Forecasting the Growth of Container Transport in Rotterdam, Antwerp, and Moerdijk: Analyzing Hybrid Model Performance through Expert-Identified Factors

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Master Thesis Supply Chain Management

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Abstract

Purpose:

This study assesses the effectiveness of a hybrid model in comparison to individual models for predicting container transport volume growth at the ports of Rotterdam, Antwerp, and Moerdijk. The objective is to support infrastructure and capacity planning in the Brabant region by providing more accurate and robust forecasts. The research contributes to both forecasting theory and practical logistics planning.

Design/methodology/approach:

Three forecasting models, Holt-Winters Exponential Smoothing, Prophet, and ARIMAX, are applied individually and in a hybrid forecasting approach. The hybrid model utilizes constrained optimization to minimize the Mean Absolute Percentage Error (MAPE) and determine the optimal weights. External variables such as GDP, trade volumes, population, and fuel prices are included to improve performance. Forecast accuracy is assessed using MSE, RMSE, MAE, and MAPE, with robustness tested through an alternative data-cleaning method. Forecasts extend approximately five years ahead under high and low economic scenarios from the CPB Netherlands Bureau for Economic Policy Analysis. Expert interviews complement the quantitative findings.

Findings:

Hybrid models generally outperform or match the best-performing individual models. When performance is comparable, a single model may be preferred for simplicity and transparency. However, when the hybrid model outperforms the individual models, it provides superior accuracy. Terminal capacity in Brabant is sufficient for forecasted volumes, suggesting that policy should focus less on higher-than-capacity scenarios and more on resolving current inefficiencies.

Originality/value:

This study provides empirical evidence on the value of hybrid forecasting models in maritime transport. It offers guidance on model selection and demonstrates how hybrid approaches can inform long-term infrastructure and policy planning in a practical, data-driven manner.

Declaration of Academic Integrity

I solemnly declare that this work has been written solely by me and that, with the exception of cited quotations, no part of it has been copied from any scientific publications, internet sources, research works, or from any other pre-existing academic or non-academic sources authored by myself, other students, or third parties.

For any content sourced from scientific publications, internet sources, or other documents, I have explicitly indicated the source at the end of the quotation or in a footnote and enclosed verbatim text within quotation marks where applicable.

Regarding the use of AI, I have used ChatGPT in all chapters for the purpose of improving grammar and coherence, as well as generating ideas and inspiration regarding the interview protocols and the translation of interview transcripts. I accept full responsibility for all content presented, including its accuracy and reliability, and I acknowledge that I am aware of the sanctions regarding plagiarism and other forms of academic misconduct as outlined in the Academic Integrity policy (including but not limited to fraud, plagiarism, data fabrication/falsification, and personation).

Student Name: Nina G. H. Koolen

Date: __June 9th 2025__________________

Signature: ______________________________

Preface

This thesis represents a significant milestone in completing my Master's degree and the conclusion of an intellectual experience of enrichment, discovery, and perseverance. Writing this thesis has been both a challenging and rewarding experience, during which I was able to deepen my understanding of forecasting methodologies, container logistics, and the strategic use of data in decision-making.

The research presented here was conducted during my internship at MCA Brabant, a valuable and highly supportive environment that provided me with access to industry insights, regional data, and key stakeholders in the field of multimodal transport. I am deeply grateful to MCA Brabant for offering me the opportunity to work alongside their dedicated team and for trusting me with a topic of such significance to the logistical future of the region, and to Suzanne de Laat in particular for her guidance and feedback during the process.

A particular mention of gratitude to all the interviewees who were willing to spare their time to share their professional experience, expertise, and insights. Their inputs were valuable in relating the quantitative findings to real-world issues and adding depth to the practical applications of the research.

I would also like to express my gratitude to my university supervisor for his guidance, constructive feedback, and constant encouragement throughout the research process. His encouragement and advice kept me on track and improved the quality of this thesis.

List of Abbreviations

Abbreviations	Definitions
MAPE	Mean Absolute Percentage Error
GDP	Gross Domestic Product
IoT	Internet of Things
IMO	International Maritime Organization
LNG	Liquefied Natural Gas
HWES	Holt-Winters Exponential Smoothing
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
CPB	CPB Netherlands Bureau for Economic Policy Analysis
IMF	International Monetary Fund
USDA	United States Department of Agriculture
TEU	Twenty-Foot Equivalent Unit

Tables and Figures

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Chapter 1: Introduction

This chapter provides the background and context of the study, introducing the topic of forecasting container transport growth in the ports of Rotterdam, Antwerp, and Moerdijk.

In the first section, the overall context and relevance of accurate forecasting in maritime logistics are outlined. The second section presents the problem indication, introducing the problem faced currently and the objective of this research. The third section gives the theoretical contribution, explaining how this research contributes to forecasting theory by encouraging the application of hybrid models. The fourth section discusses the managerial implications, explaining how improved forecasting can support strategic decision-making for infrastructure development. The fifth section gives the problem statement, clearly identifying the primary objective of the research. The sixth section presents the conceptual model, which visually represents the relationships between key variables. Lastly, the final section formulates the research questions that guide the empirical investigation and are utilized to solve the primary problem statement.

1.1 Background

Container transport is a fundamental component of the modern global economy, shaping both how we live now and how we will live in the future. Whether it involves finished consumer goods purchased online or in-store or critical components within manufacturing facilities, nearly all companies and organizations rely on container transport to some extent. This mode of transportation is increasingly vital in a world where consumers and businesses expect products and services to be readily available in a short timeframe and across vast geographical distances. As supply chains continue to expand globally, driven by the outsourcing of operations and international trade, the role of container transport in supply chain performance has significantly increased (Lee & Song, 2016). The continuous rise in both continental and intercontinental transportation, combined with the fact that the majority of global trade is conducted via sea routes and container shipping, has further reinforced the importance of container transport. This is evidenced by the substantial growth of this sector over the past decade, particularly due to the expansion of offshoring to regions such as Asia (Fransoo & Lee, 2012). Research estimates that approximately 80% of global trade volume is transported via oceans and seas, with container ships accounting for a significant and major share (United Nations Conference on Trade and Development, 2024).

Growth, in this context, can be defined as long-term container volume transportation growth over a given time period supported by different drivers such as expanding global trade, economic development, and advancements in supply chain logistics.

Given its critical role in global trade, container transport is essential for companies, organizations, and economic systems worldwide. Ports serve as key logistical hubs within this supply chain and must continuously enhance their services to meet evolving trade demands. Accurate forecasting of global trade demand and port activity is crucial for anticipating future scenarios and developing long-term infrastructure plans accordingly (Darendeli et al., 2020). Reliable projections of container transport growth or decline provide the foundation for strategic decision-making in maritime logistics and port development.

In this context, MCA Brabant plays a vital role in promoting multimodal and sustainable freight transport, including container transport by water, within the Dutch province of Brabant. Based in 's-Hertogenbosch, MCA Brabant is committed to enhancing multimodal transport solutions by connecting governments, logistics service providers, shippers, knowledge institutions, and terminal operators. Through its extensive network, MCA Brabant works on projects and initiatives that improve regional accessibility and sustainability, with a focus on maximizing the use of inland waterways and rail transport.

The organization operates as a non-profit foundation, consisting of a compact team of five specialists, a Management Board composed of experienced professionals, and an Advisory Board providing strategic guidance. Its primary objective is to serve the public interest by advancing sustainable freight transport solutions.

The core issue MCA Brabant seeks to investigate is the impact of projected container transport growth on the current capacity of terminals in Brabant by forecasting the container transport volumes in the ports of Rotterdam, Antwerp, and Moerdijk. A highly accurate forecast of this growth is essential for assessing its implications on terminal infrastructure and ensuring that the region remains equipped to handle increasing container volumes efficiently.

1.2 Problem Indication

Container transport is a crucial aspect of global trade, shaping both current and future logistical landscapes. For MCA Brabant, understanding the expected growth in container transport by water and its implications for inland container terminals is essential for strategic planning. The capacity of these terminals must align with future demand to ensure efficient operations and prevent bottlenecks or excess capacity.

Historically, MCA Brabant has relied on terminal throughput volumes and previous research utilizing forecasting methods to estimate future growth and capacity requirements. However, these studies have often lacked the level of specificity required, as they primarily employed simplistic forecasting methods. The limitations of these methods have resulted in less detailed and less accurate predictions, leading to discrepancies between forecasted and actual terminal capacity needs.

These inaccuracies have raised concerns regarding potential supply chain inefficiencies. Insufficient capacity may result in an inability to meet growing demand, whereas excess infrastructure could lead to financial inefficiencies (Kerkkänen et al., 2008). The primary challenge is not in recognizing the importance of accurate forecasts but rather in enhancing forecasting methodologies to improve reliability and precision.

Several factors may have contributed to inaccuracies in previous forecasts. These include reliance on outdated data models and insufficient consideration of several different factors influencing forecasting methods, such as world trade developments and evolving sustainability regulations. Given the dynamic nature of these influencing factors, MCA Brabant now aims to enhance its forecasting methodologies to better anticipate future trends and make well-informed development decisions.

Accurately predicting container transport growth is inherently complex, requiring a nuanced approach that integrates advanced data analytics, market intelligence, and scenario planning. This challenge necessitates in-depth research into more sophisticated forecasting techniques, which is why MCA Brabant is investing in an updated approach. By identifying past shortcomings and exploring more robust forecasting models, the organization aims to develop a reliable framework that supports effective decision-making for the short- and long-term development of Brabant's inland container terminals.

To provide a highly accurate forecast of expected container transport growth, this study will introduce a hybrid forecasting model that integrates three well-established forecasting models: the Prophet Model, the ARIMAX Model, and the Holt-Winters Exponential Smoothing Model. These models have been selected due to their frequent application in container transport forecasting and their ability to incorporate key factors influencing this growth (Munim et al., 2023; Saeed et al., 2023; Ubaid et al., 2021; Chia et al., 2024; Gouabou et al., 2024; Intihar et al., 2017; Nieto et al., 2021; Rashed et al., 2016; Dragan et al., 2020; Dragan et al., 2014; Chaurey, 2022). By combining these models, this research aims to enhance the accuracy and reliability of growth predictions in the container transport sector.

The selection of relevant input variables for the forecasting models will be guided by a literature review and expert knowledge from professionals specializing in container transport forecasting. Incorporating expert insights will refine the model's predictive capabilities and ensure its applicability to real-world transport dynamics.

The findings of this study are essential for the effective management of container transport growth, enabling MCA Brabant to proactively address potential challenges related to capacity constraints. To ensure the feasibility and quality of the research within the available timeframe, the scope of this thesis is limited to forecasting container transport growth at the maritime ports of Rotterdam, Antwerp, and Moerdijk. These ports have been selected due to their significant influence on and substantial contribution to container transport flows toward the inland terminals in Brabant. This focus is further justified by the lack of sufficient and reliable data concerning the inland terminals themselves. Accordingly, the projected growth at the selected maritime ports will establish whether the current collective capacity of the inland terminals in Brabant is adequate to accommodate the anticipated growth. Furthermore, the study focuses exclusively on container transport via maritime shipping, with other transport modalities excluded from the scope of analysis.

Ultimately, the research will provide strategic recommendations to MCA Brabant regarding whether the forecasted growth in container transport in the ports of Rotterdam, Antwerp, and Moerdijk will exceed the existing capacity of inland terminals in Brabant and offer insights into a developed hybrid forecasting approach.

1.3 Theoretical Contributions

Building on the research of Makadok et al. (2018), this thesis contributes to existing literature by expanding an established methodological approach. Specifically, this study explores the integration of multiple forecasting models to develop a hybrid forecasting model, incorporating various factors that influence container transport growth. By combining these models, this research aims to enhance the accuracy of growth predictions and provide well-founded recommendations regarding the current capacity of inland terminals in Brabant.

A wide range of forecasting models have been developed and employed to predict both general growth trends and container transport growth specifically (Iskandar & Purba, 2024; Chen & Chen, 2009; Matczak, 2020; Seabrooke et al., 2002; Ubaid et al., 2021; Intihar et al., 2017; Darendeli et al., 2020; Ding et al., 2019). Examples include the Prophet Model, the ARIMAX Model, and the Holt-Winters Exponential Smoothing Model (Munim et al., 2023; Saeed et al., 2023; Ubaid et al., 2021; Chia et al., 2024; Gouabou et al., 2024; Intihar et al., 2017; Nieto et al., 2021; Rashed et al., 2016; Dragan et al., 2020; Dragan et al., 2014; Chaurey, 2022).

While several studies suggest that these models achieve a high level of accuracy, others emphasize their limitations and potential lack of reliability. As a result, further research is required to evaluate their relevance, applicability, and effectiveness within the specific context of container transport by water.

To enhance forecasting accuracy, this thesis proposes the development of a hybrid model integrating multiple forecasting techniques. Research indicates that combining models can achieve significant improvements in accuracy by mitigating errors caused by incorrect assumptions, inappropriate model selection, biases, or data inconsistencies (Adhikari & Agrawal, 2012; Hajirahimi & Khashei, 2019; Khashei & Bijari, 2011). By optimizing the selection and combination of these models, this thesis aims to minimize forecast error and improve predictive reliability. This research introduces a mathematically optimized model combination that allocates weights based on forecasting performance. This method aims to minimize Mean Absolute Percentage Error (MAPE), which is particularly appropriate in transport volume forecasting due to its scale-independence and interpretability in percentage terms.

A key theoretical contribution is demonstrating that such a hybrid approach can achieve more accurate and robust forecasts compared to individual models, particularly when the models are fitted according to domain-specific insights. While previous studies have applied these models separately across different forecasting contexts (e.g., Munim et al., 2023; Saeed et al., 2023; Chia et al., 2024), this research tests their performance collectively in the specific setting of inland container transport flows towards Brabant. By applying the hybrid methodology to regional ports (Rotterdam, Antwerp, and Moerdijk), the study not only tests the models' predictive accuracy in a high-relevance context but also evaluates the role of external variables.

Moreover, the integration of expert interviews into the model-building process extends theoretical frameworks by combining quantitative forecasting and qualitative sector expertise. This dual-method approach helps ensure that variables used in the models are relevant in industry reality.

Ultimately, this research adds to the transport forecasting literature by validating the effectiveness of a hybrid method that integrates statistical robustness and applied relevance, delivering an approach that can be applied in future studies in other multimodal logistics settings.

1.4 Managerial Implications

The practical value of this thesis is its ability to deliver evidence-based recommendations for strategic decision-making in the inland container transport sector in Brabant. By building and validating a hybrid forecasting model for the ports of Rotterdam, Antwerp, and Moerdijk, the study generates forecasts that are more accurate and better aligned with relevant factors influencing this growth than those based on single-model approaches.

