a lower bound for the cost savings as follows:

$$\begin{aligned} \hat{\Pi} \geq\ & \Delta q + 2L(S^B) - h\left(S_2 + q - 2\mu\right) - 2hE[O_{\infty,2}] \\ & - hE\left(S_2 - \xi\right)^+ - bE\left(S_2 - \xi\right)^- . \end{aligned} \tag{3.9}$$

Taking the first-order derivative of this lower bound with respect to (w.r.t.) q, we obtain $\Delta - h - 2h\frac{\partial E[O_{\infty,2}]}{\partial q} = 0$ with $\frac{\partial E[O_{\infty,2}]}{\partial q} = \frac{\sigma^2}{(2\mu-q)^2}$. Thus, the approximate optimal slow mode shipment $\hat{q}$ is:

$$\hat{q} = 2\mu - \sigma\sqrt{\frac{2h}{\Delta - h}}, \tag{3.10}$$

and in combination with (3.7), we obtain the approximate optimal base stock level:

$$\hat{S}_2 = \Phi^{-1}\left(\frac{b}{b+h}\right) - \sigma\sqrt{\frac{\Delta - h}{2h}}. \tag{3.11}$$

The slow mode is advantageous in terms of cost savings. When the cost difference Δ increases, it is intuitively beneficial to ship more volume in the slow mode. The disadvantage of the slow mode is a lack of flexibility due to operational constraints. When the demand is more volatile, the company needs to decrease the share in the slow mode to tackle the flexibility of the fast mode. This explains why $\hat{q}$ decreases in σ, as shown by (3.10).

Practitioners tend to believe that if they must commit a constant slow mode volume over a long period, this size of the volume should not exceed the lower bound of the demand during the cycle. Otherwise, the slow mode will not be fully loaded, and consequently, penalties might occur. Because demand is stochastic, the lower bound over a period could be rather small and approach zero. Our finding in (3.10) reveals that the size of the commitment in the slow mode is actually independent of the lower bound of demand, and it could surprisingly take a larger value close to 2μ.

We find that the base stock level in even periods $\hat{S}_2$ is less than that of the baseline model S^B. When managers already know that in the next period a constant quantity of q will be committed to arrive, they would order fewer units in the current period to maintain a relatively lower inventory level compared to the baseline model. $\hat{S}_2$ decreases in Δ, indicating an increasing effect when the slow mode is economically more attractive. The disadvantage of this approximation is that when Δ approaches h from the right side, $\hat{q}$ drops to $-\infty$ in (3.10). Later in the chapter, we provide a lower bound of $\hat{q}$ for this scenario to prevent this divergence and denote this as Scenario C.

Scenario B: $\Delta < h$

If $\Delta < h$, i.e., the marginal savings in transportation cost from using the slow mode are lower than the unit holding cost per period, the company is inclined to commit to a lower q shipped via the slow mode. By this logic, it is more likely that the fast mode order will be utilized in the second period of the cycle, diminishing the occurrence of an overshoot. We approximate this scenario by eliminating the overshoot at the beginning of the second period of the cycle. Therefore, the expected cyclic cost function can be approximated as $C^{\mathcal{D}} = c^s q + c^f(2\mu - q) + L_1(S_1 + E[O_{\infty,1}]) + L_2(S_2)$, and the cost savings function of (3.5) is estimated as:

$$\hat{\Pi} = \Delta q + \ 2L(S^B) - L_1(S_1 + E[O_{\infty,1}]) - L_2(S_2). \tag{3.12}$$

By assuming no overshoot in the second period, the expected overshoot in the first period can be approximated as:

$$E[\hat{O}_{\infty,1}] = E[S_2 + q - S_1 - \xi]^+ = \int_0^{S_2+q-S_1} (S_2 + q - S_1 - \xi)\phi(\xi)d\xi, \quad (3.13)$$

i.e., the non-negative expected difference of the inventory position of the first period ($I_1 = S_2 - \xi + q$) and the base stock level S_1. Plugging (3.13) into (3.12) and taking the first-order condition of $\hat{\Pi}$ with respect to q, S_1 and S_2 separately, we derive the approximated expressions of $(\hat{q}, \hat{S}_1, \hat{S}_2)$. The result of Scenario B is concluded using the following proposition:

Proposition 3.4.2. *When $\Delta < h$, the optimal decision variables of the MST policy can be approximated as:*

$$\begin{cases} \hat{S}_1 = \Phi^{-1}\left(\dfrac{b+\Delta}{b+h}\right), \\ \hat{S}_2 = \Phi^{-1}\left(\dfrac{b-\Delta}{b+h}\right), \\ \hat{q} = \Phi^{-1}\left(\dfrac{b+\Delta}{b+h}\right) - \Phi^{-1}\left(\dfrac{b-\Delta}{b+h}\right) + \Phi^{-1}\left(\dfrac{\Delta}{h}\right). \end{cases} \quad (3.14)$$

Similar to Scenario A, $\hat{q}$ increases in Δ, indicating a positive relationship between cost savings and the utilization of the slow mode. Moreover, a decrease of $\hat{S}_2$ in Δ is also consistent with the results from Scenario A. Similar to the situation of Scenario A, the approximation deteriorates when Δ is close to h. Specifically, when Δ approaches h from the left side, $\hat{q}$ spikes to ∞ in (3.14). Therefore, we next provide an upper bound of $\hat{q}$ for Scenario B based on Scenario C.

Scenario C: $\Delta = h$ and revised Scenarios A' and B'

The previous methods in Scenarios A and B rely on the trade-off of commitment and cycle stock effects. By comparing their relative sizes, two different approximations, based on eliminating expected overshoot terms, are implemented, and the analytic expressions are obtained. When $\Delta = h$, both effects break even, and none of the analytic expressions in Scenarios A or B provide an answer at this point. A separate method is required for Scenario C. Furthermore, the results of the previous two scenarios already deteriorate when Δ approaches h from either the left or right side. Accordingly, we revise the range over which the expressions from A and B are applied and refer to Scenarios A' and B'. Figure 3.3 shows an example of this divergence, where as Δ approaches h, i.e., the ratio Δ over h approaches one, the approximation error tends toward infinity.

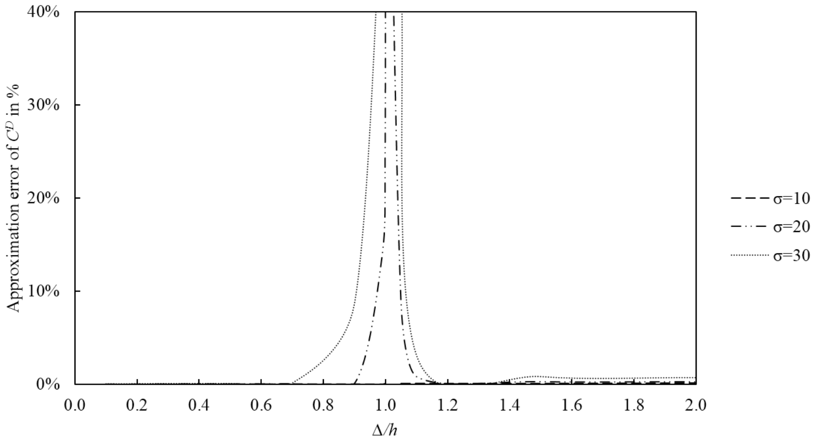

Figure 3.3: *The approximation error of $C^{\mathcal{D}}$ in %*

Additionally, when σ increases, the company needs to cope with the increased volatile demand with more flexibility in transportation decisions. This requires a higher utilization of the fast mode. However, the approximation in Scenario A forbids the utilization of the fast mode in the first period, and this leads to a larger approximation error in σ. A more volatile demand ξ increases the chance of overshoot, as indicated in the overshoot recursion function (3.2). Ignoring overshoot in period two therefore gives rise to more error in the approximation, as described in Scenario B. This explains the increase in approximation error for this scenario when σ increases. The results obtained from Scenario C are then used as a correction for Scenarios A and B to improve the approximation accuracy in this region.

Managerially, $\Delta = h$ is a break–even point at which managers are indifferent in terms of choosing the solutions from either Scenario A or B. Comparing (3.10) and (3.14), only the approximation of S_2 is tractable. We take $\hat{S}_2 = \Phi^{-1}\left(\frac{b-\Delta}{b+h}\right)$ from (3.14) of Scenario B. (Note that the solution from Scenario A, i.e., $\hat{S}_2 = \Phi^{-1}\left(\frac{b}{b+h}\right)$ from (3.10), can also be applied, and it offers a similar accuracy in our numerical tests.) The base stock level obtained in Scenario B is slightly smaller than that in Scenario A because in Scenario B, the overshoot term $O_{\infty,2}$ is assumed to be zero. If overshoot is not eliminated, the order-up-to level in period two should be $S_2 + O_{\infty,2}$. The advantage of using the result from Scenario B is that in this Scenario, $O_{\infty,2}$ can be assumed to be zero.

An indifferent choice of S_1 is also expected. In other words, whether or not we order via the fast mode in the first period does not affect the expected cost of the modal split policy. We use $\hat{S}_1 = \hat{S}_2$ for the following reason: a free choice of $\hat{S}_1$ also indicates the independence of the overshoot $O_{\infty,1}$ with respect to $\hat{S}_1$ or $\hat{S}_2$. The set of $\hat{S}_1 = \hat{S}_2$ eliminates this dependency in the definition of $O_{\infty,1}$ in (3.2), where the overshoot is shown to be a function of the difference between two base stock levels. Given $\hat{S}_1$ and $\hat{S}_2$, we further obtain $\hat{q}$ as follows.

In the deterministic case, regardless of the value that q^* takes in the range of $[\mu, 2\mu]$, the value of the objective function remains the same because both commitment and cycle stock effect break even. q^* cannot be any value outside of this range: if q is smaller than μ, an extra backorder cost exists at the end of period one; if q is larger than 2μ, an extra spending on holding cost at the end of period two is expected. When the demand is stochastic, these two costs are brought into the system with certain probabilities. We denote the sum of these two costs $\bar{C}$, and q is set to minimize these costs. Denote $\hat{I}_1$ as the expected starting inventory position at the beginning of a steady state cycle, where $\hat{I}_1 = \hat{S}_2 - \mu$,

$$\bar{C}(q) = b \int_{\hat{I}_1+q}^{\infty} (\xi - \hat{I}_1 - q)\phi_\xi(\xi)d\xi + h \int_0^{\hat{I}_1+q} (\hat{I}_1 + q - \eta)\phi_\eta(\eta)d\eta, \qquad (3.15)$$

where $\eta = 2\xi$ denotes the accumulated demand in the steady state cycle with two periods, ϕ_η is the pdf of η, and ϕ_ξ is the pdf of ξ. By taking the first-order condition of $\bar{C}$ with respect to q, the optimal volume in the slow mode $\hat{q}$ can be approximated by solving the following transcendental equation:

$$h\Phi_\eta\left(\hat{S}_2 - \mu + \hat{q}\right) + b\Phi_\xi\left(\hat{S}_2 - \mu + \hat{q}\right) = b. \qquad (3.16)$$

In summary, the result of Scenario C is:

$$\begin{cases} \hat{S}_1 = \Phi^{-1}\left(\dfrac{b-h}{b+h}\right), \\ \hat{S}_2 = \Phi^{-1}\left(\dfrac{b-h}{b+h}\right), \\ h\Phi_\eta\left(\hat{S}_2 - \mu + \hat{q}\right) + b\Phi_\xi\left(\hat{S}_2 - \mu + \hat{q}\right) = b. \end{cases} \qquad (3.17)$$

The policy in (3.17) can further be used as an alternative result for Scenarios

A and B when the analytic approximations deteriorate. Because $\hat{q}$ increases in Δ as shown in (3.10) and (3.14), $\hat{q}$ obtained from Scenario C can be set as the lower bound of Scenario A and upper bound of Scenario B (Figure 3.4), and therefore, the ill-measured $\hat{q}$ in the two Scenarios when Δ is close to h (the dotted line) is then discarded. This leads to revised ranges for Scenarios A and B, which we refer to as A' and B', as indicated in Figure 3.4. More specifically, we denote $\hat{q}^A$, $\hat{q}^B$, and $\hat{q}^C$ as the approximated q from Scenarios A', B' and C, respectively. If $\hat{q}^A < \hat{q}^C$, we then use (3.17) to replace the result from (3.10); if $\hat{q}^B > \hat{q}^C$, we use (3.17) to replace the result from (3.14). We set the range for Scenario C according to how we apply the bounded $\hat{q}^C$.

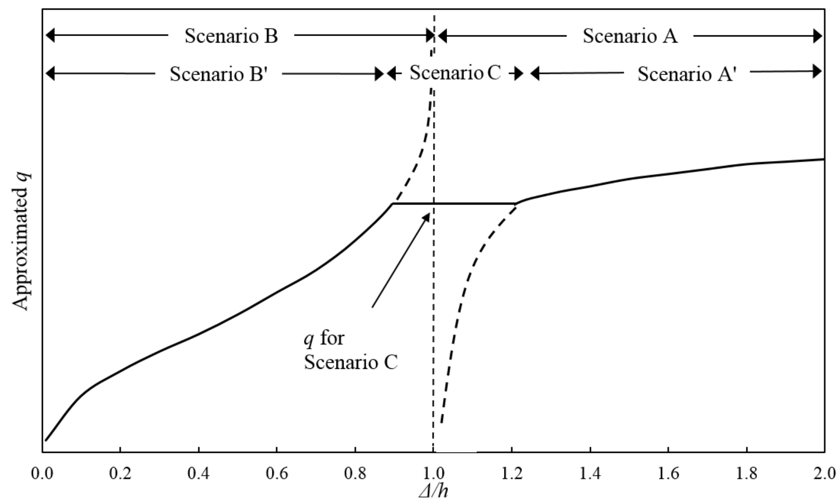

Figure 3.4: *Approximation of $\hat{q}^C$ and combined Scenarios A', B' and C*

3.5 Numerical analysis

In this section, we perform a numerical study to obtain further insights into the MST policy. Specifically, we analyze the approximation accuracy relative to the optimal solution. We therefore determine the optimal solution using a complete enumeration. In addition, we use various parameters to understand the expected modal split and the cost savings induced by the MST policy. We also show an analysis when the unit delivery cost of the fast mode c^f depends on its delivery quantity.

The following assumptions are used in this section. The distribution center serves a large region; thus, the accumulated demand from all customers is pooled and can be assumed to follow a gamma distribution. The mean of the demand is standardized to 100 units. A unit could be an item, a carton, or a pallet in practice. Three different standard deviation values, 10, 20, and 30, are separately tested. This type of demand with high mean and low variability is of particular interest for the company because it focuses on high volume products, which maximize the impact on the company's supply chain innovation projects. The gamma distribution with mean 100 and standard deviation 30 represents a typical fast-moving product. Recall that the objective of the numerical analysis is to understand the accuracy of the approximation, and the ratio of modal split, the exact magnitude of the demand does not affect the percentage findings.

The unit holding cost h is generally measured as a percentage of the product value and is endogenously fixed. It is normalized to 1 in the numerical analysis. The unit backorder cost b is used to indirectly secure the company's non-stockout probability (α-service level) at 95%, which gives by using the newsvendor ratio $\frac{b}{b+h}$ a backorder cost $b = 19$. The unit transportation cost saving of the slow mode over the fast mode, Δ, is an exogenous variable because it depends not only on the LSP's transportation cost offers but also on the packaging and loading method of the company. According to the company's experience and discarding the negative values it could take, Δ could be as high as 500% of h. A range of Δ/h from 0 to 5 is tested.

3.5.1 Approximation accuracy

To understand the quality of the approximations, we conduct three different analyses. Our solution in Scenario A' is built on the assumption that no fast mode is utilized in the first period of the steady state cycle. We validate this approximation by calculating the share of fast mode orders in period one as an expected percentage of the total demand during a cycle for the unconstrained model. Similarly, we examine the practicability of the approximation in Scenario B' by analyzing the expected percentage of overshoot over demand. Finally, we validate the overall accuracy of our MST solution against the optimal solution.

To understand the approximation in Scenario A (and A'), we test the expected ordering quantity via the fast mode in period one as a percentage of the expected cyclic demand 2μ. Figure 3.5 shows that the expected fast mode orders in period one decrease in Δ/h. The values in the region of $\Delta > h$ are all signifi-

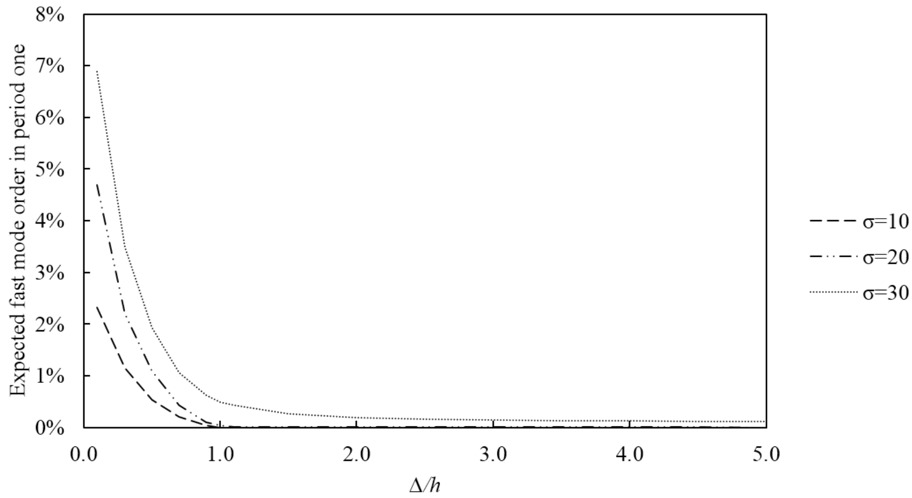

Figure 3.5: *Expected fast mode order in period one as a % of the total demand of a cycle*

cantly smaller than those in the region of $\Delta < h$. More specifically, for $\sigma = 10, 20$, fast mode ordering in the first period drops to zero for $\Delta < h$. Recall that the parameter regime $\Delta > h$ is our Scenario A, where we approximate the problem using a TBS model that assumes zero utilization of the fast mode. Accordingly, the approximation appears to be reasonable.

To understand the approximation in Scenario B (and B'), we numerically test the average overshoot in period two as a percentage of the expected cyclic demand 2μ. The results are shown in Figure 3.6. When $\Delta < h$, the curves are flat and close to zero. This behavior provides numerical support for our Scenario B, where we approximate the MST problem with a TBS policy that has zero overshoot in the second period. When $\Delta > h$, the curves increase substantially, and the overshoot values cannot be eliminated. This effect becomes stronger as σ increases.

To validate the overall accuracy of the tool outlined in Section 4.2.4, we calculate the percentage error in the average total cost per steady state cycle, i.e., $\%C^{\mathcal{D}} = \frac{C^{\mathcal{D}^*} - \hat{C}^{\mathcal{D}}}{C^{\mathcal{D}^*}}$. The optimal result $C^{\mathcal{D}^*}$ is calculated using a complete enumeration. The approximation errors are shown in Figure 3.7.

In general, our method provides a robust estimation. When $\Delta < h$, our approximated analytical expressions (3.14) in Scenario B provide very good results, and the approximation error is almost zero. When $\Delta > h$, the approximate result

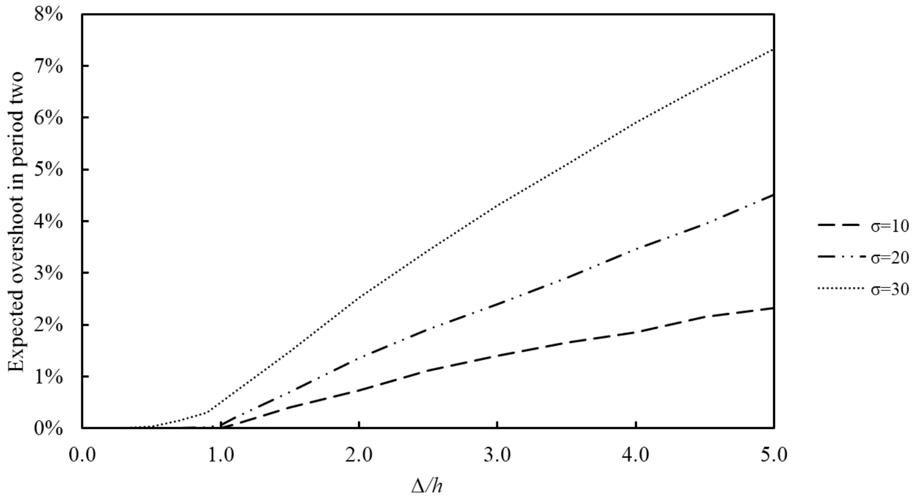

Figure 3.6: *Expected overshoot in period two as % of the total demand of a cycle*

in (3.10) is less accurate than that in Scenario B but still provides robust results with an approximation error less than 3%. We have to distinguish between two different types of errors in our overall solution: the approximation error when the TBS approach is implemented to solve MST problems and the endogenous error of the TBS policy itself. The first type of error is prominent around $\Delta = h$ under the assumption that the fast mode is not utilized in Scenario A and the overshoot is neglected in Scenario B. By introducing a separate solution in Scenario C, the error shown in Figure 3.3 is smoothed, as shown in Figure 3.7. The second type of error occurs when $\Delta > h$ and a TBS approach with heavy traffic analysis is applied. Allon and Van Mieghem (2010) and Janakiraman et al. (2014) observe this error in their TBS studies. They find that the error of the TBS policy increases when the cost difference between the two modes increases. Our solutions are aligned with their findings, showing an increase in error in Δ in Figure 3.7.

3.5.2 The results of the modal split transportation model

Next, we aim to obtain detailed insights into the results of the MST policy. We are particularly interested in the expected volume that is shipped in the slow mode at the optimum cost. This is particularly important as it provides an indication of the practical feasibility of the MST policy: the slow mode can only be organized for sufficiently large volumes. Next, we study the overall cost savings induced

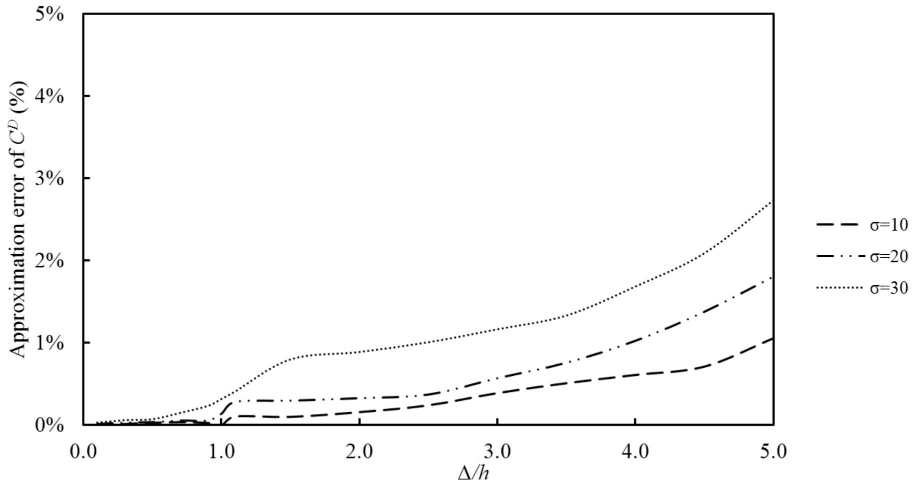

Figure 3.7: *The approximation error of $C^{\mathcal{D}}$ as a % compared to the optimal results*

by the MST policy. Finally, we would like to understand the expected volume shipped in the slow mode in case the company aims to implement the MST with the objective of zero cost savings. This case is important if a company aims to apply the slow mode in line with her sustainability agenda rather than for cost minimization.

Figure 3.8 shows the optimal slow mode volume expressed as a percentage of the mean demand per cycle. The solid line characterizes (as shown in Section 3.4.1) the deterministic benchmark scenario where either 50% of the cyclic demand (if $\Delta < h$) or 100% of the cyclic demand (if $\Delta > h$) is shipped via the slow mode.

When Δ increases, i.e., the slow mode shipment becomes cheaper, the expected optimal volume in the slow mode increases. Interestingly, the expected ratio in the slow mode is surprisingly high: for a typical SKU with $(\mu, \sigma) = (100, 30)$, even when the ratio of transportation cost savings to holding cost is rather low, i.e., $\Delta/h = 0.01$, approximately 22% of the expected transportation volume per cycle can be shifted to the slow mode; when $\Delta/h = 5$, this ratio increases to approximately 85%. These ratios do not depend on the lower bound of the stochastic demand but are a function of its mean and the cost savings of the slow mode. Supply chain managers could work more aggressively on modal split projects with larger consignments on slow modes.