Accurate growth forecasts can enable MCA Brabant to proactively assess whether existing infrastructure will suffice under expected transport volumes or whether capacity expansion or reallocation is necessary. Additionally, by identifying key exogenous variables that significantly affect growth, this thesis supports relevancy in the context of container transport growth. The use of both expert input and empirical modeling ensures that recommendations are grounded in operational experience while retaining analytical rigor.

For MCA Brabant and other regional or international stakeholders in the port and logistics sectors, this thesis offers a methodological approach for developing hybrid forecasting models that can be adapted to their specific environments.

As such, the managerial implications extend beyond a single organization, providing a generalizable, usable conceptual approach for improved forecasting practices in container transport logistics.

1.5 Problem Statement

The problem statement to be addressed and answered within this thesis is constructed as follows:

To what extent does the hybrid forecasting model outperform individual forecasting models in terms of predictive accuracy, considering key factors identified through expert knowledge, in forecasting container transport volumes for the ports of Rotterdam, Antwerp, and Moerdijk?

1.6 Conceptual Model

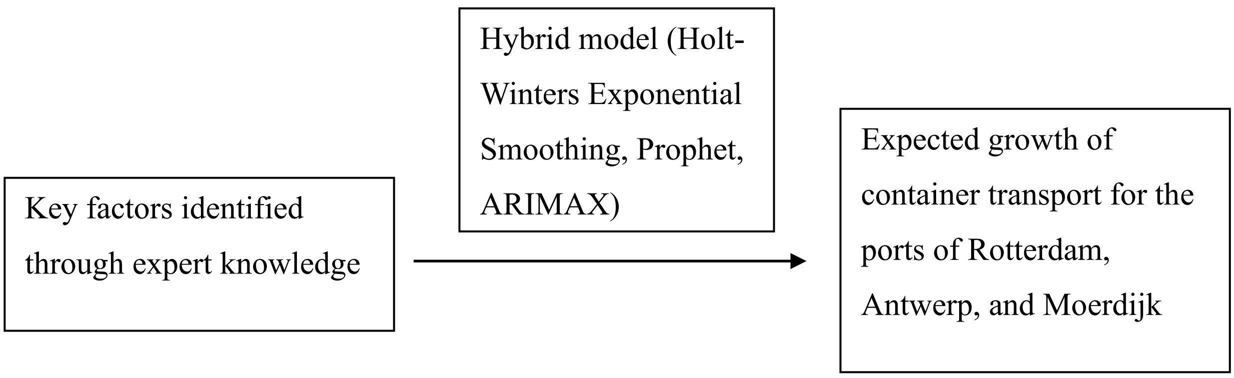

Figure 1. Conceptual model

1.7 Research Questions

The following research questions have been constructed to answer the problem statement and will help to give an appropriate understanding of and answer the problem statement.

Theoretical questions:

- What key factors are identified in the literature for forecasting the expected growth of container transport?
- Why are hybrid forecasting models used?

- Which individual forecasting models are integrated into the hybrid forecasting model, and what are the reasons for their selection?

Empirical question:

- What are the key factors to be included in the forecasting models as identified through expert knowledge?
- How is the hybrid forecasting model constructed?
- How does the predictive accuracy of the hybrid forecasting model compare to that of individual forecasting models?
- What is the expected growth of container transport for the ports of Rotterdam, Antwerp, and Moerdijk according to the most accurate forecasting model identified in this study?

Chapter 2: Literature Review

This chapter introduces and examines the theoretical framework essential for addressing the research questions outlined in Chapter 1, providing the foundation for the subsequent chapters.

The first section explores the key factors identified in the literature that influence the expected growth of container transport and should, therefore, be incorporated into forecasting models. The second section examines the rationale behind the use of hybrid models in forecasting, emphasizing their advantages and relevance in this context. Finally, the last section investigates the existing forecasting models that will be integrated into the hybrid forecasting model, explaining their selection and their contribution to improving predictive accuracy.

2.1 Key Factors in Forecasting Models according to Literature

This subchapter examines the theoretical question: *'What key factors are identified in the literature for forecasting the expected growth of container transport?'*.

To develop an understanding of the factors utilized in forecasting container transport growth, the following table presents an overview of these factors along with the academic articles in which they are discussed.

Factors used to forecast the expected growth of container transport	**Examples of literature in which the corresponding factor is taken into account**
Macroeconomic indicators	Seabrooke et al. (2002), De Langen (2003), Kim et al. (2011), Gosasang et al. (2011), Intihar et al. (2015), Rashed et al. (2016), Intihar et al. (2017), Gosasang et al. (2018), Matczak (2020).
Port performance/infrastructure	Seabrooke et al. (2002), Kim et al. (2011), Gosasang et al. (2011), Intihar et al. (2015), Gosasang et al. (2018), Matczak (2020), Saeed et al. (2023), Munim et al. (2023), Shang et al. (2023).

Technological advancements	Amoako (2002), Evseev et al. (2021).
Fuel pricing	Gosasang et al. (2011), Gosasang et al. (2018).
Trade policies	Amoako (2002), Seabrooke et al. (2002), Shibasaki et al. (2010), Sou and Ong (2016).
Environmental regulations	Gosasang et al. (2018), Chupin et al. (2024).
Supply chain disruptions	Koyuncu et al. (2021), Saeed et al. (2023), Shang et al. (2023).

Table I. Factors and corresponding literature.

The subsequent subchapters will provide a detailed explanation of how these factors influence the expected growth of container transport.

2.1.1 Macroeconomic Indicators

Several studies highlight the strong interrelation between port growth, throughput dynamics, and macroeconomic indicators (Intihar et al., 2015; Kawasaki et al., 2021; Hackett, 2012). Macroeconomic conditions significantly influence trade volumes and port throughput, shaping container transport growth (Hackett, 2012). Economic expansion typically leads to increased container movements, whereas downturns result in reduced transport volumes (Kawasaki et al., 2021). Kawasaki et al. (2021) further note that economic fluctuations impact container transport with a delayed effect, as changes propagate through supply chains.

Macroeconomic indicators enhance the accuracy of forecasting models, leading to more reliable predictions (Stock & Watson, 2002; Stock & Watson, 2002a). Key indicators include Gross Domestic Product (GDP), trade volumes, and population growth. GDP is widely recognized as one of the most influential factors, given its direct correlation with trade activity (Wang et al., 2013). Economic growth drives production and consumption, increasing demand for goods and containerized transport. Conversely, a GDP decline slows trade activity, reducing transport volumes.

Trade volumes, encompassing import and export flows, reflect market demand and economic health (Matczak, 2020). Rising trade volumes indicate increased international and domestic demand, driving container transport expansion. In contrast, declining trade volumes, caused by economic downturns or trade restrictions, may hinder growth. Population growth also influences container transport (Gosasang et al., 2011). A growing population stimulates demand for consumer goods and infrastructure, increasing trade volumes. Conversely, population stagnation or decline may suppress demand, limiting transport growth.

Ports, in turn, significantly influence macroeconomic conditions. Research suggests that port activities and freight traffic contribute positively to regional economic growth (Park & Seo, 2015; Bottasso et al., 2014; Shan et al., 2014). Given the critical role of macroeconomic indicators in container transport dynamics, their inclusion in forecasting models is essential for improving predictive accuracy and supporting informed decision-making in maritime logistics (Intihar et al., 2015; Stock & Watson, 2002).

2.1.2 Port Performance and Infrastructure

Port infrastructure and performance are critical determinants of efficiency, directly influencing trade facilitation and container transport growth (Mlambo, 2021). Higher efficiency enables ports to handle goods more smoothly, increasing throughput capacity.

Inefficient port operations, by contrast, raise transport and trade costs, prompting firms to seek alternative ports. This shift can reduce trade volumes at inefficient ports, potentially limiting container transport growth (Notteboom et al., 2021a). While inefficiencies constrain a port's ability to accommodate trade, they do not directly reduce transport volumes but rather create unfavorable conditions that may hinder growth.

Operational efficiency also impacts macroeconomic indicators in surrounding regions. Improved port performance can lead to increased employment, higher trade values, and greater economic output, thereby stimulating regional development (Notteboom et al., 2021a). A well-performing port enhances trade flows, minimizes delays, and reduces costs, creating a competitive advantage that attracts investment and fosters container transport growth (Jarumaneeroj et al., 2023).

Therefore, although port performance facilitates trade expansion, it does not independently drive container transport growth. Instead, it establishes the necessary conditions for growth, while external variables such as global trade trends, economic fluctuations, and policy decisions determine actual developments. Consequently, incorporating port performance into forecasting models enhances their accuracy by providing a comprehensive representation of influencing factors. Historical port performance data is particularly valuable in identifying trends, enabling more precise predictions of future container transport growth. Throughput volume, which measures total cargo handled over a given period, remains the primary metric for assessing port efficiency and performance (De Langen et al., 2007; Talley, 2011).

Additionally, technological advancements help improve port performance and infrastructure and have significantly shaped the growth of container transport and altered global trade patterns by enhancing efficiency, reliability, and scalability across the sector. Key innovations such as automation, digitalization, and data analytics have played a pivotal role in both the expansion and transformation of containerized shipping. Automation, in particular, has streamlined port operations by reducing labor costs and minimizing human error, as seen in the Port of Rotterdam, which utilizes automated stacking cranes and remotely guided vehicles to optimize performance (Rodrigue & Notteboom, 2021; Dávid, 2019). Meanwhile, digitalization through technologies like blockchain and the Internet of Things (IoT) has improved transparency and traceability in supply chains, enabling more efficient coordination among stakeholders (Paulauskas et al., 2021; Kusumawati et al., 2023). The use of big data analytics and artificial intelligence further contributes by supporting predictive maintenance and improving asset utilization (González et al., 2020; Kusumawati et al., 2023). Nevertheless, these technological shifts also present challenges, including the need for substantial capital investments and the increased risk of cybersecurity threats, along with potential labor displacement (Kusumawati et al., 2023; Dávid, 2019). Therefore, while these advancements offer substantial operational benefits, they also introduce complex financial and strategic considerations. It is crucial that forecasting models account for the pace and direction of technological change in order to accurately assess its impact on future container transport growth.

2.1.3 Fuel Pricing

Fuel pricing significantly influences container transport growth, as fluctuations in fuel costs are often passed on to customers through surcharges, impacting consumer behavior (Notteboom, 2012). Higher fuel prices increase overall shipping costs, which may slow or even reduce container transport growth. Conversely, lower fuel prices create cost advantages that can stimulate trade and increase transport volumes.

Fuel costs constitute a substantial share of total transport expenses. Limao and Venables (2001) found that a 10% rise in transport costs can cut trade volumes by 20%, highlighting the sensitivity of container transport to fuel price fluctuations. Haralambides (2019) further emphasizes that lower transport costs enhance the viability of long-distance container shipping, shifting the focus from geographical distance to economic distance, which accounts for total transport costs, including fuel prices.

Beyond direct cost implications, fuel price fluctuations influence strategic decisions within the shipping industry. Rising fuel costs prompt companies to optimize routes, invest in fuel-efficient vessels, or adopt slow steaming, which conserves fuel but extends transit times (Cariou, 2011). These measures can mitigate cost increases but may affect supply chain efficiency and trade flows. Conversely, lower fuel prices allow shipping firms to prioritize speed and flexibility, improving overall transport efficiency.

Given its broad implications, fuel pricing is a significant factor in container transport growth. Incorporating fuel costs into forecasting models enhances predictive accuracy by capturing the relationship between cost structures, operational strategies, and trade volumes, thereby supporting informed decision-making in the maritime sector.

2.1.4 Trade Policies

Trade policies play a crucial role in shaping global container transport by regulating the flow of goods across international borders. This instrument can either stimulate trade growth or contribute to its decline, making its inclusion essential for accurately forecasting container transport trends, an integral aspect of strategic planning in maritime logistics.

Trade policies, including tariffs, quotas, and regulatory measures, directly impact trade costs and volumes (Atacan & Açık, 2023). The imposition of tariffs increases the cost of imported goods, often reducing demand and subsequently decreasing containerized shipments (Drobetz et al., 2020). This decline in trade volumes affects overall container transport growth. Additionally, high tariffs can reduce the competitiveness of ports and shipping lines, as shippers seek alternative routes or transport modes to mitigate costs (Fernandez-Stark & Gereffi, 2019). Consequently, some ports may face reduced throughput and overcapacity, while others experience increased strain, disrupting global container transport infrastructure.

Therefore, while trade policies can protect domestic industries, they often introduce complexities that ripple through global supply chains, influencing shipping costs, trade routes, and port operations (Fernandez-Stark & Gereffi, 2019). For maritime industry stakeholders, particularly those involved in forecasting container transport growth, integrating trade policy analysis into predictive models is significant.

2.1.5 Environmental Regulations

Environmental regulations play a considerable role in shaping the growth of container transport. As global awareness of climate change increases, the maritime industry experiences rising pressure to reduce its environmental footprint (Gosasang et al., 2018). This has led to regulatory reforms and technological adaptations that influence both the expansion and contraction of containerized trade.

The shipping industry is responsible for roughly 3% of global emissions, as proposed by the latest Greenhouse Gas Study conducted by the International Maritime Organization (IMO) (International Maritime Organization, 2020). In response, international organizations, particularly the International Maritime Organization (IMO), have implemented stringent regulations aimed at reducing emissions (Joung et al., 2020). These regulations have both direct and indirect effects on container transport growth. Compliance often requires substantial investments in cleaner technologies and alternative fuels. For example, many shipping companies are adopting dual-fuel vessels powered by Liquefied Natural Gas (LNG) or other low-carbon alternatives. While environmentally beneficial, this transition imposes significant financial burdens, potentially increasing freight rates and reshaping competitive dynamics.

Environmental regulations also impact global trade patterns (Wang et al., 2020). Regions with strict emission standards may experience shifts in trade routes as carriers seek to minimize compliance costs, potentially bypassing ports with rigorous environmental requirements. These changes can affect port throughput, influencing regional economies and the distribution of container traffic.

In conclusion, environmental regulations significantly affect container transport growth. While emission reduction mandates drive technological advancements, they also introduce financial and operational challenges. Integrating environmental regulations into forecasting models is significant for understanding the interplay between regulatory policies and industry growth, facilitating informed decision-making in global trade and sustainability.

2.1.6 Supply Chain Disruptions

Supply chain disruptions significantly impact the growth trajectory of container transport, influencing both expansion and reduction in global trade. These disruptions, caused by pandemics, geopolitical conflicts, and infrastructural blockages, reshape the dynamics of containerized shipping (Notteboom et al., 2021; Kilian et al., 2021).