A further observation is that the slow mode split has different behaviors

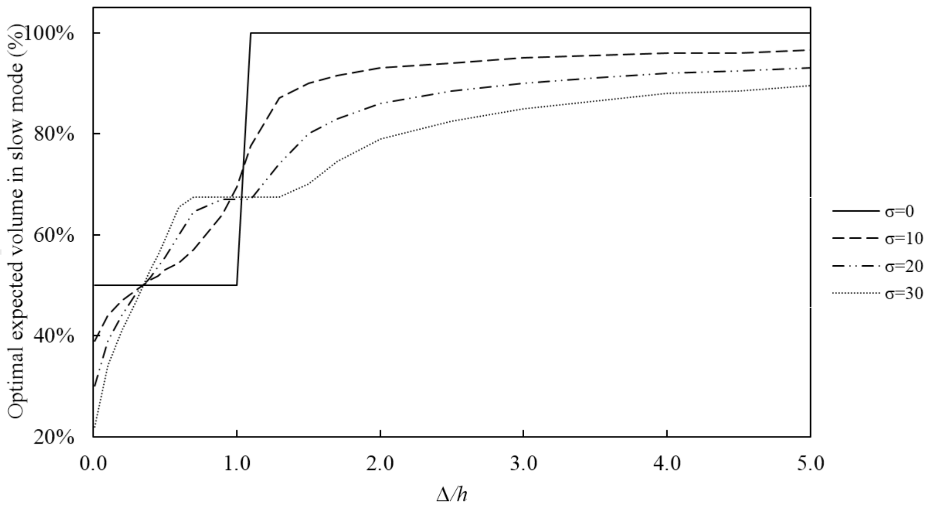

Figure 3.8: *Expected slow mode volume in % of the expected demand per cycle under profit maximization*

in σ at different Δ/h -ratios. When the demand is more volatile (σ increases), the policy prefers more flexibility in MST and favors a larger volume in the fast mode. This is the intuitive reason why q decreases in σ. Interestingly, we find that there is a certain area, when Δ is close to h from the left side, where q increases in σ. This is mainly due to the existence of a third effect: the *safety stock effect*. When the demand is more volatile, more safety stock is required to buffer uncertainty. Because of the cost advantage, the company would prefer to use the slow mode to replenish the safety stock. When Δ is close to h, both commitment and cycle stock effect almost cancel each other out and the safety stock effect dominates, increasing the size of q when σ increases. This phenomenon occurs in an area where Δ approaches h from the left side because of the following: 1). the commitment effect and the overstocking effect almost cancel out (close to the break-even point $\Delta = h$), so that the safety stock effect is left alone, and 2). the commitment effect is still small ($\Delta < h$), so that an increase in the slow mode volume does not lead to too much inflexibility in the system.

The expected total cost savings of MST compared to the baseline fast-mode-only model are shown in Figure 3.9. In the region $\Delta > h$, the curves are sensitive to σ, indicating a cost advantage of MST when the demand is less volatile and the commitment effect dominates. In the region $\Delta < h$, however, the cost savings of MST are rather insensitive to demand volatility. This result is mainly because

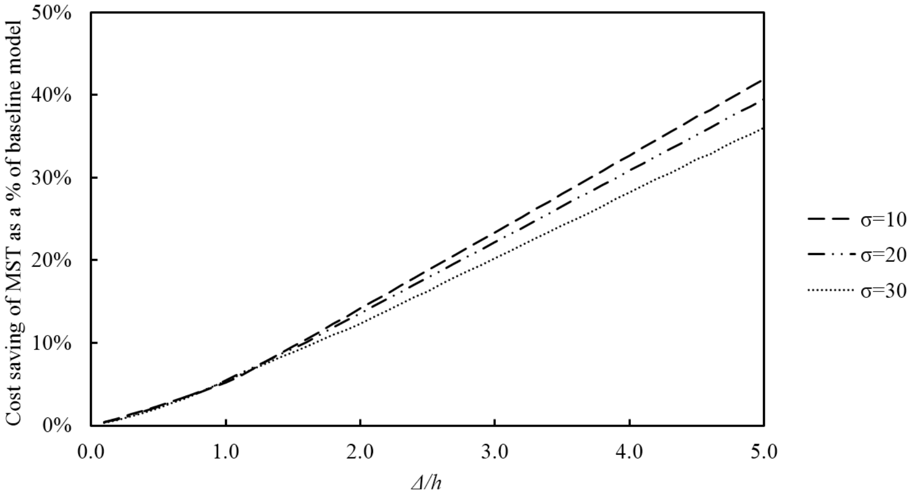

Figure 3.9: *Expected total cost savings using the MST policy*

of the existence of the safety stock effect, as also observed in Figure 3.8. When demand is more volatile, the increasing safety stock drives to a larger share in the low-cost slow mode and further leads to a cost reduction. This safety stock effect offsets the commitment effect, and therefore, the total cost savings of MST are not sensitive to σ. Practitioners generally believe that the slow transportation mode is always favorable for products with more stable demand patterns. Our numerical results reveal that this is only part of the story - if the commitment effect dominates, we find this to be the case; if the cycle stock effect dominates, the volatility of the demand is indeed insensitive to the total cost savings of MST. Again, the measurement of the sizes of the two effects can be simply achieved by a comparison of the two parameters Δ and h.

Thus far, we have assumed that companies intend to minimize the total expected costs using the MST policy. However, companies could have an alternative objective: rather than minimizing the cost, they could intend to improve their sustainability or carbon agenda by minimizing the use of fast transportation modes. In this case, the MST policy could be applied to cost-neutrally shift volumes to the slow transportation mode. Figure 3.10 shows the resulting cost savings from shifting volume to the slow transportation mode for $\sigma = 20$ at different transportation cost savings Δ. The slow mode maximizing volume is reached for the zero-cost case with $\Pi = 0$. The numerical results highlight that a large fraction of the total volume can be shipped using the slow mode if no cost decrease compared

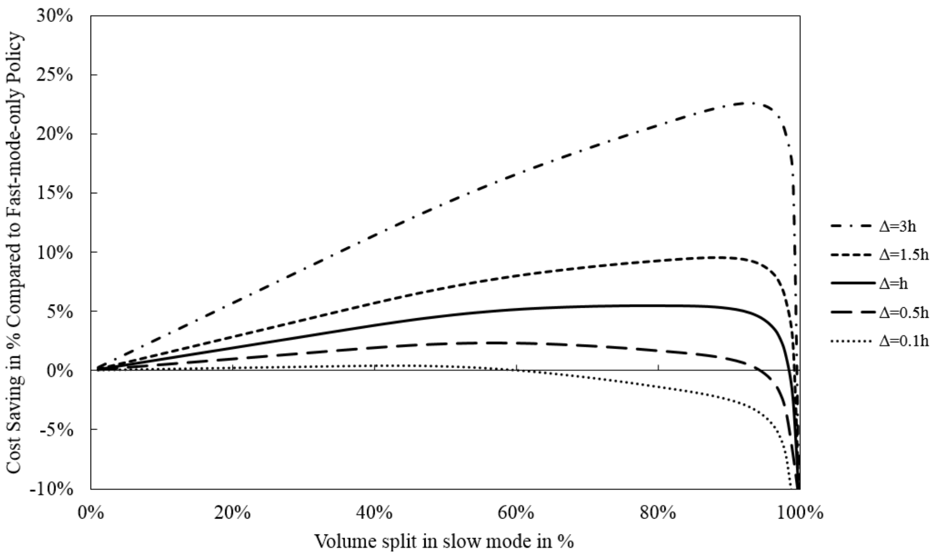

Figure 3.10: *Cost savings based on the expected slow mode volume in % of mean demand.*

to the baseline setting is required: even for low transportation cost savings compared to holding costs $\Delta = 0.1h$, almost 60% of the volume is shipped in the slow mode. For higher Δ, the overall cost savings decrease with the slow mode volume but only become negative as the slow mode volume approaches 100%. Here, the full reliance on the slow mode leads to a complete loss of flexibility.

3.5.3 The implications of the modal split transportation model

Similar to previous literature on dual-sourcing, e.g., Veeraraghavan and Scheller–Wolf (2008), Allon and Van Mieghem (2010), and Janakiraman et al. (2014), our model thus far assumes that the unit transportation cost of the fast mode, c^f, is constant and does not depend on other external factors such as volume or variability changes. However, many LSPs offer freight rates that depend on the volume shipped (Coyle et al., 2015): The more volume an LSP receives from a shipper, the cheaper is the unit transportation cost. Likewise, an LSP could also raise the unit transportation cost as the variability of the freight volume increases. We next analyze the volume and variability implications of the MST policy.

Volume implication. Figure 3.11 shows the mean usage of the fast mode, separately illustrated for the first and second periods of a steady state cycle, as well as for a general period without distinguishing between the cycle periods. It can be observed that when q is rather low and is increased, the average fast mode delivery in the first period of a cycle is immediately affected due to the slow mode order arriving in that period. In contrast, the expected fast mode quantity of the second period of the cycle remains almost the same if q is rather low. It only increases for higher q as slow mode quantities are carried over to the second period of the cycle. For an arbitrary period (generally, the average implication of the first and second periods) we find that the average fast mode delivery almost linearly decreases in q. As q reaches the mean demand of the full cycle, the expected fast mode delivery in both periods tends to zero.

Suppose the fast mode LSP installs a volume-dependent freight rate tariff with an *m+1*-tier structure depending on the expected fast mode usage per cycle. More specifically, the LSP charges a unit transportation cost c_j^f if the expected fast mode shipment per cycle, denoted as q^f, exceeds or is equal to a threshold $\bar{q}_{m-j}^f$, for $j = 0, ..., m$. The fast mode transportation cost per unit is then:

$$c^f = \begin{cases} c_0^f & \text{if } \bar{q}_m^f \leqslant q^f \leqslant 2\mu, \\ c_1^f & \text{if } \bar{q}_{m-1}^f \leqslant q^f < \bar{q}_m^f, \\ \vdots & \vdots \\ c_m^f & \text{if } 0 \leqslant\ q^f < \bar{q}_1^f, \end{cases} \tag{3.18}$$

where $c_0^f < c_1^f < ... < c_m^f$, indicating that the less expected volume q^f the fast

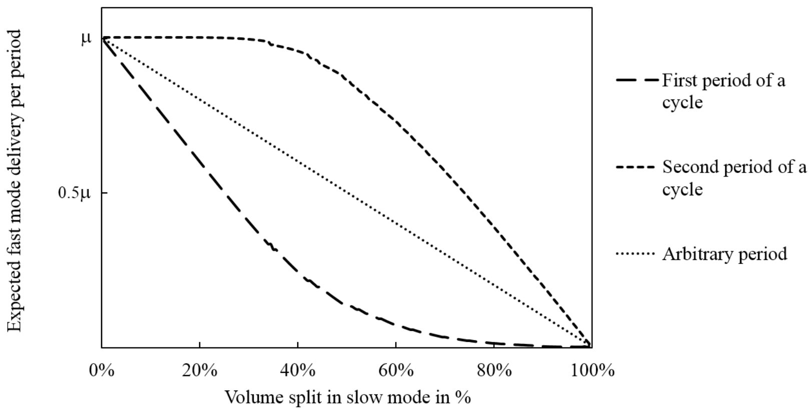

Figure 3.11: *Expected fast mode delivery in the first and second periods of a cycle and for an arbitrary period.*

mode LSP receives from the shipper, the higher is the unit fast transportation mode cost c^f. The above volume-dependent tariff is richly studied in the literature (see, e.g., Swenseth and Godfrey, 2002; Ventura et al., 2013).

Since the expected fast mode shipment per cycle is a linear function of the slow mode shipment, i.e., $q^f = 2\mu - q$, the fast mode cost per unit is c_j^f if the slow mode shipment $q \leqslant 2\mu - \bar{q}_{m-j}^f$. Therefore, the expected cost function of an MST policy with a volume-dependent tariff is multi-fold with $C^{\mathcal{D}} = c^s q + c_j^f(2\mu - q) + \sum_{i=1}^{2} L_i(S_i + E[O_{\infty,i}])$, for $q \leqslant 2\mu - \bar{q}_{m-j}^f$ and j from $0, ..., m$. We assume in the baseline situation where all volume are shipped in the fast mode, a lowest unit cost c_0^f is charged by the fast mode LSP, such that the expected cost is $C^{\mathcal{B}} = c_0^f 2\mu + 2L(S^B)$. The functional form of the expected cost savings of the MST policy $\mathcal{D}$ over the baseline policy $\mathcal{B}$ depends on the fast mode tariff and changes to:

$$\Pi_j(q, S_1, S_2) = (c_j^f - c^s)q + (2L(S^B) - \sum_{i=1}^{2} L_i(S_i + E[O_{\infty,i}])) - (c_j^f - c_0^f)2\mu. \quad (3.19)$$

Compared to the case without the volume-dependent tariff, there is an additional term $-(c_j^f - c_0^f)2\mu$ that reduces the total cost savings, which characterizes the additional fast mode cost that the company faces due to the higher price caused by the lower expected fast mode volume.

This problem can be solved by using a modified version of the classical algorithm for the standard economic order quantity (EOQ) problem with quantity discount, illustrated in (Silver et al., 1998, p. 162). For all cost levels c_j^f, we calculate the transportation cost savings $\Delta_j = c_j^f - c^s$ and the resulting $\hat{q}_j, \hat{S}_{j1}, \hat{S}_{j2}$. The problem is that this solution may be infeasible if $\hat{q}_j > 2\mu - \bar{q}_{m-j}^f$ since this cost savings function is only valid for $\hat{q}_j \leqslant 2\mu - \bar{q}_{m-j}^f$. In such a case, the slow mode volume for this cost level is set to $\hat{q}_j = 2\mu - \bar{q}_{m-j}^f$ and $\hat{S}_{j1}, \hat{S}_{j2}$ are calculated accordingly based on the previously discussed scenarios A, B, and C. The cost savings, Π_j, for cost level c_j^f are then determined by (3.19), and the optimal approximate solution is:

$$(\hat{q}, \hat{S}_1, \hat{S}_2) = \arg\max\{\Pi_j(\hat{q}_j, \hat{S}_{j1}, \hat{S}_{j2}) | j = 0, ..., m\}. \tag{3.20}$$

Installing a volume-dependent tariff by the fast mode LSP may lead to both a higher or lower volume shift to the slow mode depending on the specific cost tariff. The explanation is the following: Given the unit transportation cost in the baseline model is c_0^f, the total expected fast mode volume is 2μ. Once the shipper implements MST and ships q units via the slow mode, the expected fast mode shipments during a two-period cycle would decrease to $q^f = 2\mu - q$, which may have negative consequences to the fast mode LSP. By installing the volume-dependent tariff, the fast mode LSP charges higher prices, if the expected fast mode shipments fall below certain thresholds. Depending on the magnitude of these price increases, the shipper may either shift even more volume to the slow mode, if the relative cost savings between the two transportation modes is even more beneficial; or the shipper may shift volume back from the slow mode to the fast mode in order to utilize the better fast mode price due to a larger volume.

The following numerical example will illustrate these two effects. We use the same data as in Section 5, i.e. the mean demand per period follows a Gamma distribution with $\mu = 100$ and $\sigma = 30$. Suppose the unit fast mode cost in the baseline model is $c_0^f = 10$. As the shipper implements MST, the optimal volume shifted to the slow mode LSP is $A = 179$ as illustrated in Figure 3.12. We now assume that the fast mode LSP installs a two-fold tariff as such $c_0^f = 10$ only if $q^f \geqslant 100$ (equivalently, if the slow mode volume $q \leqslant 100$). If $q^f < 100$ (equivalently, $q > 100$), we distinguish two alternative unit cost scenarios $(i)\, c_1^f = 12$ and $(ii)\, c_1^f = 20$. The volume-dependent tariff can be formalized as follows:

$$c^f = \begin{cases} c_0^f = 10 & \text{if } 100 \leqslant q^f \leqslant 2\mu, \\ c_1^f \in \{12, 20\} & \text{if } 0 \leqslant q^f < 100. \end{cases} \tag{3.21}$$

Figure 3.12 illustrates the expected total cost per cycle as a function of slow mode volume q for the different unit fast mode costs. The solid line represents the region in which this cost function is feasible, hence the dotted line represents the region in which this cost function is infeasible. For $q \leqslant 100$, the expected fast mode volume q^f exceeds the threshold of 100, therefore, the lowest unit cost $c_0^f = 10$ is feasible and the lowest total cost is reached at $q = 100$ (point D). For $q > 100$, the expected fast mode volume q^f would be less than the threshold of 100 such that the higher price $c_1^f \in \{12, 20\}$ is charged. If $c_1^f = 12$, one can see that the cost-minimal slow mode quantity is at B, i.e., $q = 183$, whose cost is lower than the expected cost at D. Therefore, if $c_1^f = 12$, the shipper would shift even more volume to the slow mode LSP (from A to B) with the consequence that the expected volume for the fast mode LSP decreases. However, if $c_1^f = 20$, the cost-minimal expected cost is at $q = 192$ (point C), which is larger than the expected cost at the threshold $q = 100$ where the lower cost $c_0^f = 10$ is still feasible (point D). In this case, the shipper would move volume back from the slow mode to the fast mode (from A to D) to benefit from the lower price.

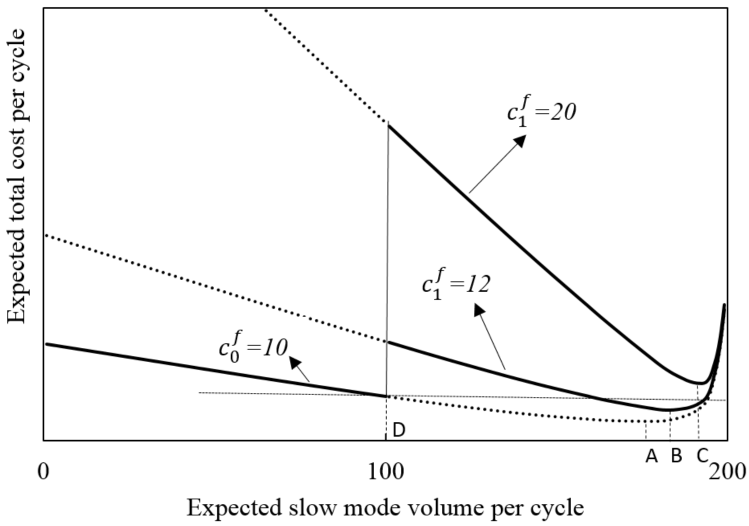

Figure 3.12: *Expected total cost per period with a volume-dependent tariff of the fast mode*

In short, the volume-dependent tariff can lead to both more and less usage of the slow mode. The impact depends on the specific design of the tariff.

Variability implication. Besides the volume implication, implementing an

MST policy also affects the variability of the fast mode shipments. When fast mode shipments become more volatile, the fast mode LSP must put more effort in capacity management, e.g., for empty truck reposition and truck driver retention (Jonathon et al., 2002), and might consequently raise the freight rate.

Suppose the fast mode LSP needs to plan its fleet capacity based on more volatile orders from the shipper. The expected fast mode shipment during a two-period cycle is q^f with $q^f = 2\mu - q$, and the standard deviation of the shipment is σ^f. Assuming that the fast mode LSP plans its capacity, denoted as C^f, via a simple newsvendor-style model: $C^f = q^f + z\sigma^f$. The parameter z is linked to the safety capacity factor to be met by the fast mode LSP. If $\bar{c}$ is the cost to install one unit of fleet capacity, then the fast mode LSP's average capacity cost for one unit shipped is: $\bar{c}^f = \bar{c} \cdot C^f / q^f$. We can simplify the equation by substituting the capacity $C^f = q^f + z\sigma^f$ and the coefficient of variation of the fast model shipment $CV^f = \sigma^f / q^f$. Therefore, the average capacity cost for one unit shipped can be written as: $\bar{c}^f = \bar{c}(1 + z \cdot CV^f)$, which shows the importance of the coefficient of variation of the fast mode shipment.

Figure 3.13 shows CV^f, separately illustrated for the first and second period of a steady state cycle, as well as for a general period without distinguishing between the cycle periods. It can be observed that all three curves increase monotonously, indicating that the fast mode shipment is more volatile when more volume is shifted to the slow mode. In addition, the CV^f of the first period of a cycle is larger than that of the second period, because the mean fast mode shipment in the first period is smaller (shown in Figure 3.13), provided that a substantial part of demand is already satisfied by the slow mode in this period.

To consider the variability implication in the MST policy, an approach similar to the one implemented for the volume implication analysis can be applied. To be more specific, the fast mode LSP could install the following CV^f-dependent tariff with the unit transportation cost c_j^f :

$$c^f = \begin{cases} c_0^f & \text{if } 0 \leqslant CV^f < \bar{CV}_1^f, \\ c_1^f & \text{if } \bar{CV}_1^f \leqslant CV^f < \bar{CV}_2^f, \\ \vdots & \vdots \\ c_m^f & \text{if } \bar{CV}_m^f \leqslant CV^f, \end{cases} \tag{3.22}$$

where $c_0^f < c_1^f < ... < c_m^f$, indicating that the more volatile the fast mode shipment, the higher the unit fast mode transportation cost c^f.

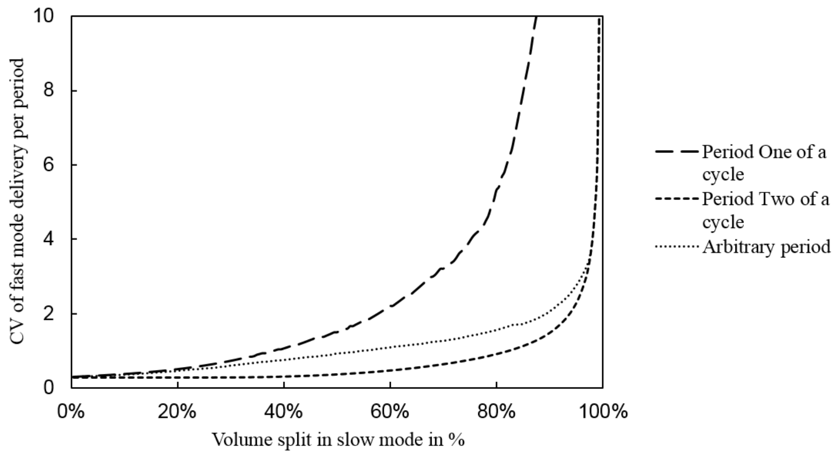

Figure 3.13: *Coefficient of variation of fast mode delivery in the first and second periods of a cycle and for an arbitrary period.*

The implication of the variability-dependent tariff is similar to that of the volume-dependent tariff. Suppose the fast mode LSP observes a higher variability in its shipment due to the shipper's MST implementation, and wants to raise the freight rate according to the tariff (3.22). Similar to the volume-dependent implication, the shipper may either increase or decreases the volume shifted to the slow mode LSP, depending on the freight rate increase (see Figure 3.12). If the unit transportation cost increase (due to the variability-dependent tariff) is not too large, the shipper will shift even more volume to the slow mode LSP since it minimizes its total cost. If the unit transportation cost increase (due to the variability-dependent tariff) is large, then the shipper would shift the volume back to the last threshold where he still obtains a lower fast mode freight rate. Similar to the case with the volume-dependent tariff, the final decision of the shipper depends on the specific parameters of the variability-dependent tariff (3.22). Note, an LSP could combine the volume-dependent and variability-dependent tariffs to account for both slow mode implications. Since both implications lead to either more or less usage of the slow mode, a combination of both tariffs will hence be expected to have a similar impact.

In summary, due to the slow mode shipment, the LSP observes lower freight volumes and higher variability in the fast mode. Consequently, he might raise the freight rate under a specified tariff. We find that the specific design of the freight tariff can lead to either an increase or a decrease of the shipper's slow mode usage.

3.6 Summary

The main contribution of this chapter is the development of a modal split transportation (MST) policy that enables volume allocation into two transportation modes and that integrates inventory controls. An attractive feature of the MST policy is the cost-efficient slow mode shipment in the first period of each two-period cycle. This constant slow mode volume is complemented by flexible volumes that can be shipped via the more costly fast mode every period. Accordingly, the MST model needs to consider different delivery frequencies of the two modes and therefore has an extended mathematical structure compared to the classical tailored base-surge problem, which assumes that the cheap and the expensive supplier deliver in every period. However, a "heavy traffic" phenomenon, shown in the TBS problem, is not guaranteed in the MST model and requires new solution procedures. We approximate the steady state cost function of the MST problem and derive closed-form expressions for the modal split policy using three distinct scenarios. This solution provides a simple and easy-to-implement tool for practitioners. We find that the trade-off between the commitment effect and the cycle stock effect drives the optimal level for the slow mode quantity. When a constant quantity is committed in the slow mode, the company on one side gains a transportation cost savings every cycle, but on the other side incurs extra cycle stock cost in the first period of the cycle. Using a numerical study with practically based data from a company, we find that the solution approach provides an approximation error of less than 3%. We also analyze the cost reductions and find that they can be significant based on the relationship between the transportation cost savings in the slow mode and inventory holding costs.

The proposed MST policy has important managerial implications as it bridges a key dilemma that MST has been facing in practice over the years: despite receiving increasing attention from the industry, government, and academia, real-world implementations have ground to a halt. Based on our discussions with the company, we found that practitioners were particularly challenged by integrating multimodal transportation decisions with inventory controls. The proposed model can provide practitioners with the confidence that these decisions can be well integrated and handled. The numerical results are encouraging with respect to the practical feasibility of the slow mode. The supply chain managers that we interviewed were concerned about the volume split between the fast and the slow transportation modes in the cost-optimal solution. Managers tend to believe that if they need to commit a constant volume in the slow mode cyclically in the long run, the size of this fixed volume should not exceed the lower bound of the demand over the entire period. In contrast to their expectations, we found that the volumes on the slow mode are sufficiently large to justify the implementation of new slow mode transportation routes. For fast-moving products with high demand and relatively low demand variation, the volume for the slow mode can be as high as 85% of the total volume. Our insights are also relevant for companies that apply the MST policy to reduce carbon emissions via the slow transportation mode rather than costs. If the objective is to implement MST in a cost-neutral way, the numerical results indicate that large volumes are shipped in the slow mode even if the transportation cost savings are relatively small. This is encouraging because it provides the potential to trigger an even larger demand for the slow mode that is required to facilitate the MST approach.

Multiple extensions of the MST study could be considered in future research. Our model is limited because it assumes a slow mode delivery frequency that is half of that of the fast mode and a cycle has two periods, i.e., the steady state cost function of the MST policy has at most three decision variables, the slow mode volume q and the base stock levels S_1 and S_2 of the fast mode policy. Our approximated analytic solution builds on the fact that under certain circumstances (the relationship between transportation cost savings and holding cost) specific elements of the cost function (in particular expected overshoot terms) can be omitted, which allows us to derive closed-form expressions for the relevant decision variables. When $n > 2$, the trade-off between transportation cost savings and inventory costs still exists and a similar approximation method could be applied. However, the number of decision variables increases linearly, i.e., the number of decision variables is $n + 1$, which makes the analytical tractability more difficult. To keep the model analytically tractable and to derive closed-form expressions, more terms of the cost functions have to be eliminated, which is theoretically possible but would increase the approximation error. Therefore, this type of approximation would not be appropriate for larger cycle lengths. Numerical solutions are recommended for more accurate results. Theoretically, our analysis can be extended to any arbitrary n; however, when n increases, in the absence of any other relevant adjustments, the stochasticity of the cyclic demand will increase, and this might deteriorate the performance of the approximations.

Thus far, n is only studied as an exogenous parameter. Occasionally, larger shippers with substantial volume could have strong bargaining power in the transportation market and can negotiate the delivery frequencies of the slow mode with LSPs. The delivery frequency will then be an endogenous decision variable to be optimized, rather than an exogenous parameter. This entails further changes of the MST model, e.g., the cost structure of the slow mode, and optimality decisions of the fast mode. The approximation used in this article might not work, and further solution methods are required. In Chapter 3 of the dissertation, we discuss this type of MST model and propose an algorithm to solve it numerically. The algorithm is established based on stochastic dynamic programming.

The scope of MST could be further broadened by incorporating multiple products. The solution of the single–product model can be applied as a first approximation for the multi–product problem by optimizing the modal split for each individual product separately. However, this procedure does not fully capture the advantages of multi–product management, e.g., when the demand for one product drops, that of the others might still be adequate to fill in the slow mode. The aggregated demand might have a lower coefficient of variation and drives a pooling effect. The company could then reserve a pooled capacity in the slow mode for all products, rather than booking capacities for each product separately. The pooling effect might foster a larger modal split into the slow mode. Still, the downside of the multi–product management is that the company needs to make extra decisions in the allocation of products to the pool. Extra handling costs will occur in the allocation operations, e.g., to pack, transit, declare, and load the products with different sizes, weights and safety instructions. Additional data and parameters are needed to further analyze the trade-off and profitability of the multi–product problem.

3.7 Appendix

3.7.1 Appendix A: Proof of Proposition 3.4.1

We take one cycle of two periods as the inventory review time unit. Because there are no fast mode orders in the first period of a cycle, both the fast and slow modes are utilized only once in a cycle, and S_2 is the only order-up-to level in this model. The demand of one cycle follows an i.i.d distribution with mean 2μ and standard deviation $\sqrt{2}\sigma$. The dynamics of this inventory model are shown in Figure 3.14.

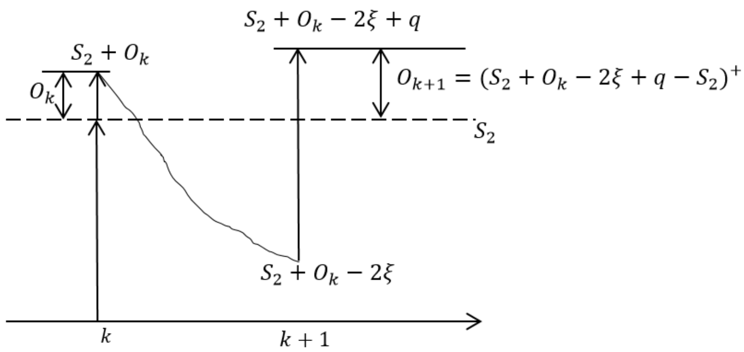

Figure 3.14: *The overshoot in a cyclic inventory model*

The overshoot of the cycle is explained as follows: denote as O_k,($O_k \geqslant 0$) the overshoot in cycle k, and the inventory position after the deliveries from both modes and before the realization of demand is $S_2 + O_k$. During the cycle, a demand of 2ξ is realized, and the inventory is $S_2 + O_k - 2\xi$ at the end of the cycle. At the beginning of the next cycle, q arrives and the overshoot in the next cycle is calculated in (3.23). Note that the overshoot recursion does not depend on any inventory base stock levels.

$$O_{k+1} = (O_k + q - 2\xi)^+ . \tag{3.23}$$

As a comparison of the inventory system, we consider a GI/D/1 queue in Figure 3.15, where the customer inter-arrival time t follows an i.i.d distribution with mean μ_t and standard deviation σ_t, and the service time q is deterministic.

Assume that at time 0, customer k arrives and that her waiting time is w_k with $w_k \geqslant 0$. The queue will be busy in the next time interval $q + w_k$. In period t, customer $k+1$ arrives. If $t \geqslant q + w_k$, the next customer has zero waiting time; if $t \leqslant q + w_k$, he has to wait for a time interval of $q + w_k - t$. Consequently, the

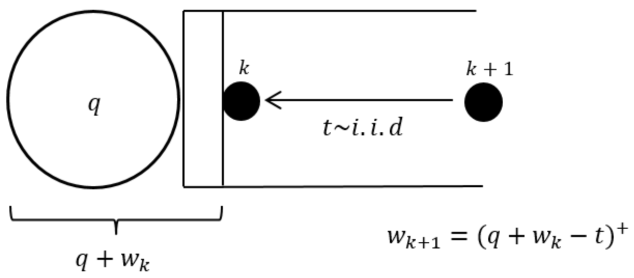

Figure 3.15: *The waiting time in a GI/D/1 queue*

waiting time of this customer is:

$$w_{k+1} = (w_k + q - t)^+ . \tag{3.24}$$

Comparing (3.23) with (3.24), the stochastic variables O_k and w_k have analogous recursion functions. Consequently, we can model the cyclic inventory model as a GI/D/1 queue, where the demand 2ξ represents the inter-arrival time of customers, the constant delivery q represents the service time, and most importantly, the overshoot is the waiting time of the queue.

Kingman (1970) provides a bound for the expected waiting time of a general GI/G/1 queue: $E[w] \leqslant \frac{\sigma_t^2}{2(2\mu_t - q)}$. The GI/D/1 queue and the cyclic inventory model are connected by $\sigma_t^2 = 2\sigma^2$ and $\mu_t = 2\mu$, and the expected overshoot at the end of a cycle is then $E[O_{\infty,2}] \leqslant \frac{\sigma^2}{2\mu - q}$.

Substituting $\bar{S}_2 = S_2 + E[O_{\infty,2}]$ within (3.6) and calculating the first-order derivative with respect to $\bar{S}_2$ gives $h + h\Phi(\bar{S}_2) - b(1 - \Phi(\bar{S}_2))$, which implies $\bar{S}_2$ as follows: $\bar{S}_2 = \Phi^{-1}\left(\frac{b-h}{b+h}\right)$. Therefore, the base stock level is $S_2 = \Phi^{-1}\left(\frac{b-h}{b+h}\right) - E[O_{\infty,2}]$.

3.7.2 Appendix B: Proof of Proposition 3.4.2

Implement the following rule: for any (x, y) such that $y \geqslant 0$, $(x+y)^+ \leqslant x^+ + y$ and $(x+y)^- \leqslant x^-$:
$L_1(S_1 + E[O_{\infty,1}]) = hE\left[(S_1 + E[O_{\infty,1}] - \xi)^+\right] + bE\left[(S_1 + E[O_{\infty,1}] - \xi)^-\right]$
$\leqslant hE\left[(S_1 - \xi)^+\right] + hE[O_{\infty,1}] + bE\left[(S_1 - \xi)^-\right] = L_1(S_1) + hE[O_{\infty,1}]$.
The parameter $\hat{\Pi}$ in (3.12) can be approximated as:

$$\hat{\Pi} = \Delta q + \ 2L(S^B) - L_1(S_1) - hE[O_{\infty,1}] - L_2(S_2). \tag{3.25}$$

$E[O_{\infty,1}]$ is approximated in (3.13): $E[\hat{O}_{\infty,1}] = \int_0^{S_2+q-S_1}(S_2 + q - S_1 - \xi)\phi(\xi)d\xi$, with $\frac{dE[\hat{O}_{\infty,1}]}{dq} = \frac{dE[\hat{O}_{\infty,1}]}{dS_2} = -\frac{dE[\hat{O}_{\infty,1}]}{dS_1} = \Phi(S_2 - S_1 + q)$.

The first-order condition of (3.25) w.r.t. q is: $\frac{d\hat{\Pi}}{dq} = \Delta - h\Phi(S_2 - S_1 + q) = 0$.

The first-order condition of (3.25) w.r.t. S_2 is: $\frac{d\hat{\Pi}}{dS_2} = -h\Phi(S_2 - S_1 + q) - (b + h)\Phi(S_2) + b = 0$.

The first-order condition of (3.25) w.r.t. S_1 is: $\frac{d\hat{\Pi}}{dS_1} = h\Phi(S_2 - S_1 + q) - (b + h)\Phi(S_1) + b = 0$.

Combine the conditions $\frac{d\hat{\Pi}}{dq}$ and $\frac{d\hat{\Pi}}{dS_2}$: $\hat{S}_2 = \Phi^{-1}\left(\frac{b-\Delta}{b+h}\right)$.

Combine the conditions $\frac{d\hat{\Pi}}{dq}$ and $\frac{d\hat{\Pi}}{dS_1}$: $\hat{S}_1 = \Phi^{-1}\left(\frac{b+\Delta}{b+h}\right)$.

Plug in $\hat{S}_1$ and $\hat{S}_2$ into the equation $\frac{d\hat{\Pi}}{dq} = 0$: $\hat{q} = \Phi^{-1}\left(\frac{b+\Delta}{b+h}\right) - \Phi^{-1}\left(\frac{b-\Delta}{b+h}\right) + \Phi^{-1}\left(\frac{\Delta}{h}\right)$.

Chapter 4

An inventory control model for synchromodality: Structural properties and optimal solution

Die Philosophen haben die Welt nur verschieden interpretiert; es kommt aber darauf an, sie zu verändern. [1]

– Karl Marx (1818-1883), German philosopher.

Abstract

In this chapter, we generalize the modal split transportation policy discussed in Chapter 2 to provide additional support for companies to implement synchromodality. The generalization is inspired by the practical insights of synchromodality problems: 1) Rail transportation (the slow mode) generally exhibits economies of scale. We therefore incorporate the fixed cost of the slow mode as an additional parameter and its delivery frequency an additional decision variable in the model. 2) The inventory control at the distribution center must not be fixed to a base stock policy and we hence release this assumption. We obtain structural properties of the generalized

[1] The philosophers have only interpreted the world in various ways. The point, however, is to change it.

model and design an algorithm to calculate the optimal decisions with minor computing effort using stochastic dynamic programming. In a numerical study, we validate our solution algorithm, and analyze the sensitivity and robustness of our modal split transportation model.

4.1 Introduction

In Chapter 3, we have discussed a Modal Split Transportation (MST) model where the slow transportation mode (e.g., intermodal rail) delivers only half as frequent as the fast transportation mode (e.g., direct trucking). This model could fit for the practical case, e.g., fast mode delivers every workday of a week (except Sundays) and the slow mode only delivers in Monday, Wednesday, and Friday. An extension of the model is to allow the company to decide the delivery frequency of the slow mode. In addition, the MST model studied in Chapter 3 imposes a strong assumption of a base stock control at the distribution center, while in practice the company could have more flexibilities in inventory management. Finally, it always remains interesting to obtain optimal solutions rather than approximations.

In this chapter, we extend the model from Chapter 3 to support a company's modal split optimization. Our extension is tailored for transportation problems by incorporating the following two practical aspects: 1) First, our MST policy considers economies of scale of rail transportation. The fixed cost of rail transportation is included as an additional parameter, and the delivery frequency of rail transportation is incorporated as an additional decision variable. 2) Second, our MST policy allows the company to exploit more flexibility of road transportation by releasing the base stock control assumption.

The practical story behind our model is as follows: A company partners with a rail carrier to operate a dedicated train connecting its plant with its distribution center (DC). The main reason for the "in-house" transportation management (instead of a complete outsourcing to third-party logistics service providers) is that, this way the company has better controls of its transportation cost and service level, and alignments between its transportation decisions and its holistic supply chain management (CapGemini, 2016). A survey by Boston Consulting Group (2015) reveals that up to 59% of the participated companies manage in-house transportation. Whereas the cost of road transportation is almost linear in the distance (Reis et al., 2013), the cost of rail transportation involves a substantial fixed part associated with, e.g., locomotive and infrastructure spendings (The World Bank, 2011; European Intermodal Association, 2012). On the other hand, the company has the freedom to decide the delivery quantity and frequency of the train. The essential advantage of operating a train connection is the low unit cost to transport a container (provided that the train has a high fill rate), whereas the major disadvantages are its long lead time, and inflexibility in delivery quantity and frequency, as a result of the scale required to fill the train and make rail transportation cost-competitive. In order to foster the strengths and circumvent weaknesses of rail transportation, the company wants to commit a constant delivery quantity every time the dedicated train operates over a mid-term time horizon. For example, every Monday in the year 2017, the train delivers 30 containers from the plant to the DC. In fact, to ship a stable freight using rail transportation is already a well-accepted principle in industry (Groothedde et al., 2005). Besides its cost advantage, other benefits from the fixed quantity commitment are: 1) When a batch is shipped out cyclically from the plant, a batch with the same quantity will arrive in the DC cyclically. The company can, therefore, eliminate the need to consider the lead time of the train (see, e.g., Baumol and Vinod, 1970; Allon and Van Mieghem, 2010). 2) A fixed flow of the shipment allows the company to level and smooth its production, and therefore acquires savings from stabilized material flow and labor requirements.

Whereas the model in Chapter 3 extends the classical tailored base-surge (TBS) policy in the dual-sourcing literature by incorporating different delivery frequencies of the two modes, the model in this chapter further extends the TBS policy by allowing any arbitrary delivery frequency of the slow mode and any arbitrary inventory control at the distribution center. However, even a simple TBS policy is not amendable to exact analysis (Allon and Van Mieghem, 2010; Xin and Goldberg, 2016). Previous relevant studies, e.g., Janssen and de Kok (1999), Allon and Van Mieghem (2010), Janakiraman et al. (2014), and Chapter 2 of the dissertation, exclusively rely on approximations. We obtain the exact optimal solution with minor computing effort for MST, an extended TBS problem with additional parameter and decision variable. The solution process is established on managerial insights and structural properties of the MST problem. The MST problem (and also, as a special case of MST, the TBS problems) is a two-stage optimization problem, where the company first tactically commits the delivery quantity and frequency of rail transportation over a mid-term time horizon, and then adjusts its operational decisions in road transportation every period. As a consequence, the solution process of the MST problem consists of two stages, but in an inverse order, first road then rail. Traditionally, dual-sourcing models are known to be complex due to the simultaneous usage of two sources/modes.

We find that "dual-sourcing" models with MST (or TBS) settings can be decoupled into two "single sourcing" problems, that can be solved sequentially and the problem complexity is hence substantially reduced. We then show that, although the assumption of the base stock control of the road transportation is released, its optimal policy indeed has a base stock structure. An infinite-horizon stochastic dynamic programming (SDP) problem is then used to obtain the base stock levels in the steady state. We find that, if the MST model is studied as a periodic-review inventory system, the base stock levels in the steady state do not converge to a single value. This is because the cost-per-period function in the SDP model depends on whether or not rail transportation delivers in that specific period, and the period-review system is hence not stationary. Nevertheless, if the MST model is studied as a cyclic-review inventory system, with a cycle being the periods between two rail transportation deliveries, the "base stock vector" consisting the base stock levels in a cycle converges in the steady state. After obtaining the optimal base stock control of road transportation in the steady state, the SDP algorithm can be replaced with simulation-based optimization to calculate the optimal rail transportation decisions, and the computing effort is significantly reduced.

Supported with the aforementioned solution technique, we then contribute to the dual-sourcing TBS (MST) literature by offering a detailed numerical study using the numbers suggested by a company. We find that the fixed cost of the rail transportation is the main driver of its delivery frequency, which further impacts its constant delivery quantity per delivery cycle. The optimal delivery frequency and quantity of the rail transportation then impact the company's daily adjustment in road transportation deliveries. The sensitivity and robustness of the MST model are also presented.

The rest of this chapter is structured as follows: Section 4.2 reviews the literature. Section 4.3 formulates the model and Section 4.4 analyzes the optimal solution of the MST policy. Section 4.5 reports the numerical validation. Section 4.6 discusses possible extensions of the model and Section 4.7 concludes the chapter.

4.2 Relevant literature

Over the years, an extensive body of literature (see, e.g., Bontekoning et al., 2004; McKinnon, 2015) has discussed the shift of freight volume from road to rail transportation, and its corresponding economic and environmental importance.

These discussions establish the basis of our study. Furthermore, two streams of literature are of immediate relevance to our study: the transportation literature that studies freight mode choice based on the total logistics (transportation and inventory) costs approach, and the inventory literature on dual-sourcing. The first stream of literature aligns with that discussed in Section 3.2.

The second stream of literature that is most closely related to our MST problem have a tailored base-surge (TBS) setting, where the slow supplier always delivers a constant "Base" quantity, and the fast supplier responds to the demand "Surge" and delivers variable quantities following a base stock policy. The main reason for the constant "Base" delivery is that it allows focusing on the cost efficiency of the slow supplier with a stable flow. Allon and Van Mieghem (2010) find that TBS policy is not amendable for simple analysis and the major complexity arises from the assessment of "overshoot": Because the slow supplier always pushes a constant quantity to the company, it is possible that the inventory position, after the delivery from the slow supplier, exceeds the base stock control level of the fast supplier. The excessive inventory is defined as overshoot. An early dual-sourcing model with TBS settings from Rosenshine and Obee (1976) allows the company to sell part of the excessive inventory back to the supplier to avoid the overshoot. They propose a heuristic approach to solve the model. Chiang (2007) studies the same model and obtains the optimal solution using dynamic programming. Later studies on TBS models release the inventory sell-off assumption and focus on overshoot assessment. Janssen and de Kok (1999) find that the overshoot is analogous to the waiting time of a GI/G/1 queue, and estimate it numerically. Combes (2011) uses simulations to estimate the mean and standard deviation of overshoot, which further result in approximate numerical solutions of the model. Allon and Van Mieghem (2010) and Janakiraman et al. (2014) obtain approximate analytic expressions of overshoot in continuous- and discrete-time models respectively, and find approximate solutions of their TBS models with simple formulae. Dong et al. (2017a) study an extended TBS policy with the fast supplier delivering two times more frequent than the slow supplier, and obtain approximate solutions. Arts et al. (2011) and Klosterhalfen et al. (2011) use Markov chain to simulate the overshoot. Boute and Van Mieghem (2015) circumvent the determination of the overshoot by using a linear control policy to replenish both the slow and fast mode, which is analytically tractable under normally distributed demand.

Our model generalizes the TBS policy (without inventory sell-off) by introducing a fixed cost in the slow supplier, adding an extra decision in its delivery frequency, and releasing the assumption of the base stock control of the fast supplier. Furthermore, we obtain the optimal solution with minor computing effort. Our approach does not require a characterization of overshoot.

4.3 Model formulation

A distribution center (D) periodically orders from a manufacturing plant (P) with unlimited capacity. The demand at D is denoted as ξ and is assumed to follow i.i.d. distribution with mean μ and standard deviation σ. The cumulative distribution function (CDF) $\Phi(\cdot)$ and probability density function (PDF) $\phi(\cdot)$ are both known. We focus on the steady state by analyzing an infinite-horizon problem. The reasons are: 1) The decision in delivery quantity and frequency of rail transportation is a commitment enduring over a long period, so that there is indeed a large number of periods in the model. 2) The analysis of an infinite-horizon problem often leads to simple and insightful decision policies that are favored by practitioners (Bertsekas, 2005). Time is discrete, represented as $t = 1, 2, ..., T$.

Two transportation modes are available: a *fast mode* (road transportation) with short delivery notice and a *slow mode* (rail transportation) that requires a longer lead time. We restrict the lead time of the fast mode to be zero because of model tractability. Transportation using the fast mode incurs a variable cost c^f per delivery unit. When the same unit is shipped via the slow mode, a lower variable cost c^s with $c^s \leqslant c^f$ is incurred, with an additional fixed cost K per delivery which is independent of the delivery volume. Note, both c^f and c^s represent not only the traditional transportation fee paid to the relevant logistic service providers, but also account for all costs incurred in the end-to-end delivery process, such as customs, duties, cost of capital due to pipeline inventory, etc.

While the fast mode has the flexibility to deliver any unit z_t as required in t, the slow mode delivers a fixed quantity q every n periods over the entire horizon. Because a constant quantity q is always shipped from P to D every n periods, the lead time of the slow mode can then be ignored (see, e.g., Allon and Van Mieghem, 2010). To cope with the frequency of the slow mode, we define a delivery *cycle* as follows: a cycle consists of n periods with q arriving in the first period. Without loss of generality, we assume that the first slow mode shipment arrives in period $t = 1$ and T is a multiple of n.

Denote x_t the net starting inventory at the beginning of period t. After the deliveries from the fast and slow modes (if t is the starting period of a cycle), demand is realized. At the end of the period, excessive inventory is kept at a unit holding cost h, and unmet demand is backordered to the next period at a unit backorder cost b. Denote $f_t(x_t)$ the optimal value function in t with starting inventory x_t, i.e., the minimal expected total costs from period t until T. When the slow mode controls (q, n) are committed over the entire time horizon, the Bellman equation solving for the optimal fast mode control z_t can be expressed as follows:

$$f_t(x_t|q,n) = \begin{cases} \min\limits_{z_t \geqslant 0} \left\{ c^f z_t + c^s q + K + L(x_t + z_t + q) + E\left[f_{t+1}\left(x_{t+1}|q,n\right)\right] \right\} & q \text{ arrives in } t, \\ \min\limits_{z_t \geqslant 0} \left\{ c^f z_t + L(x_t + z_t) + E\left[f_{t+1}\left(x_{t+1}|q,n\right)\right] \right\} & \text{otherwise,} \end{cases} \tag{4.1}$$

where $L(y) = h\int_0^y (y-\xi)\phi(\xi)d\xi + b\int_y^\infty (\xi - y)\phi(\xi)d\xi$, the one period expected inventory mismatch cost. The infinite-horizon problem is studied by truncating the number of periods to T and subsequently letting $T \to \infty$. For simplicity reasons it is assumed that at the end of the horizon, any excessive/backorder inventory in period $T+1$ is discarded, i.e., $f_{T+1} = 0$. This is a reasonable assumption because the terminal value function f_{T+1} only has a diminishing influence on the system in the long run (Karlin et al., 1958). Given f_{T+1}, the optimal value function in period T is:

$$f_T(x_T|q,n) = \begin{cases} \min\limits_{z_T \geqslant 0} \left\{ c^f z_T + c^s q + K + L(x_T + z_T + q) \right\} & q \text{ arrives in } T, \\ \min\limits_{z_T \geqslant 0} \left\{ c^f z_T + L(x_T + z_T) \right\} & \text{otherwise.} \end{cases} \tag{4.2}$$

Obviously, the formation and value of f_t depend on whether or not the slow mode delivers in t. This indicates that the optimal delivery quantity of the fast mode z_t^* might be period-dependent. In addition, z_t^* might also depend on the starting inventory position x_t in period t: With a minor inventory position at the beginning of period t, for example, the company tends to respond with larger fast mode shipment in order to avoid unmet demand. Considering that $T \to \infty$ and x_t is a stochastic variable, the total computing effort spent on obtaining $z_t^*(x_t)$ might be substantial. Previous literature studying models with a TBS setting, such as Janssen and de Kok (1999), Allon and Van Mieghem (2010), Janakiraman et al. (2014), and Dong et al. (2017a), exclusively focus on approximations instead of exact optimal solutions.

After solving for $z_t^*(x_t)$ and $f_1(x_1)$ by recursively iterating (4.1) and (4.2), the company then decides the optimal q and n that minimizes the average total costs per period in the steady state. The objective function of MST policy is:

$$C^{q,n}(x_1) = \lim_{T \to \infty} \frac{1}{T} f_1\left(x_1 | q, n\right). \tag{4.3}$$

The optimal decision variables are the optimal delivery quantity q^* and frequency $1/n^*$ (or the optimal delivery cycle n^*) of the slow mode, and the optimal delivery quantities z_t^* of the fast mode in t.

The problem setting of MST (and also the TBS policy) reveals a two-stage optimization problem: The company first makes the tactical decision by committing the delivery quantity and frequency of the slow mode over a mid-term horizon, then it makes operational decisions and determines the optimal delivery quantity in the fast mode every period.