The COVID-19 pandemic exemplifies a global supply chain crisis that severely disrupted container transport (Notteboom et al., 2021). Widespread labor shortages, port congestion, and container imbalances resulted in delays and increased shipping costs. These disruptions not only restricted the timely movement of goods but also exposed vulnerabilities in global supply chain infrastructures.

Geopolitical conflicts further heighten these vulnerabilities. For instance, the war in Ukraine has disrupted critical trade infrastructures, leading to rerouted shipping lanes and increased transit times (Allam et al., 2022). Such conflicts could increase insurance premiums, fuel costs, and operational risks, undermining the cost-effectiveness and reliability of container transport. Additionally, policy shifts, particularly those involving trade tariffs and protectionist measures, contribute to market instability by altering trade flows and increasing compliance costs for shipping companies (Kilian et al., 2021).

In conclusion, supply chain disruptions have a considerable influence on container transport growth and global trade (Atacan & Açık, 2023). Understanding these challenges is significant for developing accurate forecasting models that support strategic decision-making in the maritime industry. As the frequency and complexity of disruptions increase, the ability to anticipate and adapt to such challenges will be crucial for ensuring resilience and sustainable growth in container transport.

2.2 Hybrid Forecasting Models

This section addresses the theoretical research question: *'Why are hybrid forecasting models used?'*. By answering this question, this study provides a clearer understanding of why the research focuses on combining existing forecasting models into a hybrid approach.

Munim et al. (2023) state that hybrid forecasting models enhance predictive accuracy by leveraging the unique strengths of individual forecasting models. The improved forecasting performance results from the ability of a hybrid model to integrate the distinct capabilities of various individual models, thus capturing a broader range of influencing factors. Milenković et al. (2019) further emphasize that simple methods, which rely on a single forecasting model, produce less accurate forecasts than hybrid methods that combine multiple models. This argument is supported by Xie et al. (2013), who acknowledge that although individual forecasting models have inherent strengths, their combination yields superior accuracy, particularly in complex forecasting contexts such as container transport volumes, where seasonality and variability play a significant role.

Armstrong (2001) highlights that combining forecasts involves the integration of multiple independent forecasting models by averaging their forecasts into a hybrid model. Yang (2004) identifies two primary objectives for combining forecasting models: combination for improvement and combination for adaptation. The first objective seeks to optimize the combination of models to achieve the highest possible forecasting accuracy, whereas the latter ensures that the hybrid model performs at least as well as the best-performing individual model.

Given these findings, a hybrid forecasting model is expected to provide greater predictive accuracy than individual models alone. This assertion has motivated numerous studies to explore hybrid forecasting approaches in container throughput and demand forecasting (Pang & Gebka, 2016; Milenković et al., 2019; Munim et al., 2023) as well as in other fields, such as tourism forecasting (Wong et al., 2007; Cang & Yu, 2013).

2.3 Existing Forecasting Models

The last subchapter of Chapter 2 will research the last theoretical question included within this research: *'Which individual forecasting models are integrated into the hybrid forecasting model, and what are the reasons for their selection?'*.

2.3.1 Prophet Model

The Prophet model is a relatively new time series forecasting model introduced by Taylor and Letham (2017). Since its development, this model has been widely applied across various forecasting domains, including container transport (Munim et al., 2023; Saeed et al., 2023; Ubaid et al., 2021; Chia et al., 2024; Gouabou et al., 2024). Additionally, it has been utilized in other contexts such as railway freight forecasting (Zhao et al., 2023), air pollution prediction (Samal et al., 2019), and sales forecasting (Žunić et al., 2020), all of which have demonstrated its high level of accuracy.

The Prophet model was initially developed to provide a forecasting approach that requires minimal manual effort while remaining robust against missing data, outliers, and trend shifts (Saeed et al., 2023). It employs a decomposable time series framework consisting of three primary components: trend, seasonality, and holidays/events (Taylor & Letham, 2017). The mathematical formulation of the Prophet model, incorporating these components, is expressed as follows:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t$$

Where the forecasted data and value at time t is represented by $y(t)$. The term $g(t)$ denotes the growth function, which models the trend component, while $s(t)$ represents seasonality and its periodic fluctuations, which may follow daily, weekly, monthly, quarterly, or annual cycles. The holidays/events component, denoted as $h(t)$, accounts for the effects of special occurrences related to exogenous factors. Finally, ε_t represents the error term, capturing unexplained variations.

Where the variables that affect long-term growth can influence the growth component, for the other components no specific variables are added due to the ability of the model to infer these from the historical data.

The following mathematical formulations provide more detail on these components.

$$g(t) = (k + a\,(t)^T\,\delta)t + (m + a\,(t)^T\gamma)$$

$$s(t) = \sum_{n=1}^{N} (\,a_n \cos(\frac{2\pi nt}{P}) + \,b_n \sin(\frac{2\pi nt}{P}))$$

$$h(t) = Z(t)\,k$$

The trend component $g(t)$ is modeled using a piecewise linear approach rather than a logistic growth model. Since freight rates do not show saturating or logistic growth patterns, the piecewise linear model is the best to use for its simplicity and flexibility in capturing trend variations (Saeed et al., 2023).

In this model, k represents the growth rate, δ denotes the rate adjustments, and m refers to the offset parameters. To ensure continuity in the function, γ is adjusted in relation to δ. The parameters δ and γ are further refined based on a set of change points s_j, which can either be provided as exogenous inputs reflecting known structural changes or automatically selected by the Prophet model through the application of a sparse prior on δ. The function $a_j\ (t) \epsilon\ a\ (t)$ is a conditional function that returns 1 if $t \geq\ s_j$ and 0 if otherwise.

Seasonal effects, denoted as $s(t)$, are captured using a Fourier series representation. This is determined by a parameter vector $\beta = [\ a_1, b_1, \ldots, a_N, b_N]$ and a predefined period P. For example, if the data exhibits weekly patterns, the regular period would be set to $P = 7$.

Additionally, holiday and event effects are incorporated into the model using the function $h(t)$, where $Z(t) = [1(t \epsilon D_1), \ldots, 1(t \epsilon D_L)]$ identifies whether a given time t corresponds to a specific event i. Here, D_i represents the set of dates corresponding to event i, and $k_i\ \epsilon\ k$ quantifies the impact of the event on the time series.

The Prophet model has been incorporated into the hybrid forecasting framework due to its recent development and its advantages in flexibility, computational efficiency, and interpretability (Zhao et al., 2023). Unlike many traditional forecasting models, Prophet requires minimal manual adjustments and is highly resilient to missing data and outliers, making it particularly suitable for real-world applications where data irregularities are common. This characteristic enhances the model's reliability, which is critical in the dynamic field of container transport forecasting. Furthermore, Prophet allows for the integration of domain-specific knowledge, such as exogenous variables, which improves the accuracy of demand fluctuation predictions.

The model's decomposable time series approach is especially beneficial in handling non-linear trends, seasonal variations, and the impact of external factors (Vishwas & Patel, 2020). These aspects are crucial in the container transport sector, where shipping volumes can fluctuate due to seasonal trends, economic cycles, and external disruptions.

2.3.2 ARIMAX Model

The ARIMAX model is widely applied in research on forecasting models in the context of container transport (Intihar et al., 2017; Nieto et al., 2021; Rashed et al., 2016; Dragan et al., 2020). It has also been applied across various domains, including financial forecasting (Tamuke et al., 2018), economic indicator forecasting (Ugoh et al., 2021), public health predictions (Wangdi et al., 2010), and rainfall forecasting (Amelia et al., 2021). The ARIMAX model extends the traditional ARIMA framework by incorporating exogenous factors, thereby enhancing forecasting accuracy (Intihar et al., 2017).

To fully understand the ARIMAX model, it is essential to examine its fundamental components, which can be divided into four key elements (Rashed et al., 2016; Intihar et al., 2017; Amelia et al., 2021; Abd et al., 2021). The first component is the *Autoregressive (AR)* part, which captures trends based on historical data and past values. The second component, the *Integrated (I)* part, ensures the stationarity of the time series by differencing the data. This is important since this component helps the model fit the data rather than the noise. The third component, the *Moving Average (MA)* part, accounts for past values of random shocks, leveraging historical information to enhance the accuracy of future forecasts. The final component, which differentiates ARIMAX from ARIMA, is the *Exogenous Variables (X)* part. This component allows the model to incorporate external variables that are not inherent to the time series but have a significant impact on the forecast. By including exogenous variables, the ARIMAX model provides a more comprehensive analysis of the underlying patterns and improves forecasting performance (Dragan et al., 2020; Intihar et al., 2017).

The mathematical formulation of the ARIMAX model varies across studies (Nieto et al., 2021; Schramm & Munim, 2021; Abd et al., 2021). However, the formulation adopted in this research follows the works of Intihar et al. (2017) and Dragan et al. (2020), as these studies focus on forecasting container throughput in a similar context. Their approach is based on the research of Ljung (1995), which is frequently referenced in studies utilizing the ARIMAX model. The mathematical representation of the ARIMAX model is as follows:

$$A\,(q) \times \Delta y\,(t) = \sum_{i=1}^{m} B_i\,(q)\, \times u_i\,(t) + C(q) \times\, \varepsilon\gamma\,(t)$$

With,

$$A\,(q) = 1 + a_1\, \times\, q^{-1} + \cdots\, a_{na}\, \times\, q^{-na}$$

$$B_i(q) = b_{0i} + b_{1i} \times q^{-1} + \cdots b_{nbi} \times q^{-nbi}, i = 1, 2, \dots m$$

$$C(q) = 1 + c_1 \times q^{-1} + \cdots c_{nc} \times q^{-nc}$$

$$\Delta y(t) = y(t) - y(t-1)$$

In this formulation, $u_i(t)$ represents present values, while na, nb, and nc correspond to the oldest output delay, input delay, and random noise delay, respectively. The term $\varepsilon\gamma(t)$ denotes historical values of random errors, and q is the backshift operator.

The ARIMAX model is integrated into the hybrid forecasting model due to its superior forecasting accuracy, which results from the possible inclusion of exogenous variables. Unlike traditional ARIMA models, ARIMAX accounts for external factors that influence the time series, making it particularly suitable for forecasting container transport in ports (Intihar et al., 2017). This capability is crucial for container throughput forecasting, as macroeconomic indicators and other external factors significantly affect shipping volumes. By incorporating exogenous variables, ARIMAX enhances predictive accuracy and effectively captures the dynamic interactions between container throughput and influencing external factors. For example, Intihar et al. (2017) demonstrated that integrating macroeconomic indicators into the ARIMAX model significantly improved the accuracy of container throughput forecasts, further validating its applicability in this domain.

2.3.3 Holt-Winters Exponential Smoothing Model

The Holt-Winters Exponential Smoothing (HWES) model is an extension of earlier smoothing models, namely Holt's Linear Trend model and the Double Exponential Smoothing model. Unlike its predecessors, the Holt-Winters model accounts for both trend and seasonality, making it more suitable for forecasting data with recurring patterns (Winters, 1960; Munim et al., 2023).

The HWES model can be applied in two different forms: additive and multiplicative (Hyndman & Athanasopoulos, 2018; Pongdatu & Putra, 2018). The choice between these forms depends on the nature of the seasonal variation. The additive form is used when the seasonal component remains relatively constant over time, whereas the multiplicative form is applied when the seasonal effect varies proportionally to the level of the time series (Lima et al., 2019; Munim et al., 2023).

The mathematical formulation of the Holt-Winters model differs between these two forms (Chernick et al., 1994; Lima et al., 2019):

The additive Holt-Winters method is to be formulated as,

$$Y_t = T_t + S_t + \varepsilon_t$$

And the multiplicative Holt-Winters method can be formulated as,

$$Y_t = T_t \times S_t + \varepsilon_t$$

The recursive mathematical formulation of the HWES model further details its computation (Munim et al., 2023):

The additive Holt-Winters method recursive mathematical formulation is written as,

$$Y_{t+h/t} = (l_t + hb_t) + s_{t+h-m(k+1)}$$

$$l_t = \alpha\,(y_t/s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1})$$

$$b_t = \beta^*\,(l_t - l_{t-1}) + (1-\beta^*)b_{t-1}$$

$$s_t = \gamma\,(y_t - l_{t-1} + b_{t-1}) + (1-\gamma)s_{t-m}$$

And the multiplicative Holt-Winters method recursive mathematical formulation is written as,

$$Y_{t+h/t} = (l_t + hb_t)\,s_{t+h-m(k+1)}$$

$$l_t = \alpha\,(y_t/s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1})$$

$$b_t = \beta^*\,(l_t - l_{t-1}) + (1-\beta^*)b_{t-1}$$

$$s_t = \gamma\left(\frac{y_t}{(l_{t-1} + b_{t-1})}\right) + (1-\gamma)s_{t-m}$$

Here, l_t represents the estimated level of the series at time t, while b_t signifies an estimate of its trend at the same time. The parameter α serves as the smoothing factor for the level and s_t captures the seasonal component. Additionally, α, β^*, and γ act as the corresponding smoothing factors. The variable m denotes the seasonality period, and k represents the integer part of $(h-1)/m$.

The Holt-Winters Exponential Smoothing model has been widely used in research on container transport forecasting (Dragan et al., 2014; Chaurey, 2022; Munim et al., 2023).

Additionally, it has been applied in various other fields, including economic forecasting (Lima et al., 2019) and sales forecasting (Pongdatu & Putra, 2018).

The Holt-Winters Exponential Smoothing model is included in the hybrid forecasting model due to its extensive use in prior studies exploring the same context. This model is particularly effective in forecasting time series data that exhibit both trend and seasonal patterns. Given that container transport volumes often fluctuate in response to economic cycles, seasonal demand, and other periodic factors, the Holt-Winters model is well-suited for this application.

Unlike the other models in the hybrid approach, Holt-Winters does not incorporate exogenous variables; however, it remains essential as a baseline model, providing a foundation where additional key factors identified through expert knowledge are not considered in ensuring accuracy and is particularly valuable in cases where expert knowledge regarding influential external variables is unavailable or unreliable. By decomposing the time series into level, trend, and seasonal components, the Holt-Winters model enables a more structured and interpretable representation of underlying data patterns, thereby enhancing forecast accuracy (Munim et al., 2023).

Chapter 3: Methodology

This chapter outlines the methodology used in this research, providing a structured approach to addressing the research questions. The first section examines the nature of the research, defining its fundamental characteristics and underlying approach. The second section discusses the research strategy, detailing the chosen framework and methods used to achieve the study's objectives.