4.4 Analysis on the optimal policy

It is not cost-efficient for the company to use the slow mode only. Given its inflexibility in delivery quantity and schedule, the optimal decision in the slow mode is to ship the average demand each cycle, i.e., $q = n\mu$. In order to satisfy stochastic demand using deterministic supply, significant inventory is needed to secure a required service level. The inventory required grows to infinite when t approaches to infinite. If $c^s \geqslant c^f$, it is optimal for the company to use the fast mode only because the slow mode is neither cheaper nor more flexible in delivery quantity and frequency. This problem is then degenerated to a single-sourcing problem and it is already known that a base stock policy is optimal with the order-up-to level $S^B = \Phi^{-1}(\frac{b}{b+h})$ (Arrow et al., 1958).

When both the fast and the slow modes are simultaneously used, the MST is a two-stage decision problem: the tactical decision stage in which the delivery quantity and frequency of rail transportation are committed over a mid-term time horizon, and the operational decision stage in which the delivery quantity of road transportation is adjusted on a daily basis. Consequently, the solution process of the MST problem can then be decoupled into the following three steps:

(i) Given the fixed delivery cycle n and quantity q of the slow mode, obtain the corresponding optimal delivery quantities $z_1^*(q,n), z_2^*(q,n), ..., z_T^*(q,n)$ of the fast mode by minimizing $f_1(x_1|q,n)$.

(ii) Given the fixed delivery cycle n of the slow mode, obtain the corresponding optimal delivery quantity $q^*(n)$ of the slow mode by minimizing $f_1(x_1|q)$.

(iii) Find the optimal delivery cycle n^* of the slow mode so as to minimize $f_1(x_1)$.

Step 1 represents the operational decision stage and steps 2 and 3 solve for the optimal controls of the tactical decision stage. Traditionally, dual-sourcing inventory models are known to be complex because it involves a simultaneous decision making of two trade-off supply sources. We show, however, in the MST (as well as TBS) dual-sourcing model, the decisions on two different supply sources (transportation modes) are separately planned in different levels: one tactical and the other operational. The solution process can then be divided into a sequential optimization of three subproblems. We next illustrate the solutions of the subproblems separately.

4.4.1 The optimal operational decision of the fast mode

The operational decision stage solves for the optimal policy of the fast mode deliveries, given fixed delivery quantity q and delivery cycle n of the slow mode.

Theorem 4.4.1. *(PROPERTIES OF THE OPERATIONAL DECISION STAGE) For any given delivery quantity q and delivery cycle n of the slow mode, the optimal controls of the fast mode have the following properties:*

(a). (BASE STOCK STRUCTURE) A base stock policy is optimal in each period t.

(b). (BOUNDS ON BASE STOCK LEVELS) The base stock level in period t, denoted as Y_t, is upper–bounded by $S^B = \frac{b}{b+h}$, the classical order-up-to level in the fast-mode-only single sourcing problem.

(c). (PROPERTY ACROSS CYCLES) If the delivery cycle of the slow mode has more than one period and t is the last period of a cycle, the base stock level in the first period of the next cycle satisfies the inequality: $Y_{t+1} \leqslant Y_t + q$.

(d). (PROPERTY INSIDE A CYCLE) if the delivery cycle of the slow mode has more than one period and t is the last period of a cycle, the base stock levels of the other periods of the same cycle satisfy the following inequalities: $Y_{t-n+1} \geqslant \ldots \geqslant Y_{t-1} \geqslant Y_t$.

The Appendix provides detailed proofs to the theorem. Here we offer first explanations of the theorem. When q and n are both fixed, the MST model is analogous to the classical single sourcing (with the fast mode only), dynamic inventory model with deterministic changes every cycle as follows: In the first period of each cycle, a fixed term of $(c^f - c^s)q - K$ (the transportation cost saving from using the slow mode) is subtracted from the objective function, and a fixed term of q (because the slow mode already delivers q units of the product, the use of the fast mode is aimed to satisfy a smaller demand) is subtracted from the random demand ξ. These two deterministic changes are not relevant for the optimal fast mode controls. The optimality of a base stock policy remains valid in the case of a general distribution of demand (Arrow et al., 1958, p. 110). As a result, the optimal policy should remain a base stock type. This explains *(a)* of Theorem 4.4.1. The size of the base stock level is a direct reflection of the uncertainty of the demand in an inventory system. In an MST problem with a simultaneous usage of two modes, this uncertainty is shared between two transportation modes and the base stock levels of the fast mode, being one of the two models, is therefore smaller than S^B. This explains *(b)* of Theorem 4.4.1.

The cyclic delivery of q acts as cycle stock of the inventory system. When the cycle stock arrives in $t + 1$, the probability of replenishing extra inventory from the fast mode is low. This is the reason why the base stock control Y_{t+1} of the fast mode should be upper-bounded by a value positively related to q, which is illustrated in *(c)*. If the company is at the end of a cycle (period t) and knows that q will arrive in the next period, it prefers to place a small order in the fast mode because any excessive inventory at the end of a cycle tops up the cycle stock of the next cycle, and possibly increases the holding cost of all periods of the next cycle. An excessive inventory at the end of the previous period $t - 1$ could also increase the cycle stock in the next cycle, but not so directly as that in period t. This clarifies why Y_{t-1} should be no less than Y_t, and thereafter, *(d)* of Theorem 4.4.1.

Theorem 4.4.1 demonstrates that, although a base stock policy is not imposed, the optimal control of the fast mode in MST (fast source in TBS), given that the optimal control of the slow mode (slow source) is fixed, indeed follows a base stock control. The existence of an optimal base stock policy allows for a solution of the SDP from "value iteration", i.e., solving for $z_t^*(x_t)$, to "policy iteration", i.e., solving for Y_t. Recall the Bellman equation (4.1), the state space of the SDP problem in period t consists of all possible values of inventory position x_t at the beginning of t, and the action space includes all possible fast mode delivery quantities z_t in t. The solution of the SDP requires a search for $z_t^*(x_t)$ for all x_t, with t ranging from 1 till T. Significant computing effort is needed. With the results from Theorem 4.4.1, the solution of the SDP problem shifts from finding numerous values of $z_t^*(x_t)$ to a single target: the base stock level Y_t in t. Y_t is independent on the starting inventory x_t. The more general notation indicating this policy iteration of the SDP problem is then:

$$f_t(x_t|(q,n)) = \inf_{Y_t} \{r_t(x_t, Y_t) + E[f_{t+1}(x_{t+1}|q,n)]\}, \tag{4.4}$$

where $r_t(x_t, Y_t)$, the cost-per-stage function, represents the total transportation and inventory costs in period t when applying policy Y_t and the later term is the value-to-go function.

One stage of the SDP problem is now equivalent to one period. Comparing (4.1) with (4.4), the cost-per-stage function is then:

$$r_t(x_t, Y_t) = \begin{cases} c^f(Y_t - x_t - q)^+ + c^s q + K + L(x_t + (Y_t - x_t - q)^+ + q) & q \text{ arrives in } t, \\ c^f(Y_t - x_t)^+ + L(x_t + (Y_t - x_t)^+) & \text{otherwise}, \end{cases} \tag{4.5}$$

where $(Y_t - x_t - q)^+$ and $(Y_t - x_t)^+$ indicate the fast mode delivery quantities by following the base stock decision policy Y_t. Apparently, depending on whether or not the slow mode delivers in t, r_t does change from stage to stage. This violates the condition mentioned in (Bertsekas, 2005, p. 402), and the corresponding infinite-horizon periodic review inventory system is therefore not stationary. In pursuit of a stage-independent cost-per-stage function, we study the same MST model as a cyclic review inventory system. Denote τ the starting period of a cycle, and $\widetilde{Y_\tau}$ the decision policy of the cycle with n periods, i.e., $\widetilde{Y_\tau} = (Y_\tau, Y_{\tau+1}, ..., Y_{\tau+n-1})$, (4.4) can then be rewritten as:

$$f_\tau(x_\tau|(q,n)) = \inf_{\widetilde{Y_\tau}} \left\{\widetilde{r_\tau}\left(x_\tau, \widetilde{Y_\tau}\right) + E[f_{\tau+n}(x_{\tau+n}|q,n)]\right\}. \tag{4.6}$$

One stage of the SDP problem is then one cycle with n periods, and the corresponding cost-per-stage function is:

$$\begin{aligned} \widetilde{r_\tau}(x_\tau, \widetilde{Y_\tau}) = {} & c^f(Y_\tau - x_\tau - q)^+ + c^s q + K + L(x_\tau + (Y_\tau - x_\tau - q)^+ + q) \\ & + E\left(\sum_{j=1}^{n-1} \left[c^f(Y_{\tau+j} - x_{\tau+j})^+ + L(x_{\tau+j} + (Y_{\tau+j} - x_{\tau+j})^+)\right]\right), \end{aligned} \tag{4.7}$$

where $x_{\tau+1} = x_\tau + (Y_\tau - x_\tau - q)^+ + q - \xi$, $x_{\tau+2} = x_{\tau+1} + (Y_{\tau+1} - x_{\tau+1})^+ - \xi$, and so on. According to Bellman's "Principle of Optimality", an optimization of the SDP problem over the entire time horizon can be broken down into a sequential optimization of subproblems. In equation (4.4), a subproblem is a periodic problem, whereas in (4.6), a subproblem represents a cyclical problem. The solution of the SDP will then focus on cyclic rather than periodic results.

Now the system equation (4.6), the cost-per-stage function (4.7), and the random disturbance, represented by the i.i.d. demand ξ, do not change from one stage (cycle) to the next. According to (Bertsekas, 2005, p. 402), the cyclic-review inventory system is stationary. We denote the "base stock vector" in the steady state of the infinite-horizon problem $\mathbb{S} = (S_1, S_2, ..., S_n)$. The optimal MST decision in the operational decision stage is then simplified to find the optimal $\mathbb{S}$, for any given (n, q).

Until now, the analysis in this section only secures the existence of a base stock policy of the fast mode. In order to obtain the exact values, stochastic dynamic programming (SDP) is required. The state space of the SDP is defined as all possible values of inventory position x_t at the beginning of period t and the action space is defined as all possible fast mode order quantity z_t in this period. The objective of the SDP is to obtain the optimal decision rule in the steady state cycle, denoted as the base stock vector $\mathbb{S}(S_1, S_2, ..., S_n)$.

4.4.2 The optimal tactical decision of the slow mode

In order to calculate the optimal decisions of the slow mode, the objective function (4.3) requires an evaluation of $\frac{1}{T} f_1(x_1|n, q)$ with $T \to \infty$. Although the convergence of the optimal policy of an infinite-horizon SDP problem, i.e., in our case $\mathbb{S}(S_1, S_2, ..., S_n)$, is often "surprisingly short"(Veinott, 2008), the convergence of the optimal value $\frac{1}{T} f_1(x_1|n, q)$ requires more iterations. The computing effort of the SDP increases exponentially in the number of iteration, and leads to "curse of dimensionally".

We propose a simulation-based optimization to solve for the optimal decisions of the slow mode efficiently. The algorithm works as follows: After we backwards iterate the inventory system using SDP and obtain the optimal decision policy of the fast mode $\mathbb{S}(S_1, S_2, ..., S_n)$ with a given (n, q), we forwards simulate the inventory system from period 1 till T and calculate $f_1(x_1|n, q)$. Comparing the value of $f_1(x_1|n, q)$, the optimal n^* and q^* can be obtained. This simulation-based optimization involves two steps: first to obtain $q^*(n)$ by a given n, and then to obtain n^*. For simplicity reasons, we assume the system starts with zero inventory, i.e., $x_1 = 0$. For the relationship between $f_1(x_1|n, q)$ and q, we obtain the following theorem:

Theorem 4.4.2. *(PROPERTY OF THE TACTICAL DECISION STAGE): For* *any given delivery cycle of the slow mode n, the average total cost per period in the steady state, stated in (4.3), is convex in the delivery quantity of the slow mode q.*

The utilization of the slow mode has two trade-off impacts. On the one hand, it reduces the total transportation cost for each unit of product shifted to the slow mode; on the other hand, the fixed delivery quantity weakens the flexibility of the MST policy and brings extra inventory cost into the system. This trade-off drives the convexity of f in q. Based on this theorem, a bisection search over q (q is upper-bounded by $n\mu$ because the slow mode can not supply more than the expected demand in a cycle) is possible to reduce the computing effort of the numerical solution.

The last step of the optimal MST policy is to search for the optimal delivery cycle of the slow mode. This is the final outer loop of the entire MST algorithm, outside of the middle loop (bisectional search for the delivery quantity of the slow mode), and the inner SDP (searching for the optimal base stock levels of the fast mode). Because the delivery cycle of a rail transportation is practically a small integer, e.g., the rail transportation delivers once every two days ($n = 2$), or at least once per week ($n = 7$), an enumeration of all possible integers is sufficient to search for the optimal delivery cycle.

4.5 Numerical analysis

In this section, we conduct a numerical study to illustrate the modal split transportation problem based on our solution algorithm discussed before. The objective of this numerical study is to answer two questions: 1) How can our model and algorithm be implemented to support companies' modal split transportation optimizations? 2) How sensitive/robust is our MST policy against the uncertainties of parameters?

4.5.1 Numerical design

In order to preserve commercial confidentiality, we do not use real data from any specific company. Instead, we use realistic industry-level values in the model. We then appoint uncertainties of the different parameters in a sensitivity analysis.

Since the volume of freight transportation is measured and the corresponding transportation cost is paid at the standard unit of a full container load (FCL), we set FCL as the basic unit of our model. One FCL is equivalent to the volume loaded in a standard 45-foot container, a full truck load, or a full railcar load. The demand in the model is assumed to follow a gamma distribution with $\mu = 30$ and $\sigma = 10$. The company pays $c^f = 550$ EUR to transport one FCL from plant (P) to distribution center (D) via road transportation. Based on data from European Intermodal Association (2012), to transport one FCL using rail transportation incurs a variable cost of $c^s = 224$ EUR, and the fixed cost of the train operation, regardless of the volume delivered, is $K = 8170$ EUR. The inventory holding cost includes the storage and handling spending incurred in the warehouse, as well as the cost of capital, i.e., by holding the inventory on hand, the company loses the opportunity to use the capital linked to the inventory for other investments. The general "rule of thumb" is that the annual inventory holding cost is 25% of the stock value. Given that the average value of an FCL cargo is assumed to be about 100,000 EUR, $h = 100000/365 \cdot 25\% = 68$ EUR. The company keeps a non-stockout probability of 98%. The unit backorder cost b is hence set to be $49h = 3332$ EUR, indicating the non-stockout probability calculated by the newsvendor ratio is $b/(b + h) = 98\%$. The company operates the train with the least frequency of once per week, i.e., n should not exceed seven. A list of the parameters is shown in Table 4.1.

Table 4.1: *A list of the parameters used in the model with normalized values.*

Notation	Description	Value	Unit
μ	Mean of demand	30	FCL
σ	Standard deviation of demand	10	FCL
α	Service level	98%	pct
h	Unit holding cost at the DC	68	EUR per FCL per day
b	Unit backorder cost at the DC	3332	EUR per FCL per day
c^f	Unit transportation cost via the fast mode	500	EUR per FCL
c^s	Unit transportation cost via the slow mode	224	EUR per FCL
K	Fixed transportation cost via the slow mode	8170	EUR per train

On the basis of the calibrated parameters, we validate our algorithm and illustrate the drivers of the optimal road and rail transportation decisions. Our efficient algorithm allows applying a sensitivity analysis of the MST policy, in which the impact of demand volatility, service level, cargo value, and transportation cost savings are analyzed. Finally, we show if the MST policy is already being applied, how robust is the whole system against exogenous noises. The noises are categorized into two types: 1) on the operational level, the misspecifications of base stock controls of road transportation. 2) on the tactical level, the mismatch of fixed rail transportation decisions over time and the fluctuating demand volatility.

4.5.2 Numerical results

On the basis of the benchmark parameters, our algorithm finds that the optimal modal split transportation operates as follows: A train delivers a fixed quantity of $q^* = 81$ FCLs every $n^* = 3$ days, and trucks deliver to bring the inventory level to $S_1 = 54$, $S_2 = 54$ and $S_3 = 45$ in the three periods of a cycle. Note, the base stock levels are also measured in the unit of FCL, representing the corresponding amount of inventory that can be loaded into the containers. Under this policy, the optimal volume split in rail transportation is 90%. The ratio aligns with the findings in Chapter 3 that the volume shifted to the slow mode is high. The total computing effort using a laptop with i5-3320 CPU, 4GB RAM, and 64-bit Windows 7 Professional, is 39 seconds.

Figure 4.1 shows the values of S_1, S_2, and S_3 calculated by the SDP algorithm in the first six cycles of iteration, when the optimal delivery quantity q and delivery cycle n of the rail transportation are fixed. The optimal policy, i.e., the base stock vector (S_1, S_2, S_3), converges and the convergence process is surprisingly short.

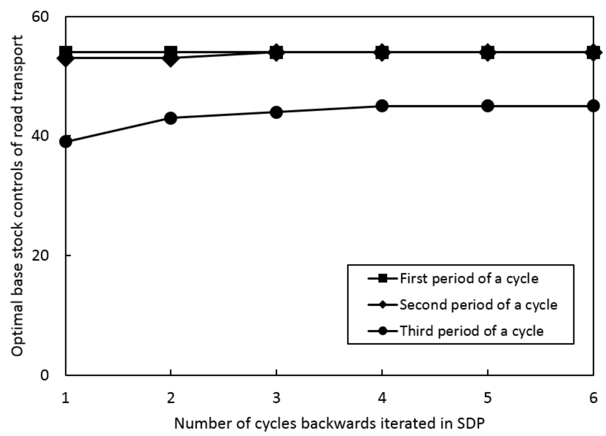

Figure 4.1: *The convergence of the base stock controls of road transportation*

The impact of the rail transportation delivery quantity q on the base stock controls of the road transportation is shown in Figure 4.2. When more volume is shifted into rail transportation, the road transportation will be less utilized via reduced base stock control levels. Nevertheless, the base stock level in the last period of a cycle, in this case S_3, is more sensitive to q compared to the previous periods. This is because of the cyclical arrival of q acts as cycle stock for the inventory system. Any excessive inventory at the last period of a previous cycle (in this case period 3) will top up the cycle stock of the next cycle, and possibly leads to higher inventory holding costs for every period of the next cycle.

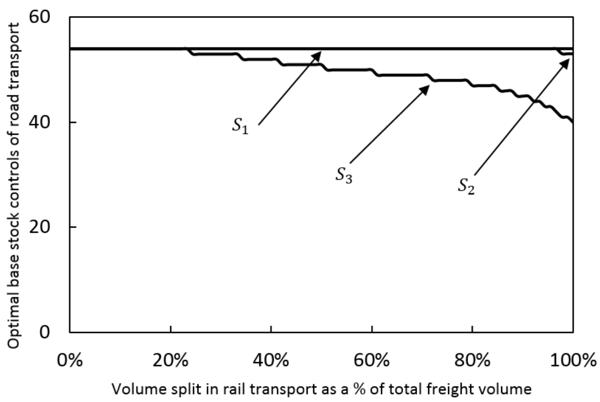

Figure 4.2: *The impact of delivery quantity of rail transportation on the base stock controls of road transportation*

The delivery cycle n of rail transportation impacts the base stock controls of road transportation indirectly via its delivery quantity q. The curve in Figure 4.3 shows that q increases in n: when the size of the cycle increases, the company could order a larger q via the rail transportation to satisfy the demand of more periods of a cycle. Nevertheless, the curve indicates that q increases in n with a decreasing margin. This is because the larger the cycle stock linked to q is, the more inventory holding cost will be generated in the cycle, which will offset the transportation cost savings from the use of rail transportation.

Thus far, we have validated the impact of the rail transportation decisions on the road transportation controls. Figure 4.4 shows that the main driver of the optimal rail transportation decision is its fixed cost K. The larger the fixed cost is, the less frequent the company wants to use rail transportation. The three-stage optimization problem addressed in Section 4.4 is therefore numerically validated: The fixed cost of rail transportation drives its delivery cycle and quantity, and the delivery cycle and quantity of rail transportation impact the base stock controls of road transportation. In practice the company could collaborate with other shippers to fill in the empty wagons of the train on the same corridor, the fixed

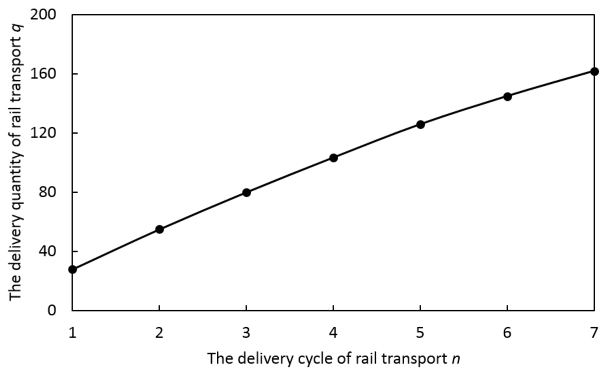

Figure 4.3: *The impact of rail transportation delivery cycle n on its delivery quantity q*

cost of the slow mode is shared and K in the MST model is reduced. On the other hand, the company could also expect an increase in K due to e.g., extra maintenance or toll charges of railway infrastructures. Our analysis reveals that the change in K is particularly important because they will tactically impact the entire decision of both rail and road transportation controls.

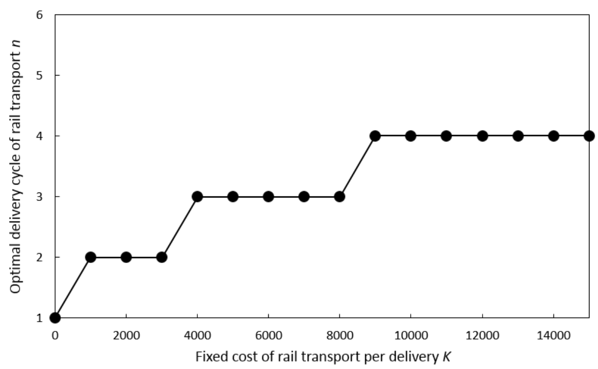

Figure 4.4: *The impact of the fixed cost of rail transportation to the delivery cycle of rail transportation*

In the classical inventory theory with one single supplier, the introduction of a fixed cost changes the optimal base stock policy to an (s, S) policy (see, e.g., Arrow et al., 1958). In the dual-sourcing MST problem, the fixed cost of rail transportation impacts its optimal delivery frequency. Nevertheless, the impact of the fixed cost in both cases is similar: the fixed cost encourages economies of scale so that the company will decrease the number of orders placed, and increase the average ordering quantity. Previous literature in TBS models, e.g., Allon and Van Mieghem (2010), Janakiraman et al. (2014), and Dong et al. (2017b), did not address the impact of the fixed cost K, partly because the introduction of the fixed cost term will make the model intractable via analytic approximation. Our study, however, fills this gap by proposing an algorithm to calculate the optimal numerical solutions with minor computing effort.

4.5.3 Sensitivity analysis

We conduct four different analyses to understand how sensitive the MST results are against the coefficient of variation (CV) of demand, the service level of the inventory system (represented by the unit backorder cost b), the value of the cargo shipped (associated with the unit holding cost h), and the variable transportation cost saving of rail over road ($c^f - c^s$). The performance measurement is twofold: 1) The optimal delivery cycle n^* of rail transportation, because it is already shown in Section 4.5.2 that the delivery cycle of rail transportation is the major driver of its delivery quantity, and consequentially impacts the base stock controls of road transportation. 2) The modal split ratio in rail transportation, i.e., $q^*/(n^*\mu)$, because shifting volume from road to rail transportation is companies' key objective of implementing MST.

The previous baseline model was based on the demand with CV 0.3, which is a typical ratio of a fast-moving SKU in the industry. A transfer of the knowledge in MST requires analyses for other classes of SKUs, and the SKUs are typically classified under the criteria of CV (see, e.g., Van Kampen et al., 2012). Figure 4.5 shows that when the demand is more volatile, the modal split ratio in rail transportation decreases because the company needs to increase the flexibility of the MST system by a higher usage of road transportation. Figure 4.6 shows that the optimal delivery cycle increases in CV, indicating that rail transportation is less frequently used.

The service level of the inventory system might vary across industries, and hence impacts companies' decision in MST. The service level in our model is measured as the in-stock probability, presented by the newsvendor ratio $\frac{b}{b+h}$. Table 4.2 shows the optimal MST decisions when the service level changes from 60% to 99.5%. Interestingly, the optimal delivery cycle and delivery quantity of rail transportation remain unchanged, and the company merely needs to increase its optimal base stock controls of road transportation facing a higher service level.

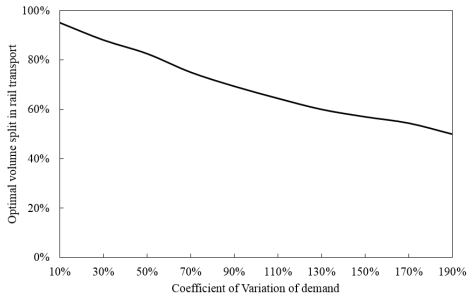

Figure 4.5: *The impact of CV on the optimal modal split ratio in rail transportation*

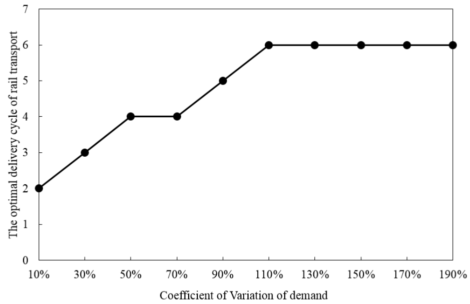

Figure 4.6: *The impact of CV on the optimal delivery cycle of rail transportation*

The results again address the advantage of the setup of our MST policy: It allows comopanies to capture the responsiveness of the transportation system by using road transportation, and to focus on cost savings of the transportation system by using rail transportation. A change of the service level therefore only impacts the decisions on the road transportation.

Table 4.2: *The impact of service level on the optimal controls of rail and road transportation*

Service Level	n^*	q^*	S_1	S_2	S_3	C
60%	3	81	30	29	8	12023
70%	3	81	34	33	14	12430
80%	3	81	38	37	22	12736
90%	3	81	43	43	32	13339
95%	3	81	48	48	38	13681
98%	3	81	54	54	45	14082
99%	3	81	58	58	49	14317
99.5%	3	81	62	62	54	14544

The product value might influence the companies' MST decisions. In our model, the product value indirectly impacts the MST decisions via its unit holding cost h, i.e., the annual average holding cost is measured as 25% of the product value. Figure 4.7 shows that when the product value increases, the company prefers to use more road transportation compared to rail transportation. A transportation mode with a higher service level (in this case, road transportation), is favored for deliveries of high-value products. Figure 4.8 shows that the higher the product value, the less frequent the usage of the "low service" transportation mode (in this case, rail transportation).

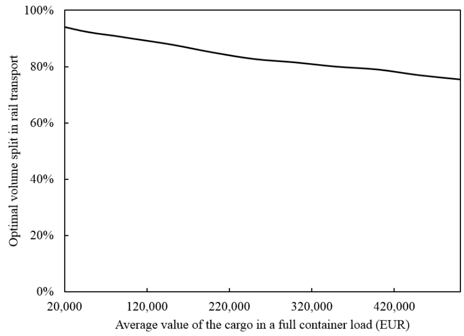

Figure 4.7: *The impact of the product value on the optimal modal split ratio in rail transportation*

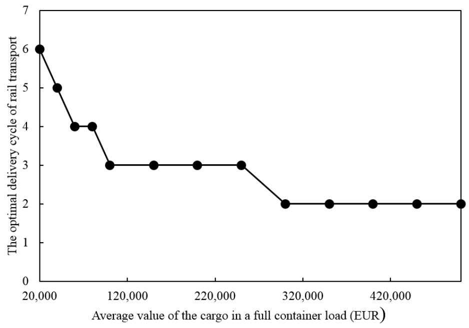

Figure 4.8: *The impact of the product value on the optimal delivery cycle of rail transportation*

Whereas the cost of road transportation is rather straightforward, the cost of rail transportation is often lumpy and highly dependent on the specific corridors (European Intermodal Association, 2012). We therefore fix the unit cost of road transportation c^f, and observe how the MST decisions will behave when the unit cost of rail transportation c^s changes. Figure 4.9 shows that when c^s approaches zero, the optimal ratio in rail transportation is close to 100%; when $c^s = 0$, the corresponding ratio is zero; and the curve decreases in c^s. However, the curve is flat until a certain threshold and then quickly drops to zero. In this specific example, this interesting threshold is around c^s being approximately 70% of c^f. To the left of this point, even if the cost savings increase substantially, the incremental modal split into rail transportation is moderate; to the right of this point, the modal split ratio will decrease significantly when c^s increases. The identification of this point could help companies better utilize the MST policy and promote the modal shift into rail transportation. Figure 4.10 shows that the optimal delivery cycle of rail transportation remains stable until approximately $c^s = 70\%$ of c^f, and then surges to infinite: when the cost savings of rail transportation is subtle, the company needs to have a very large (approaches to ∞) delivery cycle to secure the economies of scale of rail transportation.

4.5.4 The robustness of the modal split transportation model

When the MST policy is already implemented by the company, exogenous noises might impact its performance. We distinguish between two types of noise: 1) On

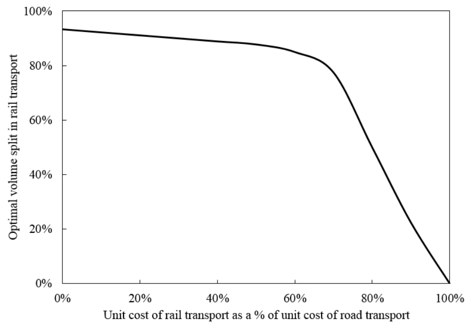

Figure 4.9: *The impact of transportation cost savings on the optimal modal split ratio in rail transportation*

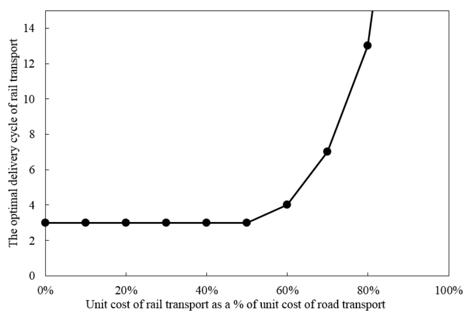

Figure 4.10: *The impact of transportation cost savings on the optimal delivery cycle of rail transportation*

the operational level, managers might misspecify the base stock controls of road transportation. 2) On the tactical level, the pre-fixed delivery cycle and quantity of rail transportation over a mid-term period might not be able to match the posterior changes in demand uncertainties. These noises impact the robustness of the MST policy. The performance measure of the robustness is the error in the average total cost of a steady state period.

Since the base stock controls in a steady state cycle differ from each other, it is reasonable to presume that the exact position of the base stock misspecification in a cycle will impact the performance of the MST policy. In order to better understand the impact of the position, we consider a large cycle with seven periods, i.e., $n = 7$. Figure 4.11 illustrates how the misspecifications of the seven base stock levels lead to errors in average total costs per period. When a misspecification of 100% happens in the first period of a delivery cycle, the inventory system is hardly affected. However, if the misspecification happens in the seventh period of a cycle, the cost error could be close to 10%.

After the delivery of quantity q from the rail transportation in the first period of a cycle, the company is less likely to replenish its inventory via the fast mode to satisfy the demand in this period. This is the reason that a misspecification of the base stock control of the road transportation hardly impacts the total costs of the MST system. The fixed delivery quantity of the rail transportation q acts as cycle stock in the inventory system. In the later periods of a cycle when the cycle stock is depleted, more and more volume is hence needed from road transportation to satisfy the demand. This explains the finding that when a misspecification happens in later periods, the consequence is more severe. Operational managers

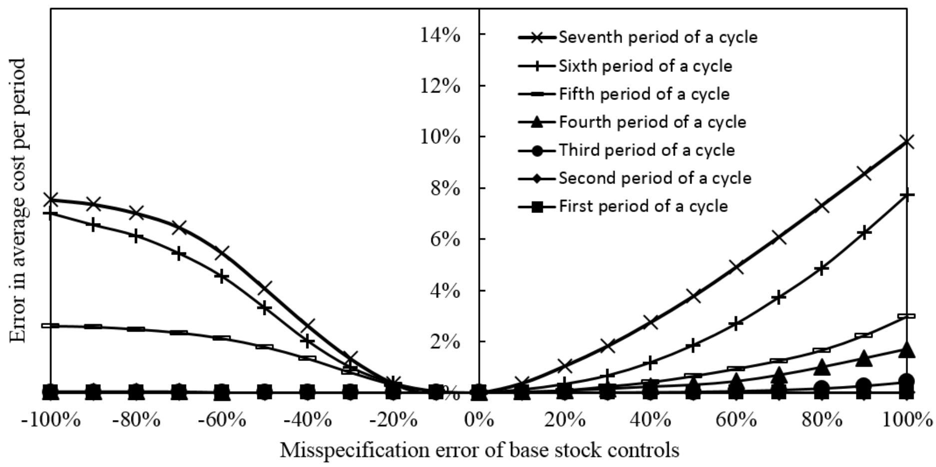

Figure 4.11: *The impact of base stock level misspecifications on the average total costs per period*

can practically "be lazy" and do not place any order via the road transportation in the periods when the train delivers, and only work with the fast mode in the period without train deliveries.

This result also provides additional help in the technical solution of the MST problem. One of the reasons for the considerable computing effort of the model is that there are n different base stock targets to be solved. If we already know that the base stock targets from the first few periods (in this example, the first three periods) only have little impact on the results of the MST policy, the solution algorithm can drop them and focus on fewer decision variables. This way the entire computing effort of the problem will be reduced.

Thus far, the analysis on the MST has been based on the assumption that the demand can be described by a probability distribution function with definite mean and standard deviation. In a practical problem, the two parameters will be forecasted on the basis of historical data. It is reasonable to suspect, however, that future demand will be described with different parameters. Even if a company can closely forecast the mean of the demand over a certain time horizon, which is relatively simple, the forecasting error in the variance of the demand could be unavoidably high. Considering that the optimal control of the rail transportation in MST is a commitment fixed over a future mid-term horizon, it is very likely that the coefficient of variation of the demand will fluctuate during this time horizon and the pre-defined MST policy will deviate from optimality. Nevertheless, the company is still able to make daily adjustments of the shipment volume via the flexible road transportation deliveries. Figure 4.12 shows that by allowing adjustments from road transportation deliveries, the commitment in rail transportation is rather robust against CV changes. For example, if the original MST policy is decided based on a forecast CV of 0.6 and in reality the CV deviates from the forecast value with an error of 50%, the average cost per period is only affected by about 1%.

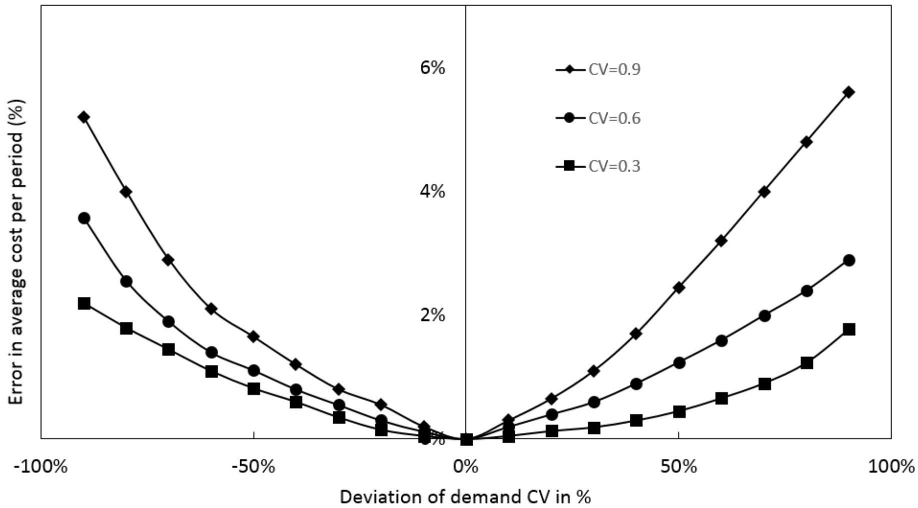

Figure 4.12: *The impact of CV on the average total costs per period*

Managers, especially from the industries with high competitions, tend to have the concern that the fixed mid-term commitment on rail transportation controls lacks the flexibility to respond to demand fluctuations. We show that by the simultaneous usage of the flexible road transportation, the commitment of rail transportation decisions is robust. This result supports the long term viability of MST policy against demand uncertainties.

4.6 Discussion

4.6.1 Alternative (non-i.i.d.) demand patterns

Thus far, our model assumes that the demand is an i.i.d. random variable. In practice, however, the demand process may be non-i.i.d.: Demand in one period might be dependent on the value of other periods, and/or demand in different periods might follow different distribution functions. Since the classical TBS policy and our MST policy are both distribution-independent, our model can still hold for non-i.i.d. demand patterns. Indeed the Bellman equations (4.1) and (4.2) can still be used to model the MST problem. And the MST problem can be solved by numerically iterating the equations over the finite time horizon (a brute-force solution). However, the structural properties obtained in Section 4.4 will not hold. To be more specific, Theorem 4.4.1 does not hold and the converged steady state will not exist due to non-stationary demand. As a result, the model with non-i.i.d. demand will not be solved efficiently with the structural properties obtained in the i.i.d. demand case, and the brute-force solution will result in the "curse of dimensionality" which requires tremendous, and sometimes unrealistic computing effort.

In Section 6.2.3 of the dissertation, we discuss a special type of non-i.i.d. demand that is often observed in practice: The demand can be considered seasonal, which follows different distributions in different periods of time. We propose a tailored transportation strategy, which involves three different transportation modes, each with its own cost and flexibility, to match and serve different demand categories. When more generalized non-stationary demand is faced, advanced data analytics methodologies will be needed.

4.6.2 Capacity constraint on the slow mode

Our model assumes an unlimited capacity of the slow mode. However, the slow mode (rail transportation) is typically subject to the maximum number of full container loads (FCLs) a train can carry, which varies across countries. For example, the maximum length of a train in France is 740 meters (European Court of Auditors, 2016), which is equivalent to about only 50 FCLs. The numerical study in Section 4.5.2 suggests to ship $q = 81$ FCLs via a train, which exceeds the capacity and is practically not feasible.

If the company can only book one train, then the MST model needs to be solved with a capacity constraint on q. Recall from Section 4.4.2 that the optimal q is calculated via a bisection search with q lower-bounded by one and upper-bounded by $n\mu$, the MST model with capacity constraint can still apply the same bisection search, but with an updated upper-bound. If there are sufficient freight trains in the market, a more practical solution is to use more trains to provide adequate capacity for the containers shipped to the slow mode. However, the fixed cost might increase depending on the number of trains ordered. This then requires running the MST algorithm multiple times with updated information on the upper-bound of the slow mode volume q and fixed cost K, so that the optimal volume shipped to the slow mode q will satisfy the capacity constraint.

4.6.3 Analysis on the slow mode delivery cycle

In Section 4.5.2 we have optimized the slow mode delivery cycle n by a straightforward enumeration. Now we present a first attempt to offer some tractable analysis on the optimization of the slow mode delivery cycle n. The analysis is presented as follows: We first show the different types of costs of the MST problem (fixed cost, inventory mismatch cost, etc.) as a function of n, and then discuss how these cost terms will change when n increases.

The average total costs in a steady state cycle with n periods can be written as:

$$c^s q + c^f(n\mu - q) + K + \sum_{i=1}^{n} L_i, \tag{4.8}$$

where $c^s q$ denotes the variable transportation cost via the slow mode, K the fixed transportation cost via the slow mode, $c^f(n\mu - q)$ the variable transportation cost via the fast mode, and $\sum_{i=1}^{n} L_i$ the sum of the expected mismatch cost of all n periods of the cycle. The objective of the modal split transportation policy is to minimize the average total costs per period by dividing (4.8) by n, generating:

$$c^f\mu - (c^f - c^s)\frac{q}{n} + \frac{K}{n} + \frac{\sum_{i=1}^{n} L_i}{n}. \tag{4.9}$$

When the delivery cycle n increases, the average fixed cost per cycle, denoted as $\frac{K}{n}$, decreases. The ratio $\frac{q}{n}$, denoting the average slow mode freight volume per period, will decrease because of the following reason: The constant delivery via the slow mode q acts as cycle stock and will result in extra holding cost in potentially every period of the cycle. The extra holding cost from using the slow mode will offset the cost savings and prevent q from increasing. Figure 4.3 in Section 4.5.2 shows a numerical example that q increases in n with decreasing margin, i.e., q/n decreases. The term $c^f\mu - (c^f - c^s)\frac{q}{n}$ in (4.9), the average variable transportation cost per period, will then increase in n. The last term $\frac{\sum_{i=1}^{n} L_i}{n}$ in (4.9), the average inventory mismatch cost per period, is not analytically tractable because of the intractability of the inventory levels in the model. Even if in a simplified special case with $n = 1$, in which the model is then equivalent to the classical TBS policy, the relevant inventory is considered not tractable in the literature (Allon and Van Mieghem, 2010). When $n > 1$, inventory levels in more than one period of a steady state cycle need to be calculated, which makes the model even more complex. We conjecture that the average mismatch cost per period $\frac{\sum_{i=1}^{n} L_i}{n}$ will decrease in n. The reason is as follows: If $n \to \infty$, the problem can be seen as the classical base stock problem with some starting inventory q. It is known that the expected mismatch cost will be minimized in all periods with $L = L(S^B)$, where S^B is the base stock target. As a result, when n increases, $\frac{\sum_{i=1}^{n} L_i}{n}$ will decrease and approach its lower-bound, i.e., $\lim_{n\to\infty} \frac{\sum_{i=1}^{n} L_i}{n} = L(S^B)$.

Adding all the terms together, the average total cost per period shown in (4.9) is analytically not tractable, and numerical analysis has to be relied on.

4.7 Summary

In this chapter, we contribute a dual-sourcing inventory model to support companies' modal split transportation (MST) decisions, i.e., how to optimally split freight volume between road and rail transportation. Our MST model is an extension of the classical TBS dual-sourcing model, by 1) incorporating economies of scale of rail transportation, i.e., adding a fixed term into its cost structure and an extra decision in its delivery frequency, and 2) releasing the base stock control of road transportation so that companies could have higher flexibility in its delivery quantity. These extensions are closely related to the nature of rail and road operations. TBS models are traditionally regarded as complex and previous literature focused on approximations. We contribute an efficient algorithm to solve the MST (and also any general TBS) problem optimally based on stochastic dynamic programming. On the basis of the efficient algorithm, we further contribute to the MST/TBS models by proposing a detailed sensitivity and robustness analysis using numbers suggested by a multinational company.

Several extensions could be applied to further support companies' modal split transportation decisions. First, our model assumes that rail transportation always delivers a constant quantity. In reality, companies could have other options to manage the freight in trains. Other inventory replenishment policies, besides TBS, can also be applied to MST decisions. Second, our model is only based on a single product and multi-product analysis will be more realistic in practice. Third, the company might want to share the capacity of the train with other shippers, and collaborative modal split transportation needs to be studied.

4.8 Appendix

4.8.1 Appendix A: Proof of Theorem 4.4.1

We borrow the idea from Porteus (2002) and introduce decision variables y_t and functions $G_t(y_t)$ to illustrate the proof. y_t is defined as the net inventory position after deliveries from the two modes and before demand realization, i.e., if q arrives in t, $y_t = x_t + z_t + q$; if not, $y_t = x_t + z_t$. The Bellman equation (4.1) and (4.2) can then be rewritten as:

$$f_t(x_t|q,n) = \begin{cases} \min\limits_{y_t \geqslant x_t+q} \{-c^f x_t + c^f y_t - c^f q + c^s q + K + L(y_t) \\ \qquad\qquad +E\left[f_{t+1}\left(y_t - \xi|q,n\right)\right]\} & q \text{ arrives in } t, \\ \min\limits_{y_t \geqslant x_t} \left\{-c^f x_t + c^f y_t + L(y_t) + E\left[f_{t+1}\left(y_t - \xi|q,n\right)\right]\right\} & \text{otherwise,} \end{cases} \tag{4.10}$$

and

$$f_T(x_T|(q,n)) = \begin{cases} \min\limits_{y_T \geqslant x_T+q} \left\{-c^f x_T + c^f y_T - c^f q + c^s q + K + L(y_T)\right\} & q \text{ arrives in } T, \\ \min\limits_{y_T \geqslant x_T} \left\{-c^f x_T + c^f y_T + L(y_T)\right\} & \text{otherwise.} \end{cases} \tag{4.11}$$

We define G_t as a function of y_t:

$$G_t(y_y) = \begin{cases} c^f y_T + L(y_T) & t = T, \\ c^f y_t + L(y_t) + E\left[f_{t+1}\left(y_t - \xi|q,n\right)\right] & \text{otherwise.} \end{cases} \tag{4.12}$$

Note, $G_t(y_t)$ is independent on whether or not q arrives in t.

Proof of *(a)* of Theorem 4.4.1 using mathematical induction:

Period T: $L(y_T)$ is convex in y_T, G_T in (4.12) is also convex in y_T. Because $\lim_{|y_T|\to\infty} G_T = \infty$ (based on the assumption $c^f < b$), there exists a unique Y_T that minimizes G_T. Therefore, the optimality of a base stock policy in T exists. By setting $G_T^{'}(Y_T) = 0$, we can obtain the base stock level:

$$Y_T = \Phi^{-1}\left(\frac{b-c^f}{b+h}\right). \tag{4.13}$$

Given the optimality of a base stock policy, f_T and $f_T^{'}$ can be written as:

If q arrives in T:

$$f_T(x_T|q,n) = \begin{cases} c^f(Y_T - x_T - q) + c^s q + K + L(Y_T) & x_T \leqslant Y_T - q, \\ c^s q + K + L(x_T + q) & x_T \geqslant Y_T - q, \end{cases} \tag{4.14}$$

and

$$f_T^{'}(x_T|q,n) = \begin{cases} -c^f & x_T \leqslant Y_T - q, \\ L^{'}(x_T + q) & x_T \geqslant Y_T - q. \end{cases} \tag{4.15}$$

If q does not arrive in T:

$$f_T(x_T|q,n) = \begin{cases} c^f(Y_t - x_T) + L(Y_T) & x_T \leqslant Y_T, \\ L(x_T) & x_T \geqslant Y_T, \end{cases} \tag{4.16}$$

and

$$f_T^{'}(x_T|q,n) = \begin{cases} -c^f & x_T \leqslant Y_T, \\ L^{'}(x_T) & x_T \geqslant Y_T. \end{cases} \tag{4.17}$$

$f_T(x_T|q,n)$ is convex in x_T and $\lim_{|x_T|\to\infty} f_T = \infty$, and $f_T^{'}$ is no less than $-c^f$ and converges to a positive number when $x_T \to \infty$. These two properties are independent of the arrival of q in T.

Period $T-1$: According to (4.12), $G_{T-1}(y_{T-1}) = c^f y_{T-1} + L(y_{T-1}) + E[f_T(y_{T-1} - \xi|q,n)]$. Combining (4.14) and (4.16), we can derive that G_{T-1} is convex in y_{T-1} with $\lim_{|y_{T-1}|\to\infty} = \infty$. There must exist a unique Y_{T-1} with $G_{T-1}^{'}(Y_{T-1}) = 0$, that minimizes G_{T-1}, i.e., the optimal delivery policy of the fast mode in $T-1$ is a base stock policy.

Given the optimality of a base stock policy in $T-1$, it can be further shown that $f_{T-1}(x_{T-1}|q,n)$ is convex in x_{T-1}, $\lim_{|x_{T-1}|\to\infty} f_{T-1} = \infty$, and $f_{T-1}^{'}$ is no less than $-c^f$ and converges to a positive number when $x_{T-1} \to \infty$. Both properties are independent of the arrival of q in $T-1$.

From any arbitrary period k to period $k-1$. We now suppose that the optimal fast mode policy in k is a base stock policy, the base stock level is Y_k with $G_k^{'}(Y_k) = 0$, and $f_k(x_k|q,n)$ and $f_k^{'}(x_k|q,n)$ are:
If q arrives in k:

$$f_k(x_k|q,n) = \begin{cases} c^f(Y_k - c_k - q) + c^s q + K + L(Y_k) & \\ \qquad + E\left[f_{k+1}(Y_k - \xi|q,n)\right] & x_k \leqslant Y_k - q, \\ c^s q + K + L(x_k + q) + E\left[f_{k+1}(x_k + q - \xi|q,n)\right] & x_k \geqslant Y_k - q, \end{cases} \tag{4.18}$$

and

$$f_k^{'}(x_k|q,n) = \begin{cases} -c^f & x_k \leqslant Y_k - q, \\ L^{'}(x_k+q) + E^{'}\left[f_{k+1}(x_k+q-\xi|q,n)\right] & x_k \geqslant Y_k - q. \end{cases} \quad (4.19)$$

If q does not arrive in k:

$$f_k(x_k|q,n) = \begin{cases} c^f(Y_k - x_k) + L(Y_k) + E\left[f_{k+1}(Y_k-\xi|q,n)\right] & x_k \leqslant Y_k, \\ L(x_k) + E\left[f_{k+1}(x_k-\xi|q,n)\right] & x_k \geqslant Y_k, \end{cases} \quad (4.20)$$

and

$$f_k^{'}(x_k|q,n) = \begin{cases} -c^f & x_k \leqslant Y_k, \\ L^{'}(x_k) + E^{'}\left[f_{k+1}(x_k-\xi|q,n)\right] & x_k \geqslant Y_k. \end{cases} \quad (4.21)$$

$f_k(x_k|q,n)$ is convex in x_k with $\lim_{|x_k|\to\infty} f_k = \infty$, and $f_k^{'}$ is no less than $-c^f$ and converges to a positive number when $x_k \to \infty$. Both properties are independent of the arrival of q in k.

In period $k-1$, according to (4.12), $G_{k-1}(y_{k-1}) = c^f y_{k-1} + L(y_{k-1}) + E[f_k(y_{k-1} - \xi|q,n)]$. Given (4.18) and (4.20), G_{k-1} is convex in y_{k-1} with $\lim_{|y_{k-1}|\to\infty} = \infty$. As a result, there must exist a unique Y_{k-1} with $G_{k-1}^{'}(Y_{k-1}) = 0$ that minimizes G_{k-1}, and the fast mode shipment in $k-1$ follows a base stock policy with base stock level Y_{k-1}.