The third section focuses on data collection, explaining the sources, techniques, and procedures used to gather both primary and secondary data. The fourth section explains how the forecasting models are implemented using Python. The fifth section describes data analysis methods, including the techniques applied to interpret and evaluate the collected data and results. Finally, the last section assesses the reliability and validity of the research, ensuring that the findings are both credible and robust.

3.1 Research Nature

The primary objective of this thesis is to investigate the research problem: *"To what extent does the hybrid forecasting model outperform individual forecasting models in terms of predictive accuracy, considering key factors identified through expert knowledge, in forecasting container transport volumes for the ports of Rotterdam, Antwerp, and Moerdijk?"*. This problem statement is inherently comparative, as it aims to evaluate the hybrid forecasting model in relation to existing individual forecasting models.

Deductive research is characterized by beginning with a theoretical framework and subsequently building upon it. This study aligns with this approach, as it begins with a literature review, followed by the development of a hybrid forecasting method, with conclusions drawn at the end of the research process. In this context, the hybrid forecasting model developed in this thesis, comprising established individual models, is supported by prior research. The existing literature provides a comprehensive understanding of these individual models and serves as the foundation for the newly developed hybrid forecasting model, which aims to estimate the expected growth of container transport within its operational context. Unlike an inductive approach, which seeks to generate new theories, a deductive approach tests existing theories (Newman, 2000). The deductive nature of this research is further justified by its objective, to evaluate the predictive accuracy of the hybrid model compared to individual forecasting models, by applying established theoretical principles and drawing conclusions based on empirical evidence.

The time horizon of this research is both cross-sectional and longitudinal, dictated by time constraints and data availability. A cross-sectional approach applies to the qualitative component of this research, as expert interviews are conducted at a single point in time to identify key factors that should be incorporated into the forecasting models (Burbridge, 1999). Conversely, a longitudinal approach applies to the quantitative component, as historical data used in the forecasting models is collected over an extended period (Caruana et al., 2015). For instance, container throughput data for the ports of Rotterdam and Antwerp has been recorded quarterly since 2005, reflecting a longitudinal data structure.

As this research is primarily concerned with the development of a new hybrid forecasting methodology rather than the analysis of a specific entity, defining a unit of analysis is not deemed necessary. Nevertheless, it is essential to clearly specify the outcome variable and its scope. The outcome variable in this study is the forecasted growth rate of container transport at the maritime ports of Rotterdam, Antwerp, and Moerdijk. These ports have been selected due to their significant influence on and substantial contribution to container transport flows toward the inland terminals in Brabant. Consequently, the projected growth at these ports will serve as a basis for assessing whether the current capacity of terminals in Brabant, considered collectively, is sufficient to accommodate anticipated future growth. The temporal scope of the forecast is confined to the near future, encompassing an approximately five-year period with quarterly or monthly forecast intervals.

3.2 Research Strategy

The primary research strategy employed in this study is modelling, in which mathematical programming techniques are used to develop both the hybrid and individual forecasting models for estimating container transport growth.

The hybrid forecasting model constructed in this research includes three established individual forecasting models: the Prophet model, the ARIMAX model, and the Holt-Winters Exponential Smoothing model. A detailed review and justification of these models is provided in Chapter 2. The selection of factors incorporated into the forecasting models is guided by findings in existing literature and expert knowledge, obtained through cross-sectional expert interviews. Once the relevant factors are identified and validated, the individual forecasting models are computed, serving as the foundation for the hybrid model.

The hybrid forecasting model is formulated using a weighted average approach, where the weights are determined through a constrained optimization process that explicitly minimizes the Mean Absolute Percentage Error (MAPE) of the hybrid forecast. The performance of the individual models is assessed using established accuracy metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The hybrid forecasting model is subsequently evaluated using the same accuracy metrics to ensure its reliability and comparability with the individual models.

The weighted average approach has been selected due to its advantages in terms of accuracy, robustness, and flexibility (Adhikari & Agrawal, 2012). Accuracy is enhanced through the integration of multiple forecasting models, which mitigates the risks associated with relying on a single model. The robustness of this approach stems from its ability to balance the strengths and weaknesses of the individual models. Moreover, the flexibility of the weighted average approach allows for the easy incorporation of additional forecasting models if necessary. Prior research by Munim et al. (2023) demonstrated that hybrid models constructed using a weighted average approach outperformed individual forecasting models in terms of accuracy. While the individual models used in that study differ from those in this research, the findings highlight the potential for further improvements by integrating different forecasting models, as explored in this study.

Mathematically, the hybrid forecast yt at time t is given by:

$$yt = w_{HWES} \times y_{HWES,t} + w_{Prophet} \times y_{Prophet,t} + w_{ARIMAX} \times y_{ARIMAX,t}$$

subject to the constraints:

$$w_{HWES} + w_{Prophet} + w_{ARIMAX} = 1, \qquad w_{HWES,} w_{Prophet}, w_{ARIMAX} > 0$$

where, $y_{HWES,t}$, $y_{Prophet,t}$, and $y_{ARIMAX,t}$ are the individual model forecasts at time t, and w_i represents the weight assigned to model i. The optimization objective is to minimize:

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \frac{y_{t-} \hat{y}_t}{\hat{y}_t}$$

where $\hat{y}_t$ denotes the observed actual value.

The MAPE is selected as the primary optimization criterion due to its interpretability and ability to express forecast accuracy as a percentage, allowing for intuitive comparison across time periods and models. Unlike MSE and RMSE, which disproportionately penalize large errors and can be heavily influenced by outliers, or MAE, which lacks scale-independence, MAPE provides a scale-free and easily interpretable measure. This makes it particularly suitable in logistics forecasting contexts, where consistency and proportional error minimization are essential for operational planning and decision-making.

Unlike the simple weighted average method, where weights are typically based on past performance metrics and determined ex-ante, this optimization-based approach dynamically adjusts weights to directly minimize the overall forecasting error on the validation set. Importantly, it ensures that all component models contribute meaningfully by imposing a strictly positive lower bound on the weights. This approach aligns with the findings of Munim et al. (2023), who demonstrated the superiority of optimized hybrid models over both individual models and those combined via simple averaging.

To address the research questions, this study employs three primary research methods: literature review, expert interviews, and secondary data collection through desk research. The expert interviews are conducted to identify the key factors that should be incorporated into the forecasting models, leveraging insights from industry professionals. A literature review is undertaken to establish a foundational understanding of the subject matter before conducting the interviews and guiding the identification of the key factors, as well as to examine the individual forecasting models and the hybrid model in detail.

The expert interviews are structured as guided discussions, where the insights of the interviewees are systematically compared with findings from the existing literature. To facilitate a well-organized and efficient discussion, each interviewee receives a questionnaire containing relevant questions in advance. Interviewees are requested to submit their written responses no later than two days before the scheduled interview. These pre-submitted responses are then used during the interview to guide the discussion and allow for a comprehensive analysis in combination with insights from academic research. This approach enables an in-depth examination of consistencies, discrepancies, and the underlying reasoning behind expert opinions. The questionnaire and interview protocols are provided in the appendix.

In instances where the questionnaire is not completed in time, the duration of the interview may be extended to ensure the same level of depth is achieved. This structured methodology contributes to a more thorough understanding of the key variables influencing forecasting models in container transport while remaining efficient within the time constraints of the research.

By adopting this approach, the discussion gains depth and analytical precision. The systematic comparison of expert perspectives with the academic literature enhances the rigor of the study, ultimately contributing to well-substantiated conclusions regarding the key factors necessary for accurate forecasting in containerized transport. The insights provided by the experts will be tested in the development of forecasting models to ensure that the most effective combination of variables is selected for the construction of the hybrid forecasting model.

Moreover, factors that are deemed important by experts or literature but are not suitable for direct inclusion in the forecasting models, due to their unpredictability or data limitations, will be addressed through scenario analysis. To complement the model-based forecasts, the 2015 and latest scenario-based projections from the CPB Netherlands Bureau for Economic Policy Analysis (CPB) are used to define upper and lower bounds. These include a high-growth and a low-growth scenario, capturing broader uncertainties such as trade policies, technological change, climate regulations, and energy prices. This approach allows for the incorporation of external influences and uncertainties, thereby improving the robustness and realism of the forecasting outcomes.

Additionally, interviews are held with experts in the container transport sector to gather insights into the challenges they face and possible solutions when the growth of container transport exceeds the capacity of the terminals.

Finally, desk research is employed to collect secondary data for computing the individual forecasting models. This data is obtained from MCA Brabant’s internal records as well as publicly available datasets. By integrating both qualitative and quantitative data, this research ensures a comprehensive and methodologically sound approach to addressing the research objectives.

3.3 Data Collection

The interviews conducted in this study will follow a semi-structured format, allowing for a combination of predetermined questions and the flexibility for participants to elaborate on their responses beyond the initial framework (Bogdan & Biklen, 1997). This approach ensures that while a consistent set of core questions is maintained across all interviews, participants are also encouraged to provide additional insights that may not have been explicitly addressed in the predetermined questions. Interview transcripts and questionnaire responses will be translated from Dutch to English when necessary to facilitate analysis and discussion.

Given the time constraints and the scope of this research, the interviews will be conducted at a single point in time, thereby adopting a cross-sectional design (Burbridge, 1999). These interviews will play a critical role in the development of the hybrid forecasting model, as they will be used to identify the key factors that should be incorporated into the individual forecasting models, and consequently, into the hybrid model itself.

The sampling method for the interviews follows a non-probability sampling approach, as interviewees are selected based on specific, non-random criteria, rather than through a random sampling process. More specifically, this study employs a snowball sampling method, whereby experts are identified through existing professional contacts at MCA Brabant. This approach is particularly suitable given the necessity for specialist knowledge, and where such specialists are unavailable to the researcher on a personal or professional level.

In addition to primary data collection through interviews, this study also relies on desk research to obtain secondary data. The secondary data is sourced from both MCA Brabant's internal databases and publicly available datasets, and it will be used for computing the individual forecasting models as well as the hybrid forecasting model. The publicly available databases used in this research include the International Monetary Fund (IMF), which provides data on macroeconomic indicators and trade statistics (including import and export figures), Eurostat, providing throughput rates of the ports of Rotterdam and Antwerp, the United States Department of Agriculture (USDA), which supplies data on average global bunker and fuel prices and CPB Netherlands Bureau for Economic Policy Analysis (CPB) for data regarding the scenarios.

Additionally, MCA Brabant's internal databases are used to obtain data that is not available from public sources, such as container throughput rates for the Port of Moerdijk. Furthermore, MCA Brabant's internal data is used to assess the current capacity of inland terminals in

Brabant, which enables an evaluation of whether the expected growth in container transport will exceed existing terminal capacity. This assessment will provide strategic insights for MCA Brabant's future development plans.

The dependent variable in this study is the growth in maritime container transport volume, measured in Twenty-Foot Equivalent Units (TEUs). Growth is defined as the percentage change in container throughput over a given period. Specifically, quarterly or monthly container volume data for each port is used, and the growth rate is calculated as follows:

$$Growth_t = \frac{TUE_t + TUE_{t-i}}{TUE_{t-i}} \times 100$$

where TUE_t represents the container throughput at period t, and TUE_{t-i} represents the container throughput at period $t-i$. In this research the growth rate is calculated for the period from the first quarter of 2024 to the first quarter of 2029 for the ports of Rotterdam and Antwerp, and for the period from the last month of 2024 to the first month of 2029 for the port of Moerdijk. Accordingly, TUE_t refers to the forecasted container volume for the first quarter or first month of 2029 and TUE_{t-i} corresponds to the observed container throughput of the first quarter or last month of 2024.

Data regarding the container throughput rates used in the models were gathered from various sources, as shown in this table:

Port	**Data Description**	**Unit**	**Frequency**	**Data Source**
Rotterdam	Container throughput volumes	TEU	Quarterly (from the last quarter of 2005 until the first quarter of 2024)	Eurostat, n.d.
Antwerp	Container throughput volumes	TEU	Quarterly (from the last quarter of 2005 until the first quarter of 2024)	Eurostat, n.d.
Moerdijk	Container throughput volumes	TEU	Monthly (from the first month of 2017 until the last month of 2024)	MCA Brabant (internal records)

Table II. Container throughput rates per Port, their description, and source.

It is important to note that the data for the Port of Antwerp may be influenced by the 2022 merger with the Port of Bruges, which resulted in the formation of the unified Port of Antwerp-Bruges. This institutional and operational merging could have affected container throughput volumes due to changes in the use of infrastructure, shipping routes, and administrative coordination. While the data used in this research is consistently sourced from Eurostat, which helps ensure comparability, the merger may still introduce structural changes that influence the recorded volumes of container throughput. These changes may not necessarily reflect underlying market dynamics but rather result from altered reporting practices, port operations, or strategic integrations. Consequently, part of the variation in the forecasts for the Port of Antwerp could be attributed to these post-merger adjustments rather than organic trends in maritime container flows.

The exogenous variables used in the Prophet and ARIMAX models are selected based on the literature review and expert interviews. Since the HWES model does not have the ability to include exogenous variables, these variables are not applicable to this model. The data and descriptions of the exogenous variables include:

Variable	**Definition**	**Unit**	**Original Frequency**	**Adjusted Frequency**	**Source**
World Trade Volume	Index of global trade in goods for import and export	Annual Growth Rate	Yearly	Quarterly (for the port of Rotterdam and Antwerp)/ Monthly (for the port of Moerdijk)	International Monetary Fund, 2024
Fuel Prices	Average global price of bunker fuel	Dollars per Metric Ton	Daily	Monthly (for the port of Moerdijk)	United States Department of Agriculture, n.d.
GDP (the Netherlands and Belgium)	Gross Domestic Product of the	National currency	Yearly	Quarterly (for the port of Rotterdam and	International Monetary Fund, 2024

	Netherlands or Belgium in constant prices			Antwerp)/ Monthly (for the port of Moerdijk)	
Import and Export Volume (the Netherlands and Belgium)	Index of trade in goods for import and export of the Netherlands or Belgium	Annual Growth Rate	Yearly	Quarterly (for the port of Rotterdam and Antwerp)/ Monthly (for the port of Moerdijk)	International Monetary Fund, 2024
Population (the Netherlands and Belgium)	Population of the Netherlands or Belgium	Persons	Yearly	Quarterly (for the port of Rotterdam and Antwerp)/ Monthly (for the port of Moerdijk)	International Monetary Fund, 2024

Table III. Exogenous variables, their description, and source.