With the knowledge of a base stock policy in $k-1$, it can be further shown that $f_{k-1}(x_{k-1}|q,n)$ is convex in x_{k-1}, with $\lim_{|x_{k-1}|\to\infty} f_{k-1} = \infty$, and $f_{k-1}^{'}$ is no less than $-c^f$ and converges to a positive number when $x_{k-1} \to \infty$. Both properties independent of the arrival of q in $k-1$.

Equations (4.18), (4.19), (4.20), and (4.21) can be iterated to $k-1$, and furthermore, any arbitrary period t.

Allowing T approaching infinity, the proof could be inducted to the infinite-horizon problem.

Proof of *(b)* of Theorem 4.4.1 using mathematical induction:

Period T: (4.13) secures $Y_T < S^B = \Phi^{-1}\left(\frac{b}{b+h}\right)$.

Period T-1: We already know from the proof of *(a)* of Theorem 4.4.1 that, G_{T-1} in is convex in y_{T-1} with $G_{T-1}^{'}(Y_{T-1}) = 0$. In order to prove $Y_{T-1} < S^B$, we only need to show that $G_{T-1}^{'}(S^B) > 0$ in the following:

If q arrives in T:

$$\begin{aligned} G_{T-1}^{'}(S^B) &= c^f + \underbrace{L^{'}(S^B)}_{=0} + E^{'}[f_T(S^B - \xi|q,n)] \\ &= c^f + \int_0^{S^B - Y_T + q} \underbrace{f_T^{'}(S^B - \xi|q,n)}_{\geqslant -c^f, \text{ refer to (4.15)}} \phi(\xi) d\xi \\ &\quad + \int_{S^B - Y_T + q}^{\infty} \underbrace{f_T^{'}(S^B - \xi|q,n)}_{= -c^f, \text{ refer to (4.15)}} \phi(\xi) d\xi \\ &= \int_0^{S^B - Y_T + q} \underbrace{c^f + f_T^{'}(S^B - \xi|q,n)}_{\geqslant 0} \phi(\xi) d\xi > 0. \end{aligned} \tag{4.22}$$

If q does not arrive in T:

$$\begin{aligned} G_{T-1}^{'}(S^B) &= c^f + \underbrace{L^{'}(S^B)}_{=0} + E^{'}[f_T(S^B - \xi|q,n)] \\ &= c^f + \int_0^{S^B - Y_T} \underbrace{f_T^{'}(S^B - \xi|q,n)}_{\geqslant -c^f, \text{ refer to (4.17)}} \phi(\xi) d\xi \\ &\quad + \int_{S^B - Y_T}^{\infty} \underbrace{f_T^{'}(S^B - \xi|q,n)}_{= -c^f, \text{ refer to (4.17)}} \phi(\xi) d\xi \\ &= \int_0^{S^B - Y_T} \underbrace{c^f + f_T^{'}(S^B - \xi|q,n)}_{\geqslant 0} \phi(\xi) d\xi > 0. \end{aligned} \tag{4.23}$$

From any arbitrary period k to $k-1$: Assume that $Y_k < S^B$ and f_k is illustrated in (4.18) and (4.20), we want to derive that $Y_{k+1} < S^B$. We already know from the proof of *(a)* of Theorem 4.4.1 that, G_{k-1} is convex in y_{k-1} with $G_{k-1}^{'}(Y_{k-1}) = 0$. In order to prove $Y_{k-1} < S^B$, we need to show that $G_{k-1}^{'}(S^B) > 0$ in the following:

If q arrives in k:

$$\begin{aligned}
G'_{k-1}(S^B) &= c^f + \underbrace{L'(S^B)}_{=0} + E'[f_k(S^B - \xi|q,n)] \\
&= c^f + \int_0^{S^B - Y_k + q} \underbrace{f'_k(S^B - \xi|q,n)}_{\geqslant -c^f,\text{ refer to (4.19)}} \phi(\xi)d\xi \\
&\quad + \int_{S^B - Y_k + q}^{\infty} \underbrace{f'_k(S^B - \xi|q,n)}_{=-c^f,\text{ refer to (4.19)}} \phi(\xi)d\xi \\
&= \int_0^{S^B - Y_k + q} \underbrace{c^f + f'_k(S^B - \xi|q,n)}_{\geqslant 0} \phi(\xi)d\xi > 0.
\end{aligned} \tag{4.24}$$

If q does not arrive in k:

$$\begin{aligned}
G'_{k-1}(S^B) &= c^f + \underbrace{L'(S^B)}_{=0} + E'[f_k(S^B - \xi|q,n)] \\
&= c^f + \int_0^{S^B - Y_k} \underbrace{f'_k(S^B - \xi|q,n)}_{\geqslant -c^f,\text{ refer to (4.21)}} \phi(\xi)d\xi \\
&\quad + \int_{S^B - Y_k}^{\infty} \underbrace{f'_k(S^B - \xi|q,n)}_{=-c^f,\text{ refer to (4.21)}} \phi(\xi)d\xi \\
&= \int_0^{S^B - Y_k} \underbrace{c^f + f'_k(S^B - \xi|q,n)}_{\geqslant 0} \phi(\xi)d\xi > 0.
\end{aligned} \tag{4.25}$$

Allowing T to tend to infinity, the proof could be inducted to the infinite-horizon problem.

Proof of *(c)* of Theorem 4.4.1:

Similar to the approach used in proving *(b)* of Theorem 4.4.1, in order to prove $Y_t > Y_{t+1} - q$ and given $G_t(y_t)$ is convex in y_t with $G'_t(Y_t) = 0$, we need to show $G'_t(Y_{t+1} - q) < 0$ as follows:

$$G'_t(Y_{t+1}-q) = c^f + L'(Y_{t+1}-q) + \int_0^{\infty} \underbrace{f'_{t+1}(Y_{t+1} - q - \xi|q,n)}_{=-c^f,\text{ refer to (4.19)}} \phi(\xi)d\xi = L'(Y_{t+1}-q). \tag{4.26}$$

Because L is convex with $L(S^B) = 0$ and $Y_{t+1} - q < S^B$ (from *(b)* of Theorem

4.4.1), $L^{'}(Y_{t+1}-q)<0$.

End of proof of *(c)* of Theorem 4.4.1.

Proof of *(d)* of Theorem 4.4.1:

We fist show that in the last cycle, $Y_{T-1} \geqslant Y_T$, and in any arbitrary cycle with t being the last period of the cycle, $Y_{t-1} \geqslant Y_t$. After that we iterate the inequalities in the following way: suppose that $k-1, k$, and $k+1$ are three sequential periods of the same cycle, and $Y_k \geqslant Y_{k+1}$, we then derive the inequality that $Y_{k-1} \geqslant Y_k$.

Recall from *(a)* that $G_{T-1}(y_{T-1})$ is convex in y_{T-1} with $G^{'}_{T-1}(y_{T-1})=0$, we prove $Y_{T-1} \geqslant Y_T$ by showing $G^{'}_{T-1}(Y_T)<0$ as follows:

$$G^{'}_{T-1}(Y_T) = \underbrace{c^f + L^{'}(Y_T)}_{=0} + \int_0^{\infty} \underbrace{f^{'}_T(Y_T-\xi|q,n)}_{=-c^f,\text{ refer to (4.17)}} \phi(\xi)d\xi < 0. \tag{4.27}$$

If t is the last period of any arbitrary cycle (note, q arrives in $t+1$), we then need to prove $Y_{t-1} \geqslant Y_t$ by showing $G^{'}_{t-1}(Y_t) \leqslant 0$ as follows:

$$\begin{aligned}
G^{'}_{t-1}(Y_t) &= c^f + L^{'}(Y_t) + \int_0^{\infty} f^{'}_t(Y_t-\xi|q,n)\phi(\xi)d\xi \\
&= \underbrace{c^f + L^{'}(Y_t) + \int_0^{\infty} f^{'}_{t+1}(Y_t-\xi|q,n)\phi(\xi)d\xi}_{=G^{'}_t(Y_t)=0} \\
&\quad + \int_0^{\infty} \underbrace{f^{'}_t(Y_t-\xi|q,n)}_{=-c^f,\text{ refer to (4.21)}} \phi(\xi)d\xi - \int_0^{\infty} f^{'}_{t+1}(Y_t-\xi|q,n)\phi(\xi)d\xi \\
&= -c^f - \int_0^{Y_t+q-Y_{t+1}} \underbrace{f^{'}_{t+1}(Y_t-\xi|q,n)}_{\geqslant -c^f,\text{ refer to (4.19)}} \phi(\xi)d\xi \\
&\quad - \int_{Y_t+q-Y_{t+1}}^{\infty} \underbrace{f^{'}_{t+1}(Y_t-\xi|q,n)}_{=-c^f,\text{ refer to (4.19)}} \phi(\xi)d\xi \\
&= -\int_0^{Y_t+q-Y_{t+1}} [c^f + \underbrace{f^{'}_{k+1}(Y_k-\xi|q,n)}_{\geqslant -c^f \text{ refer to (4.19)}}]\phi(\xi)d\xi.
\end{aligned} \tag{4.28}$$

Because $Y_t+q-Y_{t+1}>0$ is already proved in *(c)* of Theorem 4.4.1, (4.28) is non positive.

Then we want to show that, suppose $k-1$, k, $k+1$ are three sequential periods in a same cycle, and Y_{k-1}, Y_k, and Y_{k+1} are the optimal base stock levels in the three periods. If $Y_k \geqslant Y_{k+1}$, then $Y_{k-1} \geqslant Y_k$. Given the results from *(a)* of Theorem 4.4.1 that $G_{k-1}(y_{k-1})$ is convex in y_{k-1} with $G'_{k-1}(Y_{k-1}) = 0$, we want to prove $Y_{k-1} \geqslant Y_k$ by showing that $G'_{k-1}(Y_k) \leqslant 0$ as follows:

$$\begin{aligned}
G'_{k-1}(Y_k) &= c^f + L'(Y_k) + \int_0^\infty f'_k(Y_k - \xi|q,n)\phi(\xi)d\xi \\
&= \underbrace{c^f + L'(Y_k) + \int_0^\infty f'_{k+1}(Y_k - \xi|q,n)\phi(\xi)d\xi}_{=G'_k(Y_k)=0} \\
&\quad + \int_0^\infty \underbrace{f'_k(Y_t - \xi|q,n)}_{=-c^f\text{, refer to (4.21)}} \phi(\xi)d\xi - \int_0^\infty f'_{k+1}(Y_k - \xi|q,n)\phi(\xi)d\xi \\
&= -c^f - \int_0^{Y_k - Y_{k+1}} \underbrace{f'_{k+1}(Y_k - \xi|q,n)}_{\geqslant -c^f\text{, refer to (4.19)}} \phi(\xi)d\xi \\
&\quad - \int_{Y_k - Y_{k+1}}^\infty \underbrace{f'_{k+1}(Y_k - \xi|q,n)}_{=-c^f\text{, refer to (4.19)}} \phi(\xi)d\xi \\
&= -\int_0^{Y_k - Y_{k+1}} [c^f + \underbrace{f'_{k+1}(Y_k - \xi|q,n)}_{\geqslant -c^f\text{, refer to (4.19)}}]\phi(\xi)d\xi.
\end{aligned} \tag{4.29}$$

Because $Y_k \geqslant Y_{k+1}$, (4.29) is non positive.

4.8.2 Appendix B: Proof of Theorem 4.4.2:

The idea of the proof is inspired by Theorem 1 from Janakiraman et al. (2014). We drop n in the proof because it remains unchanged. Denote $C^{q,*}$ the average total cost per period of an optimal MST policy with cyclical slow mode delivery q, we will prove the theorem by demonstrating the following inequality:

$$\frac{C^{q_1,*} + C^{q_2,*}}{2} \geqslant C^{(q_1+q_2)/2,*} \qquad \text{for all } q_1 \text{ and } q_2. \tag{4.30}$$

Denote $\theta_1 = \theta_1(q^{\theta_1}; z_1^{\theta_1}, ..., z_T^{\theta_1})$ and $\theta_2 = \theta_2(q^{\theta_2}; z_1^{\theta_2}, ..., z_T^{\theta_2})$ the two optimal MST policies, and let $C^{\theta_1} = C^{q_1,*}$ and $C^{\theta_2} = C^{q_2,*}$. That is, for example, under the optimal MST policy θ_1, the company ships a fixed amount q^{θ_1} in the slow mode cyclically and $z_t^{\theta_1}, t = 1, ..., T$ in the the fast mode every period following the base stock controls. Let us now consider a third policy θ_3: The slow mode delivers a fixed amount $q^{\theta_3} = \frac{q^{\theta_1}+q^{\theta_2}}{2}$ cyclically, and the fast mode ships $z_t^{\theta_3} = \frac{z_t^{\theta_1}+z_t^{\theta_2}}{2}$ in t. Note, θ_3 is not necessarily the optimal policy of MST with a cyclical slow mode order $\frac{q^{\theta_1}+q^{\theta_2}}{2}$, because the fast mode order $z_t^{\theta_3}$ might not fit the base stock controls. As a result, $C^{\theta_3} \geqslant C^{(q_1+q_2)/2,*}$.

Since $q^{\theta_3} = \frac{q^{\theta_1}+q^{\theta_2}}{2}$ and $z_t^{\theta_3} = \frac{z_t^{\theta_1}+z_t^{\theta_2}}{2}$, the transportation cost under θ_3 in any period t is the average of the transportation cost under θ_1 and θ_2. Let us now consider the realized mismatch cost every period under θ_3. Assuming that all three policies start with the same inventory level in period 1, i.e., $x_1^{\theta_1} = x_1^{\theta_2} = x_1^{\theta_3}$, it is easy to see that $x_t^{\theta_3} = (x_t^{\theta_1} + x_t^{\theta_2})/2$ for any t. The realized one-period inventory mismatch cost is:

$$\mathcal{L}_t = \begin{cases} h(x_t + z_t + q - \xi)^+ + b(\xi - x_t - z_t - q)^+ & q \text{ arrives in } t, \\ h(x_t + z_t - \xi)^+ + b(\xi - x_t - z_t)^+ & \text{otherwise.} \end{cases} \tag{4.31}$$

It is convex in x_t for any t, independent on wether or not the slow mode delivers in that period. Considering the convexity of mismatch cost and the equality of the transportation cost explained before, the average total (mismatch and transportation combined) costs per period satisfies: $(C^{\theta_1} + C^{\theta_2})/2 \geqslant C^{\theta_3}$. Therefore we obtain: $(C^{q_1,*} + C^{q_2,*})/2 = (C^{\theta_1} + C^{\theta_2})/2 \geqslant C^{\theta_3} \geqslant C^{(q_1+q_2)/2,*}$. This completes the proof.

Chapter 5

Implementing synchromodality from a supply chain perspective

学而时习之，不亦乐乎？[1]

– 孔子。

Abstract

In this chapter, we present a practical tool to support the implementation of synchromodality and validate our findings presented in the previous chapters. The tool considers the flows between a plant and a distribution center (DC) of a manufacturer. The tool allows obtaining the optimal modal split per SKU between road transportation (the fast but expensive mode) and rail transportation (the slow but cheap mode), as well as the inventory requirements at the distribution center, that minimizes the total supply chain costs. We have used the tool to validate the research problems discussed in the earlier chapters on a real dataset. It indicates how the use of synchromodality impacts the various supply chain costs. As the synchromodality tool addresses individual SKUs, we provide a solution to aggregate the volume shifted to the slow mode from multiple SKUs to full container loads, such that the resulting total costs are minimized.

[1] Isn't it a pleasure to study and practice what you have learned? Confucius, ancient Chinese philosopher.

5.1 Introduction

We have applied our synchromodality model under a tailored base-surge (TBS) policy to companies, which address the challenge of improving the sustainability of its transportation and logistics. The products are manufactured in a plant and then shipped to distribution centers. Currently, direct trucking is the dominant means of transportation mode.

Synchromodality, where freight flow is synchronized between different transportation modes, is regarded as an innovative approach to increase the sustainability of freight transportation and one of the fundamental building stones to the Physical Internet (Verweij, 2011; ALICE, 2014). In this chapter, we present how synchromodality using a tailored base-surge (TBS) policy can be implemented by managers that are not familiar with the mathematics behind a TBS policy. Based on historical data, we validate the use of our policy. The backbone of the tool is an optimization model covering the shipper's supply chain including plant, distribution center (DC), transportation mode choices, and stochastic customer demand at the DC. The tool can be used to support shippers determine the optimal modal split policy for any given stock keeping unit (SKU). The use of the tool enables a holistic understanding of the impact of synchromodality on the shipper's supply chain performance, such as production smoothing, inventory management, bullwhip dampening, etc.

Whereas Chapter 2 focuses on the conceptual framework of synchromodality using a TBS policy and Chapters 3 & 4 capture its solution methodologies, the main objective of this chapter is to demonstrate its implementation. In addition, during the implementation of the tool, the impact of TBS synchromodality on other activities of the supply chain, such as production and inventory management, are also discussed on the basis of real data. The main contributions of this chapter can be summarized as follows:

- We present an easy-to-use tool to implement synchromodality using a TBS policy and shift freight from a flexible and fast transportation mode to a "greener" slow transportation mode on an SKU level;
- We use the tool to evaluate the impact of synchromodality on other supply chain metrics, such as the impact on inventory levels in the downstream DC, as well as the production smoothing impact in the upstream plant;
- We conduct sensitivity analyses on the input parameters such as the demand variability and lead time and provide guidance on the use of synchromodality

for different SKUs;

- We present an LP model to aggregate the freight shipments via the slow mode across multiple SKUs into full container loads.

5.2 Model formulation

We consider a two-stage supply chain, consisting of a plant (P) and a distribution center (D) facing stochastic customer demand. Figure 5.1 illustrates the supply chain under consideration.

Distribution and production are triggered by customer demand, denoted as ξ, which is assumed to follow an i.i.d. distribution with mean μ and standard deviation σ. Demand ξ is a non-negative integer, measured in units of a case. Similar to the other chapters, we assume demand to be stationary over time. The companies classifies its SKUs into different categories based on the demand distribution, which in turn determines the order (and shipment) frequency from P to D: whereas fast movers are shipped on a daily basis, slow movers may have a lower shipment frequency (e.g., weekly or bi-weekly). The replenishment frequency of the SKUs is captured in the model by considering a periodic-review inventory model with a review length of r periods. The shipment frequency, which is identical to the review frequency, is then $\frac{1}{r}$ for both the slow and fast transportation mode. For example, if a slow mover is shipped on average once per week from P to D, and the base period in the model is one day, then $r = 7$. Time is discrete and the horizon is finite, with $t = 1, ..., T$. We denote the set $\mathbb{T} = \{1, r + 1, 2r + 1, ...\}$ consisting of the "shipment" periods at which the SKU is shipped from P to D.

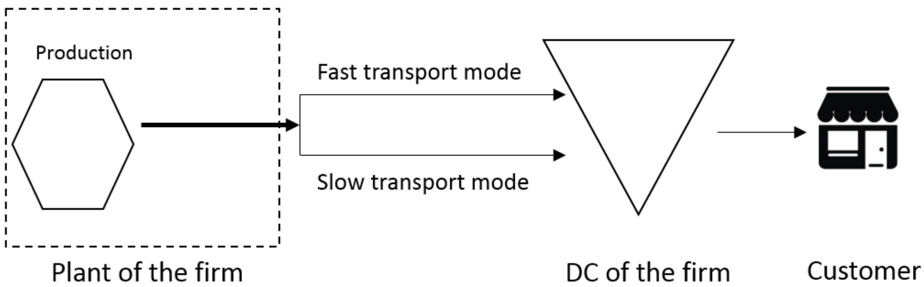

Figure 5.1: *Two-stage supply chain with parallel usage of fast and slow transportation modes*

The distribution center keeps an inventory to satisfy the stochastic demand ξ subject to a service level α. At the end of any period t, after the realization of demand ξ, excessive inventory incurs a unit holding cost h, and unmet demand will be backordered to the next period at a unit penalty cost b. The classical newsvendor ratio $\frac{b}{b+h}$ is equal to the service level α, which is an exogenous parameter to the model.

In every review period, D can replenish its inventory from P via a simultaneous usage of two transportation modes: a slow mode with a cheaper unit transportation cost c^s but a longer lead time l^s, and a fast mode incurring a higher unit transportation cost c^f but a shorter lead time l^f. In our setting, the slow mode is intermodal rail transportation, and the fast mode is direct trucking. The companies need to decide how much to ship using each transportation mode.

In this model, we use the classical tailored base-surge (TBS) policy and adopt the same delivery frequency for both transportation modes. This assumption is valid when the fixed cost of the slow mode is negligible (Section 4.5.2 shows that when the fixed cost is zero, the slow mode has the same delivery frequency as the fast mode). This may be the case when the company does not operate a dedicated train connection, but outsources the operation of rail transportation to a logistics service provider (LSP), in which case it pays a fixed rate c^s per unit shipped. Clearly, when companies (co-)operate a dedicated train and hence needs to cover a significant set-up cost linked to locomotive, infrastructure, etc., the delivery frequency of the slow mode will be lower than the fast mode. However, this leads to additional complexity, as it requires the optimization of multiple inventory reorder points within a slow mode delivery cycle with significant computing effort as a result (see Section 4.4).

Under a TBS policy, the slow mode ships a constant quantity q in each period $t \in \mathbb{T}$, and nothing in other periods. Hence, the number of units shipped using the slow mode in period t, and delivered at D in period $t + l^s$, is given by z_t^s:

$$z_t^s = \begin{cases} 0 & \text{if } t \notin \mathbb{T}, \\ q & \text{if } t \in \mathbb{T}. \end{cases} \tag{5.1}$$

Unlike the slow mode, the fast mode ships a flexible quantity controlled by a base-stock policy. Denote z_t^f the number of units shipped using the fast mode in period t (and delivered at D in period $t + l^f$), then $z_t^f = 0$ if $t \notin \mathbb{T}$; when $t \in \mathbb{T}$, the order placed raises the inventory position IP_t to the base-stock level S. The inventory position IP_t is defined as the net inventory x_t plus the pipeline inventory that will arrive within the next l^f periods:

$$IP_t = x_t + \sum_{t-l^f}^{i=t-1} \left(z_i^f + z_i^s \right). \tag{5.2}$$

The shipment quantity via the fast mode, z_t^f, placed in period t and delivered in period $t + l^f$, is then:

$$z_t^f = \begin{cases} 0 & \text{if } t \notin \mathbb{T}, \\ 0 & \text{if } t \in \mathbb{T} \text{ and } IP_t > S, \\ S - IP_t & \text{if } t \in \mathbb{T} \text{ and } IP_t \leq S. \end{cases} \tag{5.3}$$

The company produces $(z_t^s + z_t^f)$ units upon receipt of the order. As sufficient capacity is available to accomplish any production run within a time window of 24 hours, each production order can be produced before the start of the subsequent period. The total logistics costs in period t are then given by:

$$C_t = \begin{cases} h(x_t + z_{t-l^s}^s + z_{t-l^f}^f - \xi)^+ & \\ \quad + b(\xi - x_t - z_{t-l^f}^f - z_{t-l^s}^s)^+ + kI_t & \text{if } t \notin \mathbb{T}, \\ c^s q + c^f z_t + h(x_t + z_{t-l^s}^s + z_{t-l^f}^f - \xi)^+ & \\ \quad + b(\xi - x_t - z_{t-l^f}^f - z_{t-l^s}^s)^+ + kI_t & \text{if } t \in \mathbb{T}, \end{cases} \tag{5.4}$$

where $c^s q$ represents the transportation costs of the units shipped via the slow mode, $c^f z_t$ the transportation costs of the units shipped via the fast mode, $h(x_t + z_{t-l^s}^s + z_{t-l^f}^f - \xi)^+ + b(\xi - x_t - z_{t-l^f}^f - z_{t-l^s}^s)^+$ the inventory mismatch costs at D in period t, and kI_t the cost of capital linked to the pipeline inventory, defined by $I_t = \sum_{i=t-l^f+1}^{i=t} z_i^f + \sum_{i=t-l^s+1}^{i=t} z_i^s$.

The decision variables of the companies are the constant slow mode delivery quantity q, and the base stock level S to control the fast mode shipments. The objective of the companies is to minimize the average total costs per period over the horizon T:

$$\bar{C} = \frac{1}{T} \sum_t C_t. \tag{5.5}$$

We optimize the decision variables q and S using simulation-based optimization, i.e., searching over all possible values of q and S that minimize $\bar{C}$. In order to have a stationary system (where supply exceeds demand), the value of q is upper-bounded by the expected demand in the review interval $r\mu$. The base stock level

S is upper-bounded by $\Phi^{-1}(\frac{b}{b+h})$, with Φ the CDF of the demand in $(l^f + r)$ periods and $(l^f + r)$ the exposure period in the periodic review base-stock model. The optimal synchromodality policy is then characterized by the parameters (q^*, S^*).

Note that the tool uses the simulation-based optimization introduced in Chapter 2 as the solution method, instead of the other methodologies discussed in Chapters 3 and 4. The main reason is the trade-off between accuracy and effort: The approximation in Chapter 3 does not provide the optimal results, and the algorithm in Chapter 4 requires substantial computing effort. Practitioners prefer good and fast solutions and simulation-based optimization is practically favored.