Additionally, these exogenous variables and their data regarding the scenarios originate from the report of Manders and Kool (2015), as part of the CPB Netherlands Bureau for Economic Policy Analysis (CPB). The unit of these variables is the same for all variables: Annual Growth Rate over a period of time. This frequency is adjusted towards quarterly or monthly data.

Furthermore, the number of observations differs between the ports. For the ports of Rotterdam and Antwerp, the number of observations is 93 data points of quarterly data, and for the port of Moerdijk, the number of observations is 145 data points of monthly data. The exogenous variables all align with the number of observations accordingly. However, the number of observations regarding the scenarios includes 20 data points of quarterly data and 49 data points of monthly data. The scenarios build on actual data to forecast from the most recent actual data point towards the beginning of 2029. Additionally, the combinations of variables including fuel prices have a different number of observations due to the unavailability of data for this variable, while this variable is available from 2019 onwards. Therefore, the number of observations in the models including fuel prices is 72 data points of monthly data.

For model development and validation, the dataset will be divided into a training set and a test set, with 80% of the data allocated for training and 20% for testing.

3.4 Forecasting Models in Python

In this research, three individual forecasting models are computed, Holt-Winters Exponential Smoothing (HWES), Prophet, and ARIMAX, each of which captures different components of the container transport time series: trend, seasonality, and external regressors. These models are implemented using Python, specifically through established libraries such as statsmodels for HWES and ARIMAX, and the Prophet package for the Prophet model. Python automates the estimation process through underlying optimization algorithms that identify the best-fitting parameters based on historical data.

The HWES model, applied via Python's ExponentialSmoothing function, is well-suited for modeling container volume growth as it captures both trend and seasonality, which are important in transport flows. This model decomposes the time series into level, trend, and seasonal components and updates them recursively, making it appropriate for detecting gradual changes over time.

The Prophet model is designed to handle complex seasonality patterns and is particularly effective for time series with strong yearly, weekly, or holiday effects. The model detects changepoints, abrupt shifts in trends, without the need for manual specification. In Python, Prophet simplifies model training by automatically fitting piecewise linear or logistic growth curves to the time component, while internally managing seasonality as an additive component.

The ARIMAX model is implemented via Python's SARIMAX function from the statsmodels library. This model estimates autoregressive and moving average terms along with the influence of external variables. Python optimizes the model's lag structure and coefficients using likelihood-based methods, and residual diagnostics are performed to ensure model adequacy.

All three models use container throughput data as the dependent variable and are evaluated across a common time dimension (monthly or quarterly, depending on data availability). The models differ in how they incorporate explanatory variables and seasonality. HWES and Prophet manage seasonality internally, while ARIMAX requires input of time lags. Prophet and ARIMAX require explicit input of external variables, unlike HWES, since this model is not able to incorporate external variables. These individual forecasts are subsequently used as inputs to the hybrid model, aligning with the overall methodological framework described in this chapter, which focuses on forecasting container transport growth over time using interpretable and data-driven methods.

3.5 Data Analysis

The data utilized in the forecasting models is preprocessed before application, ensuring that all data is standardized to a common time frame. To convert the annual data to higher-frequency intervals, a linear interpolation approach was adopted. This method assumes that changes in variable data occur at a consistent rate between two known annual values. The interpolation process was carried out as follows:

For the ports of Rotterdam and Antwerp, annual values were distributed equally across quarters within the same year, resulting in quarterly estimates.

For the port of Moerdijk, a similar linear approach was applied, distributing annual values across months to obtain a monthly time series.

This method ensured a smooth and continuous representation of growth trends while avoiding artificial fluctuations that could distort model training. Additionally, the data was cleaned to remove anomalies, check for missing values, and ensure all entries were consistent in terms of units and formatting.

To test the robustness of the linear interpolation approach, a comparative approach using an exponential interpolation method was also performed. The exponential approach assumes that the changes in variable data follow a compounding pattern over time, which may be more appropriate for rapidly expanding or contracting time series.

To evaluate and compare the performance of the individual forecasting models and the hybrid forecasting model, several widely recognized forecasting accuracy metrics will be employed.

These include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Where lower values indicate better performance. According to Hyndman and Koehler (2006), MSE, RMSE, and MAE are scale-dependent metrics that assess forecasting accuracy based on absolute errors or squared errors. These metrics are particularly useful when comparing different forecasting methods that utilize the same dataset. Additionally, MAPE, which is based on percentage errors, is especially valuable for evaluating forecasting performance across models with different scales.

Given that the objective of this study is to compare the predictive accuracy of different forecasting models and to analyze their forecasting performance, these four metrics have been selected. Their inclusion ensures a comprehensive assessment of the models and enhances the robustness and reliability of the comparison.

The mathematical formulations of the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are to be defined as follows:

The Mean Squared Error (MSE) is represented as,

$$= Mean\ (e_t^2)$$

The Root Mean Squared Error (RMSE) is represented as,

$$= \sqrt{Mean\ Squared\ Error\ (MSE)}$$

The Mean Absolute Error (MAE) is represented as,

$$= Mean\ (|e_t|)$$

And lastly, the Mean Absolute Percentage Error (MAPE) is represented as,

$$= Mean\ (|p_t|)$$

For all these formulations applies that $e_t = Y_t - F_t$ and $p_t = 100\ e_t / Y_t$, where Y_t represents the throughput of the port at time t and F_t denotes the forecast of Y_t.

These metrics collectively provide a robust framework for assessing the accuracy of the forecasting models and determining the effectiveness of the hybrid forecasting model in comparison to individual models.

3.6 Reliability and Validity

According to Fitzner (2007), reliability is defined as the consistency of the research, indicating that the research can be reproduced under the same conditions and will result in similar results. In the same research, validity is referred to as accurately measuring what is intended to be measured.

In this research, reliability is met, where it is clarified which forecasting models are used in detail, what factors are included, and where the data is from. Therefore, the research can be reproduced and will result in similar results.

Additionally, validity is met by computing the same accuracy metrics for both the individual forecasting models and the hybrid forecasting model. These accuracy metrics are the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

Chapter 4: Findings

This chapter presents a comprehensive examination of the empirical questions introduced in Chapter 1, providing detailed explanations and analyses that contribute to addressing the problem statement.

The first section identifies the key factors to be incorporated into the forecasting models, as determined through expert knowledge and literature review. The second section outlines the construction of the hybrid forecasting model. The third section evaluates the predictive accuracy of the hybrid forecasting model in comparison to individual forecasting models.

Finally, the fourth and last section examines the expected growth of container transport for the ports of Rotterdam, Antwerp, and Moerdijk, based on the most accurate forecasting model identified in this research.

4.1 Key Factors in Forecasting Models

The following table presents the factors recommended for inclusion in the models based on a review of the literature, expert insights and practical experience, alongside the factors ultimately selected for the analysis. The rationale for the selection of these factors is discussed in detail in this chapter.

Findings Literature Review	**Findings Expert Interviews**	**Factors included in the models**
Macroeconomic indicators	Macroeconomic indicators	Macroeconomic indicators
Port performance/infrastructure	Port performance/infrastructure	Port performance/infrastructure
Technological advancements		
Fuel pricing		Fuel pricing
Trade policies		
Environmental regulations		
Supply chain disruptions		

Table IV. Comparison of recommended factors to include in the models by the literature, experts, and factors chosen.

Although the literature highlights fuel prices as a significant factor influencing container transport and recommends their inclusion in forecasting models, expert opinions gathered during this study diverge from this perspective. While acknowledging that fuel prices may be of some influence, the experts unanimously advised against incorporating this variable into the forecasting models. According to their assessment, the impact of fuel prices on container transport volumes is relatively limited and indirect.

Experts argue that fluctuations in fuel prices do not necessarily lead to changes in container transport volumes. They assert that transport must continue regardless of moderate variations in fuel costs, as fuel represents only a fraction of total logistical expenses. Rather than reducing transport demand, increases in fuel prices are more likely to trigger operational adjustments within the industry. For example, companies may adopt strategies such as slow steaming, reducing vessel speeds to conserve fuel and lower costs, or switching to alternative fuels and other cost-saving measures to mitigate the financial effects of fuel price volatility.

The expert interviews also revealed differing views regarding the most influential macroeconomic factors affecting container transport growth. The literature shows that the key macroeconomic indicators include GDP, population, and trade volumes. Several experts suggested a shift in emphasis from GDP to population growth, asserting that GDP is no longer the primary determinant. Their reasoning is that an increasing population generates a higher demand for goods, which in turn drives container transport volumes. However, this view is contested by another expert, who maintains that GDP remains the most crucial macroeconomic indicator. This expert recommended including only GDP in the forecasting model, arguing that a strong correlation may exist between GDP and other macroeconomic variables such as import and export volumes and population growth, which could compromise the model's reliability.

Additionally, one expert recommended the inclusion of relevant world trade volumes, an indicator not commonly referenced in the reviewed literature. Since the Netherlands and Belgium import and export goods to and from countries on all continents, the total world trade rates are investigated within the models. The rationale is that container transport is influenced not only by the import and export activities of individual countries but also by global trade flows. A significant portion of container traffic consists of transshipment or transit goods not destined for domestic consumption. Consequently, the expert recommended replacing country-specific indicators (e.g., national import and export volumes) with world trade volumes to better reflect the international nature of containerized transport.

Furthermore, all experts agreed that only port performance indicators and macroeconomic variables should be included as explanatory variables in the forecasting model. Other potential factors, such as technological advancements, supply chain disruptions, trade policies, and environmental regulations, were considered too unpredictable or lacking in consistent data to be reliably modeled. As such, these elements should be addressed through scenario analysis rather than being directly incorporated into the baseline forecasting models.

Moreover, several experts provided further suggestions for potential variables to consider, including consumer spending, inventory levels, inflation, transit volumes, containerization rate, and dematerialization. However, due to the correlation between GDP and both consumer spending and inflation, these factors have not been included for the remainder of this study (Olusola et al., 2022; Shiferaw, 2023; Nyamekye & Poku, 2017; Nizam et al., 2024; Asafo-Adjei et al., 2023). Moreover, the exclusion of consumer spending, inventory levels, transit volumes, containerization rate, and dematerialization is primarily due to the unavailability of sufficient and reliable data. As a result, these variables are not considered further in this study.

In conclusion, it would be valuable to explore various combinations of variables in the forecasting models concerning the following factors: macroeconomic indicators, port performance and infrastructure, and fuel pricing. This approach enables a deeper investigation into discrepancies between theoretical knowledge and expert insights and experience, and makes sure the best-performing combination is used in the remainder of the research. The proposed combinations include: (1) port performance, measured by throughput rates, and GDP; (2) port performance and GDP, with import and export rates combined with population growth; (3) port performance and world trade rates; (4) port performance, GDP, world trade rates, and population growth; (5) port performance, GDP, import and export rates, population growth, and fuel prices; and (6) port performance, GDP, world trade rates, population growth, and fuel prices. Examining these combinations may enhance the robustness and predictive accuracy of the forecasting models by capturing the most relevant and influential variables. For each forecasting model, the combination of variables that demonstrates the highest predictive accuracy will serve as the foundation for developing the hybrid forecasting model.

4.2 Construction of Hybrid Forecasting Model

The following table presents the results of the individual forecasting models and their various combinations of variables. It is important to note that the Holt-Winters Exponential

Smoothing model does not accommodate the inclusion of external variables, which explains why only a single result is presented for this model. Additionally, data for fuel prices is only available from 2019 onwards. Consequently, this variable is included solely in the Port of Moerdijk dataset, which is based on monthly observations and contains a sufficient number of data points for the relevant time frame.

Rotterdam	MSE	RMSE	MAE	MAPE
Holt-Winters Exponential Smoothing	75453.35	274.69	245.2	7.16%
Prophet: GDP	181222.67	425.7	374.44	11.09%
Prophet: GDP, Population, Import, Export	578464.28	760.57	660.17	19.56%
Prophet: GDP, Population, World Import and Export	341095.08	584.03	500.26	14.90%
Prophet: World Import and Export	408545.37	639.18	528.63	15.82%
ARIMAX: GDP	64992.68	254.94	227.91	6.50%
ARIMAX: GDP, Population, Import, Export	90916.79	301.52	255.39	7.55%
ARIMAX: GDP, Population, World Import and Export	81462.85	285.42	246.07	7.25%
ARIMAX: World Import and Export	83942.61	289.73	256.46	7.42%
Antwerp	MSE	RMSE	MAE	MAPE
Holt-Winters Exponential Smoothing	32128.58	179.24	149.82	4.98%
Prophet: GDP	198676.54	445.73	378.82	12.75%
Prophet: GDP, Population, Import, Export	169186.28	411.32	350.39	11.77%
Prophet: GDP, Population, World Import and Export	217276.82	466.13	398.2	13.41%
Prophet: World Import and Export	89281.72	298.8	245.76	8.31%
ARIMAX: GDP	188991.84	434.73	384.03	13.01%
ARIMAX: GDP, Population, Import, Export	159232.44	399.04	345.32	11.62%
ARIMAX: GDP, Population, World Import and Export	232465.67	482.15	420.05	14.16%
ARIMAX: World Import and Export	64697.79	254.36	206.94	6.97%

Moerdijk	MSE	RMSE	MAE	MAPE
Holt-Winters Exponential Smoothing	137.44	11.72	9.27	19.76%
Prophet: GDP	277.51	16.66	15.08	32.53%
Prophet: GDP, Population, Import, Export	312.34	17.67	16.12	34.84%
Prophet: GDP, Population, World Import and Export	400.47	20.01	18.12	39.24%
Prophet: World Import and Export	417.91	20.44	18.69	40.45%
Prophet: GDP, Population, Import, Export, Fuel Price	141.71	11.9	9.47	18.27%
Prophet: GDP, Population, World Import and Export, Fuel Price	132.79	11.52	8.79	16.62%
ARIMAX: GDP	113.97	10.68	7.77	16.53%
ARIMAX: GDP, Population, Import, Export	301.66	17.37	15.87	34.85%
ARIMAX: GDP, Population, World Import and Export	379.19	19.47	17.77	39.03%
ARIMAX: World Import and Export	284.45	16.87	15.22	33.50%
ARIMAX: GDP, Population, Import, Export, Fuel Price	135.58	11.64	7.94	15.84%
ARIMAX: GDP, Population, World Import and Export, Fuel Price	150.9	12.28	8.32	16.26%

Table V. Individual models with different combinations of variables and their performance metrics.