5.3 The synchromodality tool

We developed a VBA-based Excel tool to support companies in implementing synchromodality under the TBS policy. The tool allows the optimization of the parameters of the TBS policy based on historical data. Once these parameters are determined, it enables to determine the shipment quantities on both fast and slow modes on a periodic basis (for instance, daily, weekly, bi-weekly, etc.), as well as the parameters of the inventory policy at the DC and the production quantities at the plant. The tool can be used by supply chain managers without understanding the mathematics in the model. In this section, we first explain the in- and outputs of the tool and then describe the three core modules of it.

5.3.1 The in- and outputs of the tool

Figure 5.2 shows an overview of the inputs that are needed to run the tool, as well as the outputs that result from the use of it.

The input data required to run the tool are the following:

- **Demand of the SKU:** The historical daily demand of an SKU. It is measured in cases, which is the standard measurement of customer orders.
- **Loading factors of the SKU:** The loading factors of an SKU refer to how many SKU items are packed into a case, a pallet, and a full container load (FCL) respectively. Suppose 100 cases of an SKU are packed into one pallet and a full container load (FCL) contains 33 pallets[2], then as many as $100 \times 33 = 3300$ cases of the SKU can be loaded in one FCL. The introduction of the loading factor adjusts parameters on the same unit base

[2] One FTL in Western Europe except the UK contains at most 33 pallets.

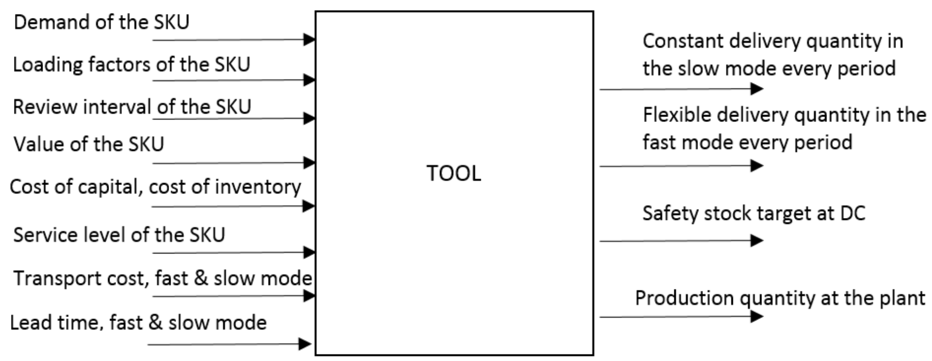

Figure 5.2: *The VBA-based Excel tool determines the shipment quantities for each transportation mode, as well as the safety stock targets at the DC.*

across multiple SKUs. For example, if it costs c^f to ship one FCL from P to D, then the shipment of one case of the aforementioned SKU incurs $\frac{c^f}{3300}$.

- **Review interval of the SKU:** Depending on the type of the SKU, the review interval r at which orders are placed can differ. Fast moving SKUs are typically shipped on a daily basis, in which case $r = 1$ day. Slow moving SKUs can be shipped for instance semi-weekly ($r = 3$ days) or weekly ($r = 7$ days). The value of r is an exogenous variable decided by the managers.

- **Value of the SKU:** The unit value of one SKU, measured in EUR per case, which is required to calculate its inventory holding cost (see next).

- **Cost of capital, cost of inventory:** The inputs are used to calculate the unit holding cost of the SKU in the transportation pipeline as well as in the DC. For example, if the "rule of thumb" cost of capital in the market is assumed to be 8%, then the daily unit cost of inventory in the transportation pipeline is $k = \frac{8\%}{365} \times \textit{Value of the SKU}$. Under the same logic, the daily unit inventory holding cost at the DC is then $h = \frac{\textit{cost of inventory}}{365} \times \textit{Value of the SKU}$. Note however that these cost parameters can be easily adjusted.

- **Service level of the SKU:** This is the minimal in-stock probability of the inventory at the DC, which will be used to indirectly calculate the unit backlog cost b through the critical fractile $\frac{b}{b+h} = \textit{the service level}$.

- **Transportation cost, fast & slow mode:** The unit transportation cost incurred from the Plant to the DC. It is measured per FTL and needs to be adjusted to the case level using the loading factors.

- **Transportation lead time, fast & slow mode:** The delivery lead times of the two transportation modes from the Plant to the DC. It is practically measured per day.

5.3.2 The modules of the tool

Fed with the data above, the tool works by a sequential execution of three modules (Figure 5.3): (1) The historical dataset is cleaned; (2) The optimal parameters of the synchromodality policy are calculated based on historical demand data; (3) Based on this optimal policy, the tool allows a real time implementation of synchromodality decisions and suggests shipment volumes on both transportation modes. The latter two modules are explained in details as follows.

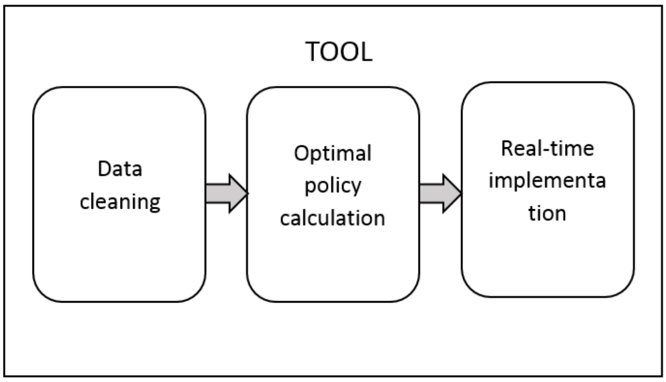

Figure 5.3: *The VBA-based Excel tool consists of three modules, which are executed sequentially*

Module: Optimal policy calculation This module determines the optimal TBS synchromodality policy, characterized by the optimal shipment quantity via the slow mode q^* and the optimal base stock control with order-up-to level S^*. The optimal policy is obtained by simulation-based-optimization, i.e., searching for all possible (q, S) to minimize the objective function 5.5.

The model calculates the average total costs per period (Equation 5.5) over a period of length T. In Chapters 2 and 3 we have demonstrated that the average cost per period converges in the steady state, which requires a large T. However, as the products of the companies often have a short life cycle, the limited number of demand data might not drive the model to the steady state. To cope with this, we employ a parametric bootstrapping approach to expand the demand time series "artificially".

The parametric bootstrapping works as follows: First, the current demand sample is used to estimate the distribution function of the demand population. After that, the estimated demand population is re-sampled to retrieve more demand observations. For example, Figure 5.4 shows the histogram of a series of demand data of a reference SKU and the estimated probability distribution function (PDF) of the demand population based on the demand sample. The fitting is based on maximum likelihood estimation given the series of demand sample data. A new data series with $T = 1000$ suffices for a proper working of the tool. Note, for confidentiality reasons, the demand data is normalized: The demand mean is normalized to 100, and all demand observations are rescaled accordingly.

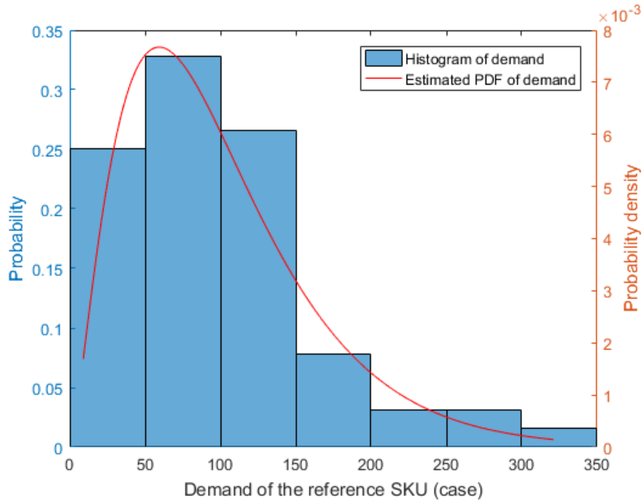

Figure 5.4: *The demand distribution (the red curve) is estimated based on the demand sample (characterized by its histogram)*

Real-time implementation Based on the optimal parameters of the TBS policy, this module supports companies make real-time synchromodality decisions based on real-time demand and inventory data. Every review period r it provides recommendations how much to ship using the fast and slow transportation mode, and how much should be produced to satisfy these shipments.

5.4 Implementation of the tool

In this section, we first validate the use of the tool with a reference SKU. We then extend the results of this specific SKU to the other SKUs that are shipped on the same lane to estimate the potential of synchromodality on that corridor. Finally, we discuss how the output of the tool can be used to aggregate the shipments of multiple SKUs into full container loads.

5.4.1 Validation of the tool

Table 5.1 summarizes the parameters of the reference SKU, that are used as inputs to the tool. For confidentiality reasons, all the parameters are rescaled: The demand mean is normalized to 100, and all other parameters are then rescaled according to the same ratio.

Table 5.1: *A reference fast-moving SKU with the following parameters are used to validate the synchromodality tool (rescaled numbers)*

Notation	Description	Value	Unit
μ	Mean of customer demand	100	case
σ	Standard deviation of customer demand	69	case
α	Service level	99%	pct
l^f	Lead time of the fast mode	5	day
l^s	Lead time of the slow mode	7	day
h	Unit holding cost at the DC	0.109	EUR per case per day
b	Unit backorder cost at the DC	10.791	EUR per case per day
k	Cost of capital	0.032	EUR per case per day
c^f	Transportation cost via the fast mode	0.999	EUR per case
c^s	Transportation cost via the slow mode	0.874	EUR per case

Figure 5.5 depicts the logistics costs resulting from the use of the tool in function of the volume that is shipped by rail service (slow mode). When more freight is shifted to the slow mode, the company saves transportation costs, but incurs additional inventory costs. The optimal synchromodality policy is given by $(q^*, S^*) = (67, 997)$, indicating that the slow mode delivers 67 cases every day and the base stock target at the distribution center is 997 cases. The share of the slow mode for this SKU is $67/100 = 67\%$, indicating that 67% of the freight volume can be shifted to the slow but “greener” transportation mode, without increasing total logistics cost or reducing the service level. In fact, the total logistics costs is expected to decrease by 5% for this specific reference SKU.

Once the optimal synchromodality policy (q^*, S^*) is determined based on the historical data, the tool can be used to implement synchromodality on a daily basis: for this SKU, the tool recommends to ship every day $q^* = 67$ cases of the reference SKU via the slow mode, and an additional shipment is carried out via the fast mode based on its daily inventory position, which takes into account the current inventory levels and the inventory pipeline to be delivered within the next l_f days. The plant then produces the total shipment volume immediately.

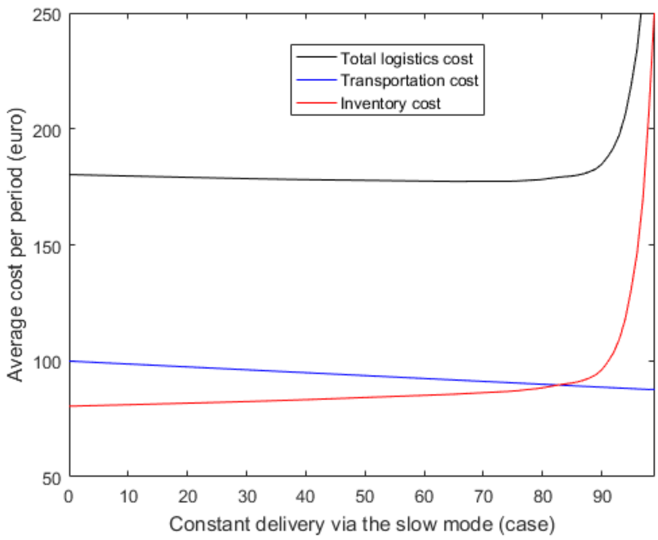

Figure 5.5: *The tool shows how the transportation and inventory are impacted by the volume shifted to the slow mode. For the reference SKU, the average total costs are minimized when the company ships 67 cases per day, which is about* 67% *of the total freight volume of that SKU on this specific corridor. This modal shift will lead to a* 5% *reduction of total logistics costs without sacrificing the service level.*

The tool can be used for each SKU. Clearly, as each SKU has specific parameters, the optimal synchromodality policy and the corresponding modal split will be different for each SKU. In order to estimate the potential of synchromodality for all SKUs that are shipped on the corridor between Northern and Southern Europe, we analyzed the coefficient of variation (CV) of demand of all these SKUs. In Figure 5.6 we show the histogram of the CV for all the SKUs that are shipped in this lane (classified per values of 0.5). The histogram is right-skewed with a long tail. In Figure 5.7 we display how much of the total volume these SKUs represent (per CV range of 0.5). Then we estimate for each CV range how much volume can be shipped using the slow mode (assuming all other parameters equal to our reference SKU), which is represented by the curve in Figure 5.7.

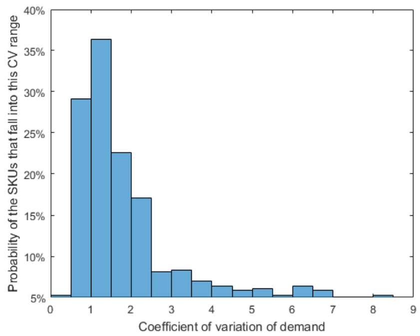

Figure 5.6: *The number of SKUs shipped on this lane classified per range of coefficient of variation (CV) of demand.*

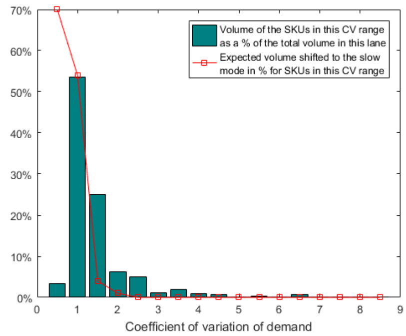

Figure 5.7: *The relative volume of the SKUs for each CV range (bars), and the corresponding optimal modal split to the slow mode (curve).*

The curve in Figure 5.7 shows that the percentage of freight shifted to the slow mode approaches to zero when the CV of the demand is large. This observation raises the question whether this rapid drop could be driven by other factors, such as the mean of demand. In other words, is it possible that the marginal modal split is due to the low volume of the SKU rather than its high variability? We test this hypothesis using a similar approach presented in the previous paragraph: First we classify all the SKUs into a number of ranges (per value of 500 cases per day), and then calculate the average modal split for each of the ranges. Figure 5.8 shows that even for the SKUs in the lowest mean range (0-500), as much as 18% of the total volume can be shifted to the slow mode in average. We additionally plot a dotted curve describing the average CV of the SKUs in each of the ranges and observe the same CV implication shown in Figure 5.7: The higher the CV, the lower the percentage shifted to the slow mode.

In summary, the validation has demonstrated that the CV is a major driver of the synchromodality modal split, whereas the impact of the mean demand is relatively minor. This result coincides with the analysis from previous chapters, e.g., Section 3.5, that the higher the demand volatility, the lower the use of the slow mode, because the slow transportation mode (e.g., rail) lacks the flexibility to cope with demand fluctuations.

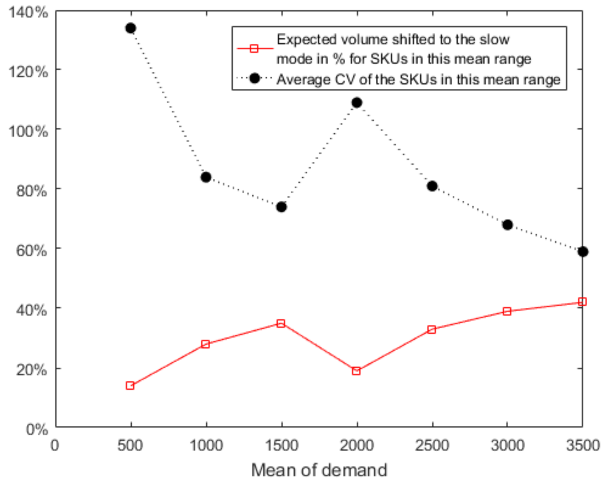

Figure 5.8: *Even for the SKUs with the lowest mean of demand, as much as 18% of the total volume can be shifted to the slow mode (the solid curve). The higher the CV, the lower the percentage shifted to the slow mode (both curves).*

Finally, we obtain an estimation of the consolidated total volume that can be shifted to the slow mode in this lane by aggregating the volumes from all SKU groups. This analysis yields that across all SKUs, about 32% of the total volume can be shifted to the slow mode on this lane. In other words, if the company would have implemented the tool over the past year for all freight transportation from the plant to the DC, it could have shifted approximately 32% of the total freight volume to the slow mode in this lane. In addition, there are significant savings in the ecological footprint when the freight volume is shifted to a "greener" transportation mode. With direct trucking emitting 75g CO_2 per tonne-kilometer of freight, and rail service 21g CO_2 per tonne-kilometer of freight (both numbers are generalized industry average values, provided by the European Environment Agency (2013)), a 32% freight shift on this lane would have entailed a $\left(1 - \frac{32\% \times 21 + (1-32\%) \times 75}{100\% \times 75}\right) = 23\%$ CO_2 emission reduction.

These results from real data once more reveal the huge opportunities of implementing synchromodality in both economic and environmental aspects. Especially considering that the company operates worldwide with many more corridors, the potential cost savings and emissions reductions will be significant.

The current industry practice reported in Groothedde et al. (2005) suggests to shift the stable and well-predictable volume to the slow mode. In the presence of the stochastic demand, this is equivalent to ship the lower-bound of the demand every day. In order to compare their method to ours, we have replicated their approach on our dataset. Surprisingly, this only results in a total modal shift of merely 3% to the slow mode in this lane, much less than the 32% obtained using our model. A plausible reason for this low ratio is that the demand for many of the SKUs are highly volatile and the lower-bounds are therefore almost zero. This comparison demonstrates that by implementing synchromodality from a supply chain perspective, companies could significantly outperform the current industry practice described in Groothedde et al. (2005), and shift more volume to the sustainable intermodal rail transportation without trading higher cost or lower service level.

The aforementioned validation is based on the assumption that all the SKUs are reviewed once per day. In practice, however, the review interval of the slow moving SKUs may be extended. Indeed, Figure 5.7 reveals that for slow moving SKUs with a high demand variability, the optimal split of the slow mode is only modest. When the CV of demand increases, the volume shifted to the slow mode drops rapidly. When CV > 1, only a minor portion of the freight can be shifted to the slow mode, and it even drops to zero when CV > 2, as the slow mode cannot cope with the demand fluctuations at all. However, extending the review interval aggregates the demand during this review period and hence dampens its variability.

Figure 5.9 illustrates the impact of extending the review interval to $r = 3$ (semi-weekly review) and $r = 7$ (weekly review). For the medium or slow moving SKUs with CV > 1, we notice that a longer review period fosters more volume to the slow mode. The accumulated demand in each review interval results in a lower CV, which enables a higher use of the slow mode. Notice that this is not the case for fast movers with CV ≤ 1, in which case the volume shifted to the slow mode goes down when we extend the review interval. This is due to the increased cycle stocks, which dominates the (modest) reduction in demand variance. Among others, this result supports the common practice of the supply chain managers to apply daily production and shipment for fast movers, and semi-weekly or weekly approaches for the medium or slow movers. Note that for the SKUs with extremely volatile demand (CV > 3.5), even a longer review period will not cause a higher use of the slow mode. A possible reason could be that these are highly promoted or customized SKUs with non-stationary demand patterns. Our synchromodality model is not advised for these SKUs.

The discussion above reveals the trade-offs impacting the optimal review

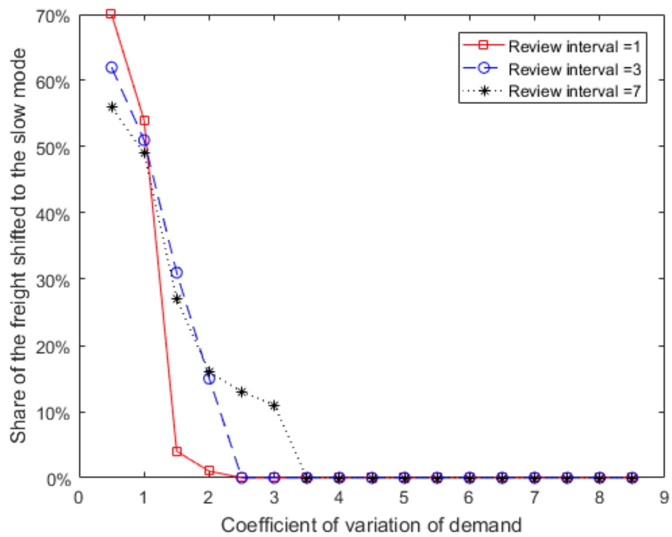

Figure 5.9: *When the review interval r is extended, the volume shifted to the slow mode changes.*

interval r^*. Although the length of the review period is currently used as an exogenous “rule of thumb”, a quantitative analysis remains interesting for further research.

5.4.2 The impact of synchromodality on other supply chain metrics

The tool also allows evaluating the impact of synchromodality on other related supply chain metrics. For instance, Figure 5.10 shows the impact of synchromodality on the inventory parameters for our reference SKU. The base stock target for the fast mode steadily decreases when more freight is shifted to the slow mode (left panel). Interestingly, the average inventory remains rather stable as more freight is shifted to the slow mode until approximately 85% of the total volume is shifted to the slow mode. However, when more volume is shifted to the slow mode, the company will lose the flexibility to cope with the stochastic demand and tremendous inventories are required.

Supply chain managers often presume that sustainability comes at a cost. To be more specific, a modal shift from road to the more sustainable rail transportation will lead to higher inventory at the destination or lower service level, due to

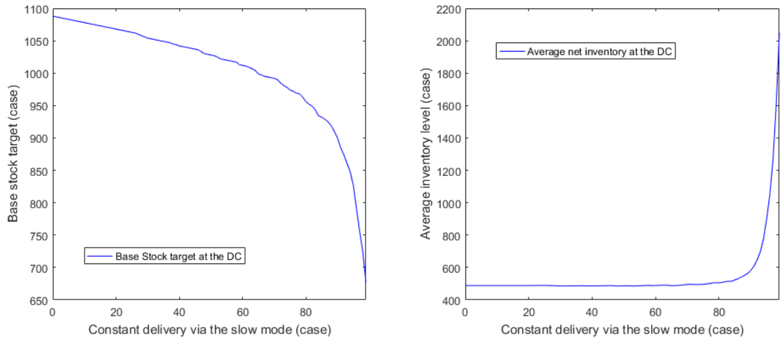

Figure 5.10: *When the freight shifted to the slow mode increases, the base stock target at the DC for the fast mode control will decrease (left). The average inventory at the plant and the DC will remain stable, unless almost all volume are shifted to the slow mode (right).*

the inflexibility of rail operations. The validation of our synchromodality model using real data demonstrates that the modal shift will indeed increase inventory at the distribution center. However, the incremental inventory cost per period is surprisingly minor (Figure 5.10). On the other hand, the transportation cost savings obtained from synchromodality will not only offset the extra spending in inventory, but also reduce the total logistics costs without sacrificing the service level (Figure 5.5).

We have used the synchromodality tool to conduct some sensitivity analyses on the transportation lead times. Table 5.2 lists how the optimal share of the slow mode drops as the slow mode's lead time increases. This is due to the increased pipeline inventory costs, which reduce the advantage of using the slow mode. Indeed, the cost difference between both transportation modes does not only include the difference in unit transportation cost itself, but also the end-to-end costs to ship one unit of freight from P to D including cost of capital, cost of taxes, etc. (Allon and Van Mieghem, 2010). Similar to Boute and Van Mieghem (2015), the cost difference between both modes is in our model given by:

$$c^f - \left(c^s + k(l^f - l^s)\right). \tag{5.6}$$

With $c^s = 0.874$, $c^f = 0.999$, and $k = 0.032$ (see Table 5.1), we find that if $l^s = 9$, the slow mode becomes more expensive than the fast mode according to Eq. (5.6). Clearly, this threshold is dependent on the SKU and the transportation mode. However, the synchromodality tool allows managers to distinguish whether or not an SKU is feasible for synchromodality in a specific corridor.

Table 5.2: *When the lead time of the slow mode increases, the freight shifted to the slow mode decreases.*

Lead time of the slow mode	Freight shifted to the slow mode
6	78%
7	67%
8	59%
9	0%
10	0%
11	0%

Finally, we observe how synchromodality results in a more smooth production when more volume is shipped using the slow mode. Figure 5.11 compares the histogram of the production quantities when only the fast mode is used with the production quantities when the optimal synchromodality policy is implemented. With synchromodality, the company will produce 67 cases per day more than half of the time, which is exactly the optimal volume shifted to the slow mode, and will produce much less frequently higher quantities. The result aligns with Boute and Van Mieghem (2015), who also link a higher reliance on the slow mode with more order smoothing. Figure 5.12 provides more evidence of this effect. As more freight is shifted to the slow mode, the CV of the production quantities goes down, indicating production smoothing when applying synchromodality under the TBS policy. For our reference SKU, if the company sticks to the optimal slow mode shipment of 67 cases every period, the CV of production will be 0.55, about 80% of the CV of demand.

This smoothing effect could allow companies to level its production volume. With production quantities varying every period, companies need to frequently adjust the raw materials, labor forces, machines, etc., and hence suffer from higher change-over costs or more working-in-process inventory. When production volume is leveled, e.g., a stable volume is often produced every period, the companies can better predict, plan, and manage the production schedule. Production efficiency and flexibility will be enhanced by eliminating waste, minimizing differences in workstation loads, avoiding workforce idles, smoothing raw material orders, etc. (Disney et al., 2006; Boute et al., 2007; Hoberg et al., 2007a).