For the port of Rotterdam, the best-performing combination for both the Prophet and ARIMAX models includes solely GDP. The ARIMAX model, including GDP, is the best-performing model with an MAPE of 6.50%, which is followed by the Holt-Winters Exponential Smoothing with an MAPE of 7.16%, and the Prophet model, including GDP, with an MAPE of 11.09%. Conversely, the poorest-performing configuration is the Prophet model that incorporates GDP, population, import, and export variables, which resulted in an MAPE of 19.56%. In the case of the port of Antwerp, the Holt-Winters Exponential Smoothing model is the best-performing with an MAPE of 4.98%, and the optimal combination for both Prophet and ARIMAX models consists of world import and export volumes, with a corresponding MAPE of 8.31% and 6.97%. The ARIMAX model performs the worst when it includes GDP, population, and world import and export volumes, resulting in an MAPE of 14.16%.

For the port of Moerdijk, the most accurate Prophet model includes GDP, population, world import and export volumes, and fuel prices, resulting in an MAPE of 16.62%. The ARIMAX model achieves the lowest MAPE of 15.84% when including GDP, population, import, export, and fuel prices. However, when considering other evaluation metrics, MSE, RMSE, and MAE, the best-performing ARIMAX model is the one that includes solely GDP. This discrepancy can be attributed to two factors: the shorter time series available for the more complex models, including fuel prices, due to limited data availability, and the relatively low throughput volumes in Moerdijk. This may render MAPE less reliable, as small absolute deviations can result in disproportionately large percentage errors. Therefore, in this case, MAE is considered the more appropriate evaluation criterion, and the ARIMAX model incorporating only GDP is selected as the best performer. The poorest-performing model for Moerdijk is the Prophet model using world import and export volumes, with a corresponding MAPE of 40.45%.

Based on these findings, the models with the highest predictive accuracy are selected for integration into the hybrid forecasting model, using the mathematical formulation described in Chapter 3.

The resulting weights for the hybrid models are as follows:

Port of Rotterdam: 0.001 for the Holt-Winters Exponential Smoothing model, 0.001 for the Prophet model, including GDP, and 0.998 for the ARIMAX model, including GDP.

Port of Antwerp: 0.80785231 for the Holt-Winters Exponential Smoothing model, 0.001 for the Prophet model, including world import and export volumes, and 0.19114769 for the ARIMAX model using the same variables.

Port of Moerdijk: 0.03387114 for the Holt-Winters Exponential Smoothing model, 0.60921554 for the Prophet model, including GDP, population, world import and export volumes, and fuel price, and 0.35691332 for the ARIMAX model, including GDP.

However, due to the unavailability of reliable future data on fuel prices, this variable is excluded from the forward-looking forecasting analysis. As a result, the second-best performing Prophet model for Moerdijk, which includes GDP, is used instead. Accordingly, the revised weights for the Moerdijk hybrid model are: 0.001 for the Holt-Winters Exponential Smoothing model, 0.001 for the Prophet model, including GDP, and 0.998 for the ARIMAX model with GDP.

4.3 Hybrid Forecasting Model Compared to Individual Forecasting Models

The following table presents the best-performing combinations of the individual forecasting models in comparison with the corresponding hybrid models.

Rotterdam	MSE	RMSE	MAE	MAPE
Holt-Winters Exponential Smoothing	75453.35	274.69	245.2	7.16%
Prophet: GDP	181222.67	425.7	374.44	11.09%
ARIMAX: GDP	64992.68	254.94	227.91	6.50%
Hybrid Model	65005.8	254.96	228	6.50%
Antwerp	MSE	RMSE	MAE	MAPE
Holt-Winters Exponential Smoothing	32128.58	179.24	149.82	4.98%
Prophet: World Import and Export	89281.72	298.8	245.76	8.31%
ARIMAX: World Import and Export	64697.79	254.36	206.94	6.97%
Hybrid Model	33922.37	184.18	147.69	4.93%
Moerdijk	MSE	RMSE	MAE	MAPE
Holt-Winters Exponential Smoothing	137.44	11.72	9.27	19.76%
Prophet: GDP	277.51	16.66	15.08	32.53%
Prophet: GDP, Population, World Import and Export, Fuel Price	132.79	11.52	8.79	16.62%
ARIMAX: GDP	113.97	10.68	7.77	16.53%
Hybrid Model With Fuel	108.12	10.4	7.03	13.41%
Hybrid Model Without Fuel	113.96	10.67	7.78	16.54%

Table VI. Individual models with their best-performing combination of variables and hybrid models with their corresponding performance metrics.

The results indicate that the hybrid models generally perform either better than or at least comparably to the best-performing individual models. This finding aligns with the objective of model combination, as proposed by Yang (2004), which is to achieve predictive accuracy that is either superior to or not significantly different from that of the most accurate individual model. Due to the weighted contributions of all component models in the hybrid approach, a minor deviation from the performance of the best individual model may occur. This is observed in the cases of the ports of Rotterdam and Moerdijk, where the hybrid models demonstrate equivalent performance to the best-performing individual models.

In contrast, the hybrid model for the port of Antwerp demonstrates a significant improvement in performance over the best individual model in terms of MAE and MAPE. Although the hybrid model presented higher MSE and RMSE values compared to the Holt-Winters Exponential Smoothing model, these metrics place a heavier penalty on large deviations. In this context, MAPE is deemed the more appropriate measure, as it provides a more consistent assessment of overall model accuracy. Based on this consideration, the hybrid model for the port of Antwerp is still regarded as superior.

Furthermore, the inclusion of fuel prices in the hybrid model for the port of Moerdijk results in a notable enhancement in predictive performance. This suggests that, when available, fuel price data can meaningfully contribute to the accuracy of forecasts. However, due to the unavailability of reliable future data for fuel prices, this variable is excluded from all forward-looking forecasts and, therefore, from the remainder of the analysis. Consequently, the second-best-performing Prophet model for the port of Moerdijk, which includes GDP, is used for future forecasting purposes.

To validate the robustness of these findings, an additional analysis was conducted using exponential data-cleaning techniques, which assume that the changes in variable data follow a compounding pattern over time. The results of this approach are shown in the following table.

Rotterdam	MSE	RMSE	MAE	MAPE
Exponential				
Holt-Winters Exponential Smoothing	75453.35	274.69	245.2	7.16%
Prophet: GDP	181592.36	426.14	374.79	11.10%
ARIMAX: GDP	64824.14	254.61	227.22	6.48%
Hybrid Model	64834.89	254.63	227.3	6.48%
Antwerp	MSE	RMSE	MAE	MAPE
Exponential				
Holt-Winters Exponential Smoothing	32128.58	179.24	149.82	4.98%
Prophet: World Import and Export	90009.12	300.02	247.23	8.36%
ARIMAX: World Import and Export	46633.84	215.95	177.93	6.02%

Hybrid Model	31713.61	178.08	142.25	4.75%
Moerdijk	MSE	RMSE	MAE	MAPE
Exponential				
Holt-Winters Exponential Smoothing	137.44	11.72	9.27	19.76%
Prophet: GDP	295.7	17.2	15.66	33.78%
Prophet: GDP, Population, World Import and Export, Fuel Price	131.76	11.48	9.4	19.25%
ARIMAX: GDP	114.15	10.68	7.74	16.41%
Hybrid Model With Fuel	89.95	9.48	7.31	14.21%
Hybrid Model Without Fuel	114.14	10.68	7.75	16.43%

Table VII. Individual models with their best-performing combination of variables and hybrid models with their corresponding performance metrics, an exponential approach.

The results confirm the consistency of the conclusions drawn from the linear data-cleaning approach. While the exponential approach enhances the accuracy of the ARIMAX and hybrid models, the Prophet model performs best when paired with the linear approach. The robustness check substantiates the validity of the model selection and confirms that the methodological choices do not critically affect the conclusions of this research.

4.4 Expected Growth of Container Transport for the Ports of Rotterdam, Antwerp, and Moerdijk

Given the results indicating that the hybrid models generally perform better than or at least comparably to the best-performing individual models, these hybrid models are deemed the most suitable for forecasting container transport flows through to the beginning of 2029. This forecasting period represents approximately five years beyond the most recent historical data point available, which corresponds to the first quarter of 2024 for the ports of Rotterdam and Antwerp and the month of December 2024 for the port of Moerdijk.

These forecasts are further complemented by scenario-based projections derived from the CPB Netherlands Bureau for Economic Policy Analysis (CPB), which serve to establish upper and lower bounds. The scenarios incorporate variables not explicitly included in the forecasting models, such as trade policies, technological advancements, environmental regulations, and supply chain disruptions. Two CPB scenarios are employed: a high-growth scenario and a low-growth scenario (Manders & Kool, 2015). The high-growth scenario assumes strong global economic and trade growth, rapid technological development, extensive climate policies, and low energy prices. Conversely, the low-growth scenario is based on restrained global economic and trade growth, slower technological advancement, limited climate policies, and high energy prices. These assumptions implicitly reflect the remaining key factors mentioned, with world economic and trade growth reflecting trade policies and supply chain disruptions; technological development representing technological advancements; climate policies serving as a proxy for environmental regulations; and energy prices potentially reflecting broader supply chain dynamics and fuel prices. In the figures, the blue dotted line represents the forecasted growth with the hybrid model, the green dotted line corresponds to the high-growth scenario of the CPB, and the red dotted line represents the low-growth scenario of the CPB.

For the port of Rotterdam, the maritime flow of container transport is projected to decline gradually by 3.9% by the start of 2029, equating to an average annual decrease of 0.8%. This trend is consistent with historical data, which shows a downward trajectory beginning in 2022, likely contributing to the continued decline observed in the forecast. This projection aligns with both CPB scenarios: the high-growth scenario predicts an even sharper decline, while the low-growth scenario anticipates a more moderate decrease.

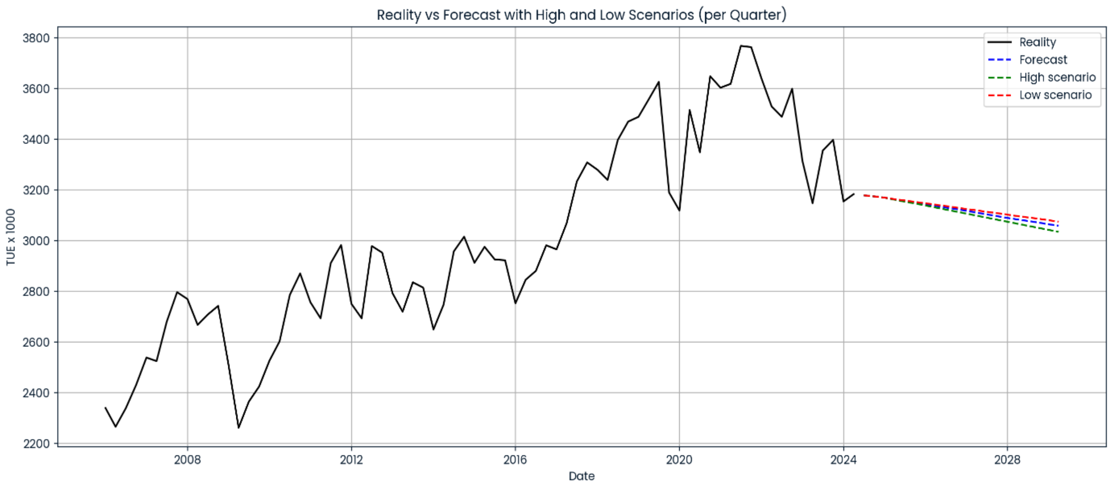

Figure 2. Historical data with the forecast for the future, including high and low scenarios for the port of Rotterdam.

For the port of Antwerp, container transport is forecasted to grow by 8.5% by early 2029, corresponding to an average annual increase of 1.7%. This upward trend is consistent with historical data, which does not show as notable a decline as the port of Rotterdam. However, the forecast falls below the growth levels anticipated in both CPB scenarios, which predict more robust increases. This discrepancy may be attributed to the fact that the most predictive variables for the port of Antwerp were identified as world import and export volumes and the CPB scenarios dating from 2015 and may not fully account for major geopolitical and economic events that have occurred since then, such as the COVID-19 pandemic, the 2016 U.S. presidential election, the war involving Russia and Ukraine, and the Suez Canal blockage, all of which have significantly affected global trade dynamics. Additionally, the 2022 merger of the Port of Antwerp and the Port of Bruges to form the Port of Antwerp-Bruges may have affected the consistency of reported container volumes. This organizational merger could lead to changes in operational reporting, infrastructure usage, and throughput, potentially introducing short-term distortions in the data. Although Eurostat remains a consistent data source, such structural changes may impact trend continuity and forecasting accuracy.

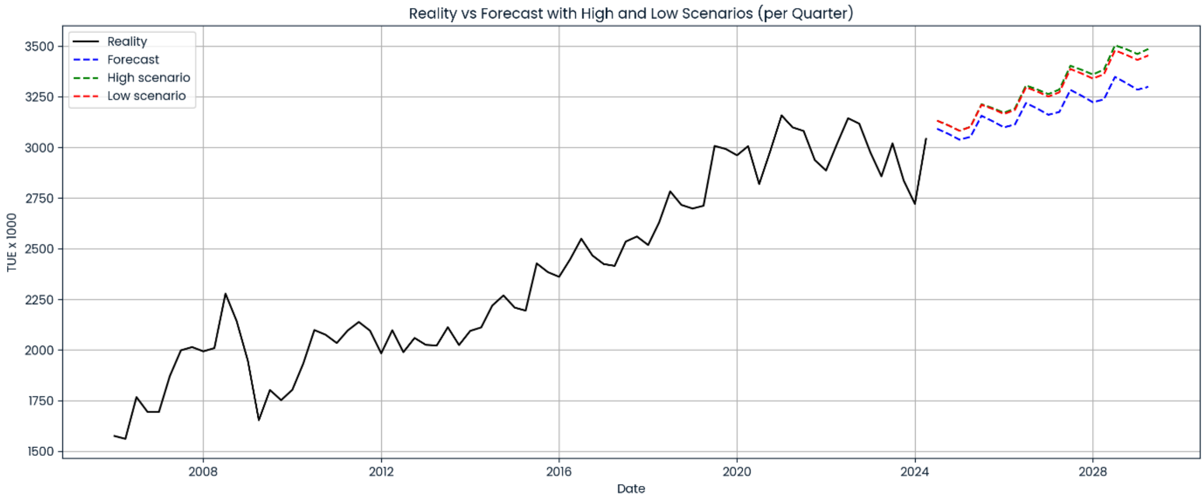

Figure 3. Historical data with the forecast for the future, including high and low scenarios for the port of Antwerp.

For the port of Moerdijk, a gradual decline of 2% in container throughput is projected by 2029, which translates to an average annual decrease of 0.4%. Similar to the port of Rotterdam, this decline is consistent with historical trends observed from 2022 onwards. The forecast aligns with both the high and low CPB scenarios, with the former indicating a steeper decline and the latter a more moderate one.