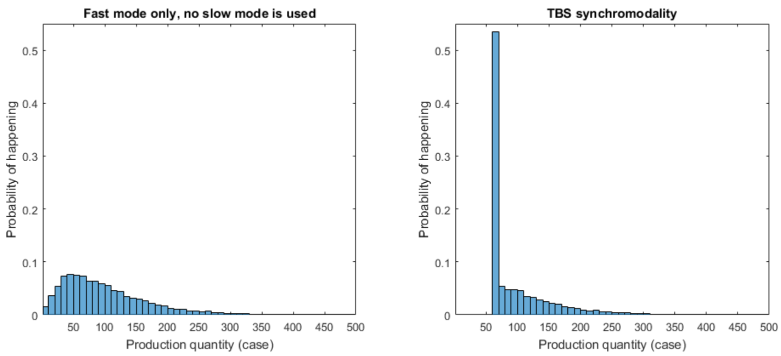

Figure 5.11: *Compared to the case with fast mode only (left), the implementation of TBS synchromodality will lead to an over* 50% *probability to produce 67 cases of the SKU, which is equivalent to the optimal volume shipped to the slow mode, and fewer probabilities for other production quantities.*

5.4.3 Aggregation of multiple stock keeping units into full container loads

The results thus far illustrate how the tool can be used to implement synchromodality for one specific SKU. However, when the tool is used for multiple SKUs, the question pops up how the resulting shipments can be aggregated into full container loads (FCLs). Indeed, in order to reap the cost benefits of the slow mode, companies should ship FCLs, which means that all containers need to be fully loaded with 33 pallets. However, when the tool is used for each SKU individually, it is likely that the aggregation across SKUs will not lead to fully loaded containers. Currently, when a fraction is met, e.g., 45 pallets or 1.36 FCLs, the managers generally rely on their experiences and drop or load extra pallets to round the number to full container loads. As our synchromodality tool allows an exact quantification of the total costs with respect to changes in pallet loads, it can support managers load full containers on the slow mode with minimized total costs.

We consider a simple example with five SKUs, which are to be shipped in full container loads in the slow mode. This requires that $q^*_{\mathrm{SKU1}} + q^*_{\mathrm{SKU2}} + q^*_{\mathrm{SKU3}} + q^*_{\mathrm{SKU4}} + q^*_{\mathrm{SKU5}} = 33m$, where m is an integer and 33 is the number of pallets loaded into a full container. Note that in this case, we measure the shipment quantities in Euro-pallets to accommodate that different SKUs are packed in different case sizes. Assume that the use of the synchromodality tool provides the output generated in Table 5.3, which lists the total costs depending on the

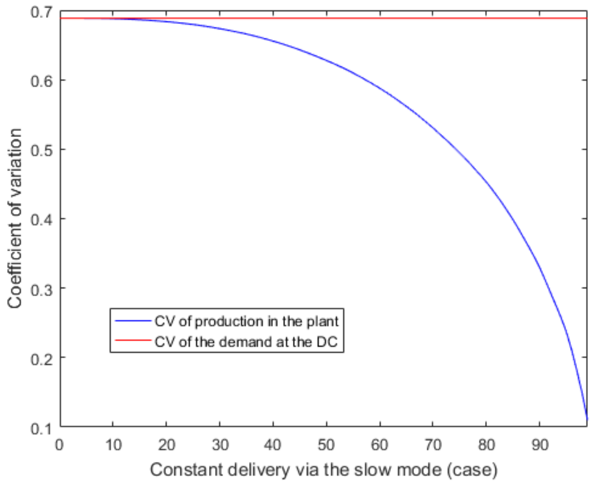

Figure 5.12: *When more freight is shifted to the slow mode, the CV of the shipment from the plant to the DC will decrease. The bullwhip of the supply chain is therefore dampened.*

volumes shipped via the slow service for each of the five SKUs (note that these numbers are generated by changing the SKU parameters in Table 5.1, and then rescaled). When we aggregate the optimal slow mode volumes for each SKU, we find that $q^*_{\text{SKU1}} + q^*_{\text{SKU2}} + q^*_{\text{SKU3}} + q^*_{\text{SKU4}} + q^*_{\text{SKU5}} = 41$ pallets, which is equivalent to 1.24. The question is now how to obtain full container loads with the five SKUs, for which the total logistics costs of all five SKUs are minimized.

We propose a linear programming (LP) approach to solve the full container loading problem. The rescaled results obtained from the synchromodality tool (Table 5.3) are the input parameters of the LP and can be modeled as follows. Denote $I = \{1, 2, ..., 21\}$ the set consisting of all possible pallet loads for this specific example and $J = \{1, 2, 3, 4, 5\}$ the set of SKUs. Given $i \in I$ and $j \in J$, the parameter $v_{i,j}$ denotes the average total costs per period for SKU j of which i pallets are shipped via the slow mode every period. For example, $v_{3,1} = 2444$ euro (see Table 5.3). We set the missing numbers in Table 5.3 equal to a sufficiently large number in the LP model, e.g., $v_{20,2} = 999999$, indicating that it is impossible to ship 20 pallets every period using the slow mode for SKU2, as this exceeds the mean demand of the SKU. Denote the decision variable m the number of full

Table 5.3: *The total average costs per period for the different shipment quantities on the slow mode (in pallets). All numbers are rescaled*

Pallets	SKU1	SKU2	SKU3	SKU4	SKU5
1	2449	1308	2438	1547	937
2	2447	1304	2433	1542	933
3	2444	1301	2428	1536	928
4	2442	1298	2425	1530	923
5	2440	1296*	2422	1530	920
6	2438	1300	2420	1519	919*
7	2436	1310	2419	1514	935
8	2435	1339	2418*	1509	1169
9	2434	1460	2422	1506	–
10	2433	2471	2430	1504*	–
11	2432	–	2443	1505	–
12	2431*	–	2461	1515	–
13	2432	–	2486	1554	–
14	2435	–	2528	2341	–
15	2440	–	2582	–	–
16	2449	–	2669	–	–
17	2469	–	2880	–	–
18	2499	–	3576	–	–
19	2567	–	–	–	–
20	2722	–	–	–	–
21	3315	–	–	–	–
	∗ The minimal cost for this SKU				

containers, and $y_{i,j}$ a binary decision variable defined as:

$$y_{i,j} = \begin{cases} 1 & \text{if } i \text{ pallets of SKU } j \text{ are loaded on the slow mode,} \\ 0 & \text{otherwise.} \end{cases} \tag{5.7}$$

The full container load problem can then be modeled as the following binary programming problem:

$$\min \sum_{i,j} (y_{i,j} v_{i,j}) \tag{5.8}$$

subject to:

$$\forall j \in J, \ \sum_{i} y_{i,j} = 1 \tag{5.9}$$

$$\forall i \in I \text{ and } j \in J, \ \sum_i \sum_j i y_{i,j} = 33m \tag{5.10}$$

$$\forall i \in I \text{ and } j \in J, \ y_{i,j} \in \{0, 1\}. \ m \in \mathbb{N}. \tag{5.11}$$

The objective function (5.8) minimizes the aggregated total logistics cost per period for the five SKUs. Constraint (5.9) secures that for each SKU only one shipment quantity is used. Constraint (5.10) assures that the total number of pallets loaded onto the slow mode is an integer multiple of 33 pallets, ensuring fully loaded containers. The problem can be solved using any linear programming solver and can be easily extended to a larger number of SKUs.

When we use the LP model to solve our example, we find that it is optimal to round down the number of containers by dropping five pallets of SKU1, two pallets of SKU2, and one pallet of SKU5. These eight containers could be shifted back to the fast mode, which offers more flexibility in shipment quantities. The impact of this reduction leads to a minor increase of total costs for these five SKUs. In general, we find that it is advised to round down the number of container loads, as the total cost curve remains fairly flat at the left side of the optimal slow mode volume, whereas it increases rapidly when the slow mode volume passes the optimal point (see Figure 5.5).

The LP model can be easily extended to a larger number of SKUs. In that case, the set J will consist of all SKUs that will be co-loaded to the full containers. The set I will be extended to $I = \{1, 2, ..., i^{\max}\}$, where $i^{\max}$ represents the largest possible volume shifted to the slow mode for any SKU $j \in J$, i.e., $i^{\max} = \max_{j \in J}\{r_j \mu_j\}$ with $r_j \mu_j$ the upper-bound of the volume of SKU j. The LP model can also be extended to support managers in making full container load decisions with fixed number of containers. For example, if the companies commit to load ten containers every time the slow mode operates, it then simply needs to set $m = 10$ and reapply the aforementioned linear programming again.

5.5 Summary

In this chapter, we have presented a VBA-based Excel tool to implement synchromodality using a tailored base-surge (TBS) policy. With a number of explicitly described inputs, the tool generates the optimal modal split of an SKU via one mouse-click, i.e., how much volume should be shipped via a fast, flexible, and expensive transportation mode (e.g., direct trucking) and a slow mode, "greener", and cheap transportation mode (e.g., intermodal rail). The tool also supports companies determine the corresponding inventory management at the DC and the resulting production quantities at the plant.

The tool allows to evaluate a synchromodality implementation in a supply chain realm and analyze the synergies among different activities of the supply chain. The tool is developed in VBA, which can be simply used by supply chain managers with Excel without knowledge of the mathematics of the synchromodality model. The presentation of the tool using real company data validates the synchromodality models discussed in the previous chapters. As the logic of synchromodality using a TBS policy can be generally applied to a variety of industries, the tool can be implemented at other companies as well.

The tool is developed on an SKU level, i.e., it provides the optimal modal split for one SKU only. Managers who deal with multiple SKUs can simply aggregate the optimal volume of each SKU and consolidate them into the transportation modes. In Section 5.4.3, an algorithm is presented to manage such aggregation into full container loads. The tool also gives managers the option to customize the review period of different SKUs. Whereas a fast moving SKU is frequently ordered by the customers, and its inventory level is typically reviewed daily, slow-moving SKUs are not frequently ordered. Managers could then increase the review period and decrease the corresponding shipment frequencies of the transportation modes, e.g., from daily shipments to weekly shipments. The interface to this optional extension is integrated in the tool.

Chapter 6

Summary and future research directions

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Although synchromodality is accepted as a promising approach to increase the sustainability of logistics systems, it is until now largely defined in transportation terms with logistics service providers being its principal agents. Despite sparking interests from shippers (or manufacturing companies) on synchromodality, little is known about how shippers can implement it and shift freight volume from road to the more sustainable transportation modes such as rail or waterway. Supply chain managers tend to presume that the use of the more sustainable transportation modes such as rail or waterway will result in higher inventory and lower service level due to their inflexibility in delivery quantity and schedule. This concern prevents them from using the “greener” transportation modes. Statistics have demonstrated that the share of road transportation in terms of tonne-kilometer remains about 70% over the last decades (EUROSTAT, 2015).

This dissertation aims to fill this research gap. The main goal is to support

[1] Never forget the very beginning mind. Mencius, ancient Chinese philosopher. Many believe that ”Stay hungry, stay foolish” from Steve Jobs (1955-2011) is *the* appropriate paraphrase.

companies in implementing synchromodality and shifting freight volumes from the fast and less sustainable transportation mode (e.g., direct trucking) to the cheaper and "greener" transportation modes (e.g., intermodal rail). In this chapter, we first briefly summarize the contributions of the dissertation and bring forward ideas for future synchromodality research.

6.1 Summary of the contributions

The contributions of the dissertation can be briefly designated into three categories: concept, methodology and practical relevance.

6.1.1 Conceptual contribution

In this dissertation, we argue that one of the reasons for the modal split being so difficult to implement is that many stakeholders have not been taking adequate account of the impact of synchromodality on shippers' supply chains. In the absence of any associated adjustment to supply chain processes, a shift from trucks to trains and barges often leads to increases in inventory or decreases in service levels, which companies typically try to avoid.

We review the development of multimodal transportation to the recent evolution of synchromodality, and find that the current synchromodality concept is indeed largely defined in transportation terms. In order to evaluate and promote synchromodality, we suggest extending the concept of synchromodality from a transportation problem into a supply chain realm, where the transportation optimization is integrated into shippers' supply chain decision-making, such as inventory management, service level control, and production planning, etc. We propose the terminology Synchromodality from a Supply Chain Perspective (SSCP) to describe the new concept.

This concept allows shippers to make transportation decisions in a broader supply chain optimization problem, which has the potential to obtain a better "global optimum". This way SSCP encourages shippers to re-think and re-optimize their transportation strategies, and involves them more directly to put the effort in accommodating changes in transportation modes. Even if they want to outsource transportation to LSPs, they can still exert control over the mode choice through a "control tower".

6.1.2 Methodological contribution

Unfortunately, little is known from the current literature, to the best of our knowledge, on quantitative analysis of companies' synchromodality decisions in the supply chain realm. However, we find that the SSCP models share a similar mathematical structure with the classical dual-sourcing inventory models, which are, despite aiming for a completely different sourcing problem, richly studied in the literature.

In an example dual-sourcing problem, a company located in Belgium purchases from two suppliers, one of them located in Germany with a short lead time but an expensive unit purchasing price (equivalent to the direct trucking in the SSCP model) and the other in China with a long lead time but a lower unit price (equivalent to the intermodal rail transportation in the SSCP model), and seeks to minimize total purchasing and inventory costs (equivalent to the total transportation and inventory costs in the SSCP model). Nevertheless, synchromodality models are mathematically more generalized: Whereas dual-sourcing models always assume identical delivery frequencies from the both sources, synchromodality models need to take into account that trains naturally deliver less frequently than trucks. We propose two novel methodologies to solve the generalized dual-sourcing models. The approximate analytic solution reported in Chapter 3 captures the key drivers and characteristics of the synchronized modal split problem. The algorithm based on stochastic dynamic programming presented in Chapter 4 determines the optimal freight split between rail and road transportation applying synchromodality, including the optimal delivery quantity and frequency of rail transportation, and the optimal delivery quantity of road transportation controlled by the corresponding optimal inventory policy at the distribution center.

In short, this dissertation contributes 1) to the synchromodality literature by offering new solution models inspired by dual-sourcing literature, and 2) to the dual-sourcing literature by extending the models by considering the nature of different transportation modes, and offering new structural insights and solution techniques.

6.1.3 Practical contribution

The dissertation is inspired and established on practical problems from a multinational company. Although the exact values of the numbers reported in the dissertation are rescaled due to confidentiality reasons, several practical contributions could be suggested to the supply chain managers to support their synchromodality decisions.

In Chapter 2, our model demonstrates that companies could shift a surprisingly large volume into the greener intermodal rail transportation, which is significantly larger than the lower bound of the stochastic demand. As a comparison, the current industry practice, e.g., Groothedde et al. (2005), reports that only the stable, well-predicable part of the stochastic demand (equivalent to its lower-bound) can be tailored for the intermodal rail transportation. The greater use of intermodal rail allows companies to jointly reduce supply chain costs and carbon emissions, rather than to trade one for the other. In Chapter 3, we offer simple approximate analytic solutions to a synchromodality model with a minor ($< 3\%$) approximation error, when the rail transportation delivers half as frequently as the road transportation. The simple formula allows managers to easily make synchromodality decisions without running complex simulations or algorithms. In Chapter 4, we show the exact optimal solution of a synchromodality model using stochastic dynamic programming (SDP), including the optimal delivery quantity and frequency of rail transportation, the optimal delivery quantity of road transportation, and the optimal inventory control policy at the distribution center. SDP is in general a powerful method but it often suffers from the "curse of dimensionality", which requires extremely long, exponentially-increasing computing effort. We find structural properties of the problem, with which the computing effort could be significantly reduced. In Chapter 5, we present a VBA-based Excel tool to support managers implementing synchromodality without necessarily understanding the mathematical details of the models. We have used the tool to validate the research problems discussed in the earlier chapters on a real dataset, and have discussed how the use of synchromodality impacts the supply chain, including production and inventory management. As the synchromodality study has been so far based on the level of the SKU, we provide a solution to aggregate the volume shifted to the slow mode from multiple SKUs to full container loads, such that the resulting total costs are minimized.

6.2 Directions for future synchromodality research

The synchromodality concept was first introduced in the 2010s, and the relevant research is still at an early stage in its development with extensive challenges and opportunities. For example, synchromodality is regarded as one of the four building blocks of the Physical Internet, of which the conceptual development is optimistically planned until the year 2050 and a large number of stakeholders are actively involved (ALICE, 2014). This dissertation offers an early exploration of the rich body of synchromodality covering both academic and industrial aspects. The results could be extended to a number of different ways.

6.2.1 Scope of synchromodality problems

In this dissertation, synchromodality is studied in a shipper's supply chain consisting of plant, distribution center, and customer orders. Future research could spread across the boundary of one shipper's supply chain to a wider network involving more stakeholders. For example, with vertical collaboration shippers and LSPs could coordinate their synchromodality decisions under specific contracts so that both can be better-off when they coordinate their synchromodality decisions. One interesting research question, among others, might be, if the shipper allows the LSP to pick-up from the plant and/or deliver at the DC within a time window instead of on particular days, how both parties could re-synchronize their freight flows and obtain additional benefits. Another potential extension of the current synchromodality network is via horizontal collaboration, where multiple shippers collaborate and co-load trucks or trains. If shippers collectively apply synchromodality along particular corridors, the potential impact of synchromodality on the freight modal split would be substantially reinforced. For example, if one shipper had a slump in demand, the others might still have sufficient volume to maintain adequate capacity utilization of the train. Stefansson (2006), Creemers et al. (2017), Gijsbrechts and Boute (2017), and Padilla Tinoco et al. (2017) could be the first start to analyze such kinds of collaborative shipping.

The concept of synchromodality in this dissertation focuses on the simultaneous use of different transportation modes in a single corridor, but does not reflect another attribute of synchromodality: the switch of transportation modes at particular times. This attribute needs to be acknowledged so that more flexibilities will be introduced to the synchromodality problem. The transportation planning algorithm proposed by Mes and Iacob (2016) and Zhang and Pel (2016) could be the starting point.

Another perspective of synchromodality is mainly applied at big ports, e.g., Port of Rotterdam (2011). When a large container vessel calls at the port, one of the inland transportation modes alone, e.g., truck, train, and inland barge, is unlikely to have enough capacity to unload all the containers from the vessel and deliver to the inland destinations. A feasible synchromodality approach is to split the volume among the three modes so that the containers can be unloaded from the container vessels efficiently. The advantage of this synchromodality approach is delivery smoothing at the destination. Since the three transportation modes are subject to different lead times, the freight on the three modes will arrive at the destination at different times, and hence avoid large inventory pile-ups at the destination.

Extensions could also focus on managing multiple SKUs in the same lane. In Section 5.4 a direct consolidation of the volumes from multiple products is presented, assuming that the same transportation and inventory policies are applied to all products. However, inventory controls of the multiple products could be different considering their complementary or substitutable nature (Transchel, 2017), or the dynamic pricing strategies driven by sales (Transchel and Minner, 2009). The production schedules and batch sizes need to be additionally optimized if multiple products are allocated in one line (Demeulemeester and Herroelen, 2006; Van Nieuwenhuyse et al., 2007), which could impact the corresponding synchromodality decisions.

6.2.2 Solution methodologies of synchromodality studies

Thus far, the synchromodality models studied in this dissertation always minimize monetary costs. This aligns with the practice that, in general, companies typically prioritize cost minimization decisions over sustainability targets such as emission reductions. However, as the climate change is becoming more critical, companies might in the future confront tighter regulations on emissions. A possible extension is to minimize total emissions instead of cost, or to apply multi-objective optimization approaches to balance the trade-off between cost and emission. Benjaafar et al. (2013) study how companies minimizes the total supply chain costs subject to carbon constraints and Cachon (2014) studies the connections between a transportation network and emissions. Andersson et al. (2013) present a tool to evaluate the total environmental and monetary costs. These are pioneer studies in analyzing the cost and emission trade-off in supply chain management.

Synchromodality is a new field, and its research requires novel methodologies and business models. A general approach to enhance a broad understanding of a new concept is to choose one theory as the dominant explanatory theory and then complement it with other theoretical perspectives (Halldórsson et al., 2007). In this dissertation, the classical tailored base-surge (TBS) dual-sourcing inventory models are used to as the major theory to solve synchromodality problems. One disadvantage of the TBS policy is the assumption of a fixed delivery quantity of the slow transportation mode (e.g., intermodal rail), reflecting the fact that trains often lack the flexibility in the delivery quantity compared to trucks. A generalized synchromodality model could release this assumption, which makes its mathematical structure similar to the most common dual-sourcing models described in Barankin (1961). Although the most generalized dual-sourcing model is intractable (Whittemore and Saunders, 1977), other dual-sourcing models besides the TBS policy could be used to solve synchromodality problems. One example is the so-called dual index policy (DIP) introduced by Veeraraghavan and Scheller–Wolf (2008), which assumes that the delivery quantities of both transportation modes are controlled by a separate base stock policy. The DIP allows flexibility in the delivery quantity of the slow transportation mode, which is realistic in some situations, e.g., the "slow mode" in the synchromodality problem is another truck service with longer lead time. Interesting DIP results discussed in Veeraraghavan and Scheller–Wolf (2008), Sheopuri et al. (2010), Arts et al. (2011), and Arts and Kiesmüller (2013) could be extended to solve synchromodality problems. Another untackled feature of the TBS policy is the capacity constraint on the transportation modes, especially the less flexible slow mode. Section 4.6.2 provides some first analysis on it. Further research could investigate the impact of transportation capacity on companies' synchromodality decisions. This could be even more interesting when companies share the capacity of a train and dynamically adjust their booking capacities based on daily demand patterns, or companies that have booked the capacity have the option not to use that fully, with or without some penalties (Gijsbrechts and Boute, 2017). The extensive literature review on dual-sourcing models by Minner (2003) could be a starting point to find appropriate mathematical models.

A recent study by Van Riessen et al. (2017) suggests using revenue management models widely adopted in the airline industry for synchromodality research. In the revenue management problem, an airline decides the number of seats in each price category to maximize its revenue. Similarly, an LSP needs to decide the capacity and price of different transportation modes in a certain corridor, and maximize its profit. The extensive literature of revenue management could be a rich source for synchromodality research.

Tavasszy et al. (2015) propose an "efficient frontier" approach to select appropriate transportation modes in synchromodality. Suppose there exists n different transportation modes (quotes) in a certain corridor, all with different cost and lead time trade-offs. Based on the n transportation modes, the decision maker will then calculate an efficient frontier of synchromodality mode choices. The frontier allows stakeholders to determine the transportation modes dominating the others, which will then be selected and used as a portfolio of transportation modes for synchromodality. Interestingly, this logic is very close to the classical portfolio theory in finance: Given a number of stocks in the market with different risk and return trade-offs, how can one best select from them when forming an investment portfolio. The methodologies in portfolio theory could then be used for synchromodality problems.

Digitalization has generated big buzz and is regarded as the future of the logistics industry. Currently, an increasing number of stakeholders are building up digital platforms to accumulate data, exchange information, and encourage collaboration. For example, Port of Antwerp is establishing a data platform to collect data from various companies linked to it (NxtPort, 2017). The EU is organizing the so-called AEOLIX project to build an online logistics information exchange portal and support logistics decisions (European Commission, 2017). An independent third-party data platform called CargoStream connects voluntary shippers to share logistics data for collaborations (Nallian, 2017). These data platforms could work as a first step to trigger algorithms in big data analysis, deep learning, and artificial intelligence, which further promotes synchromodality studies. Examples using smart goods for shipment control are presented by Arnäs et al. (2013)

6.2.3 Practical relevance of synchromodality research

The synchromodality models studied in this dissertation are built upon assumptions of specific demand distribution functions. These well-designed assumptions, on the one hand, help the stakeholders understand the insights of the models, but on the other hand, hinder the advance of the practical implementation. For example, the models assume i.i.d. stationary demand but real demand could be non-stationary. For example, we have found from data that, sales are heavily driven by seasonality, which can be well-predicted. Based on these observations, transportation could be tailored as follows: 1) Well-predicated stable volume can always be shipped via the cheapest and inflexible transportation mode (e.g., rail with fixed volume commitment); 2) Well-predicted but non-stable sales volume will be shipped via a different transportation mode at medium cost (e.g., rail without fixed volume commitment); and 3) Non-predictable demand spikes will be accommodated by direct trucking at the highest price. Solution methodology such as transfer functions can be used to deal with non-stationary demand (Hoberg et al., 2007b).

For generalized non-stationary demand patterns, the models proposed in this dissertation will be intractable for analytic analysis. The real data validation in Section 5.4 also indicates that synchromodality under a tailored base-surge policy might not be advised for SKUs with non-stationary demand. Advanced numerical methods such as big data analysis and machine learning algorithms could help companies better understand and forecast the demand patterns and deploy suitable transportation modes accordingly.

Thus far, the dissertation mainly focuses on single-SKU models and an approach to load multiple SKUs in one container is only discussed in Section 5.4.3. Synchromodality approaches to ship multiple SKUs are required. A possible result, among others, might be that the slow moving SKUs are shipped in the slow transportation modes at a lower delivery frequency, whereas the fast moving SKUs are shipped in the fast mode every period. The choice of transportation mode is then tailored to the characteristics of the SKUs.

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