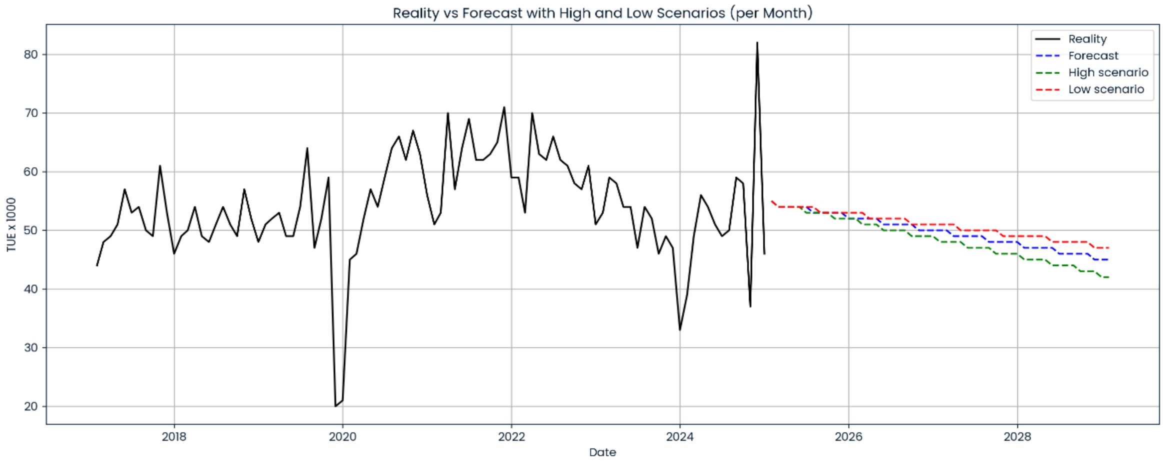

Figure 4. Historical data with the forecast for the future, including high and low scenarios for the port of Moerdijk.

In the absence of data regarding the relative contribution of each port to Brabant's container flows, the highest forecasted growth rate, corresponding to the port of Antwerp, has been used for capacity analysis. Even with this growth scenario, the current terminal capacity of all terminals combined remains sufficient to accommodate the anticipated increase in container volumes.

Chapter 5: Discussion

This chapter presents a comprehensive discussion of the research findings, relating them to the existing literature and practical implications.

The first section examines the theoretical contribution of this study, evaluating how the findings enhance current knowledge on forecasting container transport growth and the effectiveness of hybrid forecasting models. The second section provides managerial recommendations, outlining practical insights for industry stakeholders. Finally, the last section discusses the limitations of this research and identifies potential future research directions, offering suggestions for further research to enhance forecasting methodologies and address current and future challenges.

5.1 Theoretical Contributions

This research contributes to the academic field of transport forecasting by applying and comparing three well-established forecasting models, Prophet, ARIMAX, and Holt-Winters Exponential Smoothing, within the specific context of forecasting maritime container transport growth for the ports of Rotterdam, Antwerp, and Moerdijk, representing the most important and major ports for the flow to the province of Brabant. A central element of this contribution lies in the development and implementation of hybrid forecasting models that integrate these individual approaches.

The findings confirm that hybrid forecasting models tend to perform either better than or comparably to the most accurate individual models. This aligns with the theoretical foundation established by Yang (2004), who argued that the objective of combining models is to achieve predictive accuracy either superior to or at least not significantly different from that of the most accurate individual model. While previous literature has theorized the benefits of combining forecasting approaches, this research offers practical evidence of when and how hybrid forecasting models are most valuable. Rather than simply reiterating earlier theoretical claims, the study demonstrates the real-world conditions under which hybrid forecasting models add meaningful value, especially in settings marked by complex regional trade dynamics and unpredictable market developments.

The choice to implement and compare three forecasting techniques is not incidental. These models each have their benefits and reasons behind the rationale for choosing them. Holt-Winters Exponential Smoothing was chosen for its ability to provide a robust baseline forecast by decomposing time series into level, trend, and seasonal components, offering reliable performance when exogenous variables are unavailable or uncertain. Additionally, Prophet was selected for its flexibility, interpretability, and resilience to missing data and outliers, making it well-suited for real-world forecasting scenarios with irregularities and allowing integration of exogenous variables. Moreover, ARIMAX was included due to its superior forecasting accuracy through the incorporation of exogenous variables, effectively capturing the influence of external factors on container transport volumes. The comparative insights that emerge allow for a more refined understanding of how these models perform in varying port contexts and data environments.

This research shows that hybrid forecasting models are particularly effective, where combining models helps to stabilize results and reduce volatility. However, more complex models do not in all cases guarantee better forecasting performance, as shown in this research, where the hybrid forecasting models for the ports of Rotterdam and Moerdijk performed comparably to the best-performing individual model. This statement is also mentioned by Zeng and Xu (2024). In cases where a single model already performs strongly, especially when it incorporates relevant external variables, the added complexity of a hybrid model may not be necessary. This leads to one of the key practical contributions of the research: deciding when to use a hybrid forecasting model and when to rely on an individual approach. When greater simplicity and transparency without compromising forecast quality are desired, it is advisable to use a single model when the hybrid model performs comparably to the most accurate individual model. Conversely, the hybrid model should be employed when it demonstrates a clear improvement in forecasting performance, as its integration of complementary strengths enhances overall predictive accuracy. Factors such as model accuracy, transparency, and the availability of reliable input data all influence this decision.

Moreover, the integration of CPB Netherlands Bureau for Economic Policy Analysis (CPB) scenarios into future forecasts allowed for the incorporation of external factors such as trade policies, technological advancements, environmental regulations, and supply chain disruptions. This scenario approach aligns with literature emphasizing the use of scenario planning to manage uncertainty in long-term forecasting (Wright et al., 2012). However, this study's forecasts for the port of Antwerp predicted more conservative growth than the CPB's high and low scenarios. One plausible explanation for this divergence is the outdated nature of the CPB scenarios, originating from 2015, which do not account for more recent disruptive events such as the COVID-19 pandemic, the war in Ukraine, or the 2021 Suez Canal blockage in world import and export volumes, which are the best-performing variables in the models for the port of Antwerp. Recent studies suggest that such disruptions have had lasting impacts on global supply chains, making scenarios originating from before such disruptions less indicative of current realities (Ivanov & Das, 2020; Ivanov et al., 2023). In addition, the merger of the Port of Antwerp with the Port of Bruges in 2022, forming the Port of Antwerp-Bruges, may have affected reported container volumes due to operational and administrative restructuring. Although the data is consistently sourced from Eurostat, this institutional change could have introduced discontinuities or inflated growth trends that influence the forecasting outcomes.

In conclusion, this study makes a theoretical and practical contribution by demonstrating how multiple forecasting models can be evaluated and applied within a specific, policy-relevant context. It clarifies the conditions under which hybrid forecasting models are advantageous and proposes guidance for model selection.

5.2 Managerial Recommendations

This research provides several key managerial recommendations for MCA Brabant and stakeholders in the broader logistics and maritime transport sector. Demonstrated in this research is the effectiveness of hybrid forecasting models, which consistently outperformed or matched the accuracy of the strongest individual models. By integrating the strengths of multiple approaches, such as Holt-Winters Exponential Smoothing, ARIMAX, and Prophet, hybrid models could offer more robust and reliable predictions, particularly in complex systems where multiple variables interact. A key recommendation for the hybrid forecasting model is determining when to use a hybrid model and when to use an individual model. When simplicity without loss of accuracy is desired, a single model is preferable when its performance is comparable to that of the hybrid model. The hybrid model should be used when it outperforms individual models, providing superior predictive accuracy. Therefore, it is strongly recommended that MCA Brabant adopts the hybrid model approach and decision-making as a central tool in its strategic forecasting, planning, and policy support processes.

Moreover, this research highlights the potential value of incorporating fuel prices into forecasting models, where data availability permits. While experts consulted during the research questioned the usefulness of the variable, empirical results suggested that fuel prices can significantly enhance model accuracy. Therefore, even though reliable fuel price projections are not currently available for future scenarios, MCA Brabant should regularly monitor this variable and explore its inclusion in short- and medium-term forecasts as more consistent datasets become available.

In addition, to increase the level of detail and strategic value of future forecasts, MCA Brabant should seek to enhance the availability and quality of data concerning container inflows and outflows at the regional level, particularly for local terminals in Brabant. Gaining a clearer picture of the actual distribution between key ports (e.g., Rotterdam, Antwerp, Moerdijk) would enable a more precise application of forecasting models. Leveraging the hybrid forecasting model approach for each terminal's inflow and outflow could reveal whether the observed growth patterns align, diverge, or expose logistical bottlenecks unique to specific terminals. This would support more targeted infrastructure and capacity planning.

Finally, while the forecasted growth in maritime container transport appears manageable within the existing infrastructure. The operational strain reported in additional interviews with experts in the container transport sector and most terminals already nearing capacity underscores the importance of proactive planning. Rather than responding only to scenarios of higher-than-capacity growth, strategic focus should be placed on resolving current inefficiencies that are already limiting throughput. This includes improving the coordination of empty container flows, addressing port congestion, enhancing stakeholder communication, and accelerating infrastructure upgrades. A particular emphasis should be placed on digitalization and integrated data sharing platforms to support real-time decision-making across the logistics chain.

These initiatives will help ensure a resilient and data-driven approach to managing future developments in maritime container transport and multimodal logistics in the region.

5.3 Limitations and Future Research Directions

While this research offers valuable insights into the application of hybrid forecasting models for maritime container transport, several limitations must be acknowledged. These limitations also present promising research areas for future academic studies.

One significant limitation is the unavailability of future data for certain external variables, primarily fuel prices. Although empirical results demonstrated that fuel price data, which was only tested on the port of Moerdijk due to data limitations, can enhance the predictive accuracy of forecasting models. This variable was excluded from future forecasting due to a lack of reliable future data. An insight from the study is the potentially promising role of fuel prices as a predictor, requiring further investigation to confirm its broader applicability.

Another limitation is the restricted scope of this study, which focuses solely on the maritime flow of container transport, regarding the ports of Rotterdam, Antwerp, and Moerdijk, towards the terminals in Brabant. While this narrowed focus allowed for a more detailed and manageable analysis, it excludes significant portions of total transport volumes, such as rail and road freight, as well as container flows in the opposite direction. Expanding the scope to include multimodal transport chains and bi-directional flows would offer a more holistic view of regional logistics dynamics. Future research could adopt an approach to model entire supply chains, which would enhance the generalizability and applicability of the findings.

A further constraint relates to the degree of detail and quality of available data. The analysis relies on aggregated monthly and quarterly data, which may conceal short-term fluctuations or outliers in the volumes of container transport. Real-time tracking systems or port-level operating databases, which are high-frequency sources, might be valuable additions to future research. This would enable more precise modeling and offer more accurate forecasting results that more accurately represent short-term dynamics.

There is also a methodological limitation in the reliance on the hybrid combination of three specific forecasting techniques: Holt-Winters Exponential Smoothing, Prophet, and ARIMAX. While these models have proven effective, they are constrained by their statistical assumptions. Future research could investigate the integration of advanced machine learning algorithms such as Long Short-Term Memory networks, ensemble tree-based methods, or hybrid AI-statistical models.

Another limitation of the study is the use of scenario data originating from 2015, which may not fully reflect recent developments, shifts in market dynamics, or policy changes that have occurred in the intervening years. While the scenarios provide valuable structured narratives for long-term forecasting, their foundation in older data may reduce their relevance and applicability to the current and future context. As a result, there is a risk that the models based on these scenarios may overlook emerging trends or disruptions. Future research should consider updating the scenario inputs using more recent data or incorporating adaptive scenario planning methods that can better account for ongoing changes. This would improve the timeliness and reliability of the forecasting outputs, making them more responsive to today's evolving economic, environmental, and geopolitical conditions.

Additionally, the qualitative component of this research, interviews with industry stakeholders, was limited in scope and geographic representation. Although the insights provided were valuable, a larger sample of stakeholders from different ports, terminals, and transport operators would enhance the robustness of the conclusions. Future research could adopt a mixed-methods approach, combining quantitative forecasting with extensive stakeholder analysis to enhance the applicability of technical forecasting models to real-world operating conditions.

Finally, the robustness check implemented via an alternative data-cleaning method (exponential versus linear) was limited to assessing consistency in model selection and accuracy. While it confirmed the reliability and validity of the findings, it did not have the purpose of evaluating the comparative effectiveness of different cleaning methods across variable types. To strengthen the analysis, future research could expand this approach by systematically testing a wider range of data-cleaning methods. This would help identify the most effective preprocessing techniques for different variables, as the optimal cleaning approach may vary depending on the nature and behavior of each variable. Such an extension would not only enhance model performance but also provide deeper insights into the influence of data treatment on forecasting accuracy.

By addressing these limitations, future studies can build upon and enhance the results within this thesis to develop even more accurate, resilient, and comprehensive forecasting models for container transport and multimodal supply chains.

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Appendix

Appendix 1 Questionnaire questions answered before the interview, discussing the factors to include by expert knowledge

Introduction

1. Can you please state your name, job title, and briefly describe your role within the company?
2. How many years of experience do you have in the container transport sector?
3. Can you briefly introduce yourself and describe your experience and expertise in the container transport sector?
4. Do you work with forecasting models for container transport? If so, how are these models used in your work?

Core Questions

Macro-Economic Factors

5. Which macroeconomic factors, such as GDP, import/export, or population growth, do you consider to have the greatest impact on the growth of container transport?
6. Are there specific economic indicators that you see as key drivers for forecasting container flows**?**

Operational Factors

7. How important are transit speed and port capacity in predicting container transport?
8. What role do fuel prices and other transport costs play in decision-making regarding container transport volumes?
9. Are there specific bottlenecks in infrastructure or the logistics chain that significantly impact the growth of container transport?

Market Dynamics and Regulations

10. To what extent do regulatory changes and environmental policies influence the development of container transport?

11. What is the impact of geopolitical developments (e.g., trade conflicts, Brexit, sanctions) on container transport volumes?
12. Are there technological advancements (e.g., digitalization, automation) that are increasingly playing a role in forecasting container flows?

Seasonal Influences and External Shocks

13. How significant is the influence of seasonal patterns (e.g., peak periods around holidays) on container transport volumes?
14. How can unforeseen events such as pandemics, natural disasters, or strikes affect the predictability of container transport?

Demand and Supply Developments

15. How do shifts in consumer behavior and e-commerce affect the demand for container transport?
16. To what extent do changes in supply chain strategies, such as nearshoring or reshoring, impact the forecasting of container flows?

Port and Logistics Performance

17. Which port performance indicators (e.g., waiting times, efficiency, digitalization) do you consider important to include in a forecasting model?
18. How crucial is collaboration between ports, shipping companies, and logistics service providers in improving the predictability of container transport?

Conclusion

19. Are there any other factors we haven’t discussed but that you consider essential for forecasting container transport growth?
20. What are the most important factors that should be included in forecasting models for container transport?
21. Do you have any recommendations for sources and/or databases that could be valuable for my research?

Appendix 2.1 Questionnaire Answered Before the Interview Monique van den Berg

Introduction

1. Can you please state your name, job title, and briefly describe your role within the company?

   Monique van den Berg, traffic advisor, manager of the BasGoed freight transport model.

2. How many years of experience do you have in the container transport sector?

   Strictly speaking none, as modeling doesn't really fall under working within the industry.

3. Can you briefly introduce yourself and describe your experience and expertise in the container transport sector?

   Always done the scientific side, researching how to make a model of it.

4. Do you work with forecasting models for container transport? If so, how are these models used in your work?

   Yes, so it is my job. We make long-term aggregated forecasts for 2040, 2050, for different environmental and policy scenarios. These are used for infrastructure planning and design, and for policy advice.

Core Questions

Macro-Economic Factors

5. Which macroeconomic factors, such as GDP, import/export, or trade agreements, do you consider to have the greatest impact on the growth of container transport?

   Economy has been the biggest driver so far. But in the data we see that relation becoming less and less. Population seems to be playing a bigger role.

6. Are there specific economic indicators that you see as key drivers for forecasting container flows?

   We use GDP, in combination with import-export and transit (trade) statistics.

Operational Factors

7. How important are transit speed and port capacity in predicting container transport?

   I wish these could be important, but I don't have good data on them, so we can't include them in the models.

8. What role do fuel prices and other transport costs play in decision-making regarding container transport volumes?

   These play a role mainly in the choice of modality, choice of terminal and choice of route. In combination with other generalized costs such as distance and time.

9. Are there specific bottlenecks in infrastructure or the logistics chain that significantly impact the growth of container transport?

   This is what we are trying to visualize with the IMA Letter to Parliament on the Integrated Mobility Analysis 2021 | Parliamentary document | Rijksoverheid.nl, based on our models.

Market Dynamics and Regulations

10. To what extent do regulatory changes and environmental policies influence the development of container transport?

    A lot.

11. What is the impact of geopolitical developments (e.g., trade conflicts, Brexit, sanctions) on container transport volumes?

    Major.

12. Are there technological advancements (e.g., digitalization, automation) that are increasingly playing a role in forecasting container flows?

    None yet, unknown future for these matters.

Seasonal Influences and External Shocks

13. How significant is the influence of seasonal patterns (e.g., peak periods around holidays) on container transport volumes?

    We are not taking this into account now.

14. How can unforeseen events such as pandemics, natural disasters, or strikes affect the predictability of container transport?

    A lot, but the impact is unclear.

Demand and Supply Developments

15. How do shifts in consumer behavior and e-commerce affect the demand for container transport?

    No idea.

16. To what extent do changes in supply chain strategies, such as nearshoring or reshoring, impact the forecasting of container flows?

    Not yet in our forecasts, only manual submission of shifts in production or consumption locations is possible.

Port and Logistics Performance

17. Which port performance indicators (e.g., waiting times, efficiency, digitalization) do you consider important to include in a forecasting model?

    Capacity, costs, reliability, hinterland connections.

18. How crucial is collaboration between ports, shipping companies, and logistics service providers in improving the predictability of container transport?

    Unknown.

Conclusion

19. Are there any other factors we haven't discussed but that you consider essential for forecasting container transport growth?

    Bridge heights and navigability of rivers, possibilities for containerization of types of goods.

20. What are the most important factors that should be included in forecasting models for container transport?

    Availability of infrastructure, scheduled services/shuttles, ship classes, empty containers.

21. Do you have any recommendations for sources and/or databases that could be valuable for my research?

    CBS statline, inland shipping file, container chain file.

Appendix 2.2 Interview Protocol Monique van den Berg

Interview with Monique van den Berg

Objective of the Interview:

This interview is part of a study investigating the key factors influencing the growth of container transport. The interviews are structured as guided discussions, systematically comparing expert insights with findings from existing literature.

Participants receive a questionnaire in advance and are asked to submit their written responses at least two days before the scheduled interview. During the interview, these responses are analyzed in conjunction with academic research to explore similarities, differences, and underlying explanations in greater depth.

Welcome and Purpose

- Thank you for participating in this interview. The goal of this discussion is to compare expert insights with existing literature on forecasting container transport growth.
- Your input will help refine forecasting models by identifying key factors and understanding potential differences between academic research and practical applications.

Confidentiality and Consent

- Your responses will not be anonymized unless you explicitly request otherwise.
- The interview will last approximately 30 minutes. Please feel free to elaborate on your answers where necessary.
- This interview will be recorded with consent.

Macro-Economic Factors

1. The literature (Wang et al., 2013) emphasizes that GDP is a strong indicator of container transport growth. However, in your responses, you indicate that this correlation is weakening and that population growth plays a more significant role. What do you believe is causing this shift?

2. Literature considers trade volumes (import/export) as essential variables for forecasts (Matczak, 2020). You suggest that transit flows also play a crucial role. Could you elaborate on this?

Operational Factors

3. Literature (Notteboom et al., 2021a; Mlambo, 2021) states that port performance, including throughput speed and maximum capacity, is important for container transport forecasts. However, you mention that reliable data is lacking and cannot be included in models. How could better data collection improve these predictions?
4. Literature (Limao & Venables, 2001; Haralambides, 2019) sees fuel prices as a direct influence on transport volumes. You argue that fuel prices mainly impact modality and route choices. Could you elaborate on this?
5. A government report on the **Integral Mobility Analysis 2021** states that bottlenecks are emerging at various locks and some bridges, affecting navigability. Additionally, navigability is deteriorating due to soil erosion and climate change, leading to capacity and robustness issues. Are there specific bottlenecks in Brabant that should be considered or mentioned as potential impacts on forecasting?

Market Dynamics and Regulations

6. Literature (Fernandez-Stark & Gereffi, 2019; Drobetz et al., 2020) highlights that trade restrictions and tariffs significantly impact container transport. You confirm this but could you provide specific examples of recent policy measures that have had a major impact?
7. Unlike the literature (Rodrigue & Notteboom, 2021; Dávid, 2019), which sees digitalization and automation as key future trends, you indicate that these factors do not yet play a role in forecasting. What do you think explains these differences?

Seasonal Influences and External Shocks

8. Literature (Notteboom et al., 2021) mentions seasonal patterns as a factor affecting container transport, but you state that they are currently not considered in forecasts. Is this a conscious choice, and if so, why?
9. External shocks such as pandemics and geopolitical conflicts are considered unpredictable yet influential factors in literature (Kilian et al., 2021; Atacan & Açık, 2023). You acknowledge their impact but state that their effects remain unclear. Are there methods you believe could help better estimate the impact of such shocks?

Demand and Supply Developments

10. Literature (Kajuju & Mugambi, 2013) states that changing consumer behavior and the growth of e-commerce could influence container transport. You indicate that this impact is still unknown. Do you see trends that might change this?
11. Nearshoring, offshoring, and reshoring are increasingly mentioned as factors affecting supply chains (Fransoo & Lee, 2012). You indicate that these are currently not included in models. Do you expect this to change in the future?

Port and Logistics Performance

12. Literature (De Langen et al., 2007; Talley, 2011) describes transshipment volumes as crucial performance indicators. However, you highlight capacity, costs, reliability, and hinterland connections as the most important factors. How do we explain these differences in priorities? And how are these factors currently applied in forecasts?
13. The literature (Rodrigue & Notteboom, 2021) considers collaboration between ports and logistics service providers essential for reliable forecasts. You indicate that its influence is unknown. Is this something that could be incorporated into future analyses?

Conclusion and Additional Factors

14. In your responses, you mention bridge heights, river navigability, and the containerization of goods as additional factors not explicitly mentioned in the

literature. Could you explain why these factors are important for inclusion in forecasts?

15. You mention the availability of infrastructure, liner services/shuttles, vessel classes, and empty containers as key factors for forecasts. How well are these factors currently incorporated into models?

Closing

Thank you for participating in this interview. Your responses will contribute to a better understanding of the differences between academic literature and practical insights and help improve container transport forecasting models.

Appendix 2.3 Interview Transcript Monique van den Berg

Date: 25th of March, 14.00-14.30

Interviewee: Monique van den Berg

Affiliation: Rijkswaterstaat Ministry of Infrastructure and Water Management (Water, Transport and Environment)

Topic: Identifying key factors influencing forecasting container transport

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Macroeconomic Factors

Q: The literature emphasizes that GDP is a strong indicator of container transport growth. However, in your responses, you indicate that this correlation is weakening and that population growth plays a more significant role. What do you believe is causing this shift?

A: I'm not involved in operations but in model development. My colleagues and I are always searching for these types of relationships and their causes. In this case, it's difficult. CBS has observed this trend for years, the relationship between economic development and traffic is weakening. The question is, what is it being replaced by? It could be partly income, population size, or demand for goods, but we haven't found a definitive explanation. Each statistic suggests something, but nothing conclusive.

Q: Literature considers trade volumes, import and export, as essential variables for forecasts. You suggest that transit flows also play a crucial role. Could you elaborate on this?

A: Increasingly, goods move through the Netherlands without playing any direct role here. Sometimes they pass through to Germany and return, showing up in different statistics. The size and growth of that stream are difficult to determine since it's influenced by business logistics strategies.

Q: Would that match with the throughput rates of a port?

A: Transshipment with transloading is included in import/export. Pure transit (straight through) isn't separately recorded, as far as I know.

Operational Factors

Q: Literature states that port performance, including throughput speed and maximum capacity, is important for container transport forecasts. However, you mention that reliable data is lacking and cannot be included in models. How could better data collection improve these predictions?

A: We use hinterland connection data to build port choice models. Port characteristics matter, but ports are private companies and cautious about releasing sensitive data. Port fees are public and do improve models when used, however for the future it is not known and could go in all directions and therefore it is not a variable that you can use. Capacity can be estimated from crane counts or available space, which we do for inland ports. For seaports, this is nearly impossible. If data were available, models would improve, but the chance of obtaining it is slim.

Q: Literature sees fuel prices as a direct influence on transport volumes. You argue that fuel prices mainly impact modality and route choices. Could you elaborate on this?

A: Whether goods are needed rarely depends on transport costs since these are a small share of the total product price. Logistics planners aim for the cheapest solution, influencing mode and route choice rather than total volume.

Q: A government report on the Integral Mobility Analysis 2021 states that bottlenecks are emerging at various locks and some bridges, affecting navigability. Additionally, navigability is deteriorating due to soil erosion and climate change, leading to capacity and robustness issues. Are there specific bottlenecks in Brabant that should be considered or mentioned as potential impacts on forecasting?

A: There are several. The IMA (Integrated Mobility Analysis) document includes a bottleneck map, especially for eastern and southeastern corridors. Issues include overfilled locks and major highway congestion.

Market Dynamics and Regulation

Q: Literature highlights that trade restrictions and tariffs significantly impact container transport. You confirm this but could you provide specific examples of recent policy measures that have had a major impact?

A: The road toll has caused route changes. Even minor disruptions, like a closed bridge or lock, can have huge impacts. COVID-19 is a clear example. The war in Ukraine shifted imports from Russian gas to U.S. and African biofuels. Such decisions can completely change trade patterns. There's also the question of reshoring production back to Europe.

Q: Unlike literature, which sees digitalization and automation as key future trends, you indicate that these factors do not yet play a role in forecasting. What do you think explains these differences?

A: Everyone says they're important, but no one knows the effect. Models already assume perfect information, costs and durations, so digitalization may simply make existing models more accurate. But it remains unpredictable for now.

Seasonal Influences and External Shocks

Q: Literature mentions seasonal patterns as a factor affecting container transport, but you state that they are currently not considered in forecasts. Is this a conscious choice, and if so, why?

A: Partly. We work with average annual data. Splitting into seasons reduces significance, and for seasonal products like flowers, data becomes easily traceable to individual companies.

Q: Would you split data into quarters?

A: We use annual data, but quarterly is possible. You'd need to rebalance other variables, for example, regions and goods types to maintain significance. And you need a minimum amount of data to forecast something significant.

Q: I'm planning quarterly data from 2005 until 2024. I have the throughput rates of the ports in Rotterdam, and Antwerp, population, GDP, and import and export of these years. The interviews will show whether there are other factors that are important to implement

A: That's a solid basis. CBS is also building a container transport dataset which is not yet public. It connects the full chain, for example, loading in China until use in Poland. You could visit CBS to explore it, or it could be great for follow-up research.

Q: External shocks such as pandemics and geopolitical conflicts are considered unpredictable yet influential factors in the literature. You acknowledge their impact but state that their effects remain unclear. Are there methods you believe could help better estimate the impact of such shocks?

A: We use scenario modeling, not just trend extrapolation. For instance, with new technology such as digitalization or electric trucks, nothing is known yet so it is impossible to predict however, shifting production from China to Europe can be modeled. But whether that shift happens is unpredictable. Scenario models help show the consequences if something happens.

Demand and Supply Developments

Q: Literature states that changing consumer behavior and the growth of e-commerce could influence container transport. You indicate that this impact is still unknown. Do you see trends that might change this?

A: That’s a level of detail I don’t typically work with.

Q: Nearshoring, offshoring, and reshoring are increasingly mentioned as factors affecting supply chains. You indicate that these are currently not included in models. Do you expect this to change in the future?

A: Only when it’s known to happen. We don’t predict them, we model the impact if they occur, using scenarios.

Q: Do you use standard scenario frameworks?

A: Yes, we use PBL’s "WLO" (Welfare, Prosperity and Quality of the Living Environment) scenarios, usually two: high-growth and low-growth. These include projections for GDP, population, and traffic. They’re public reports. Our goods transport forecasts are based on them.

Port and Logistics Performance

Q: Literature describes the throughput rates as a crucial performance indicator. However, you highlight capacity, costs, reliability, and hinterland connections as the most important factors. How do we explain these differences in priorities?

A: The throughput rates are the output. The others are inputs that influence it. Trend models extrapolate throughput rates. Explanatory models use influencing factors to understand why and how outcomes change.

Q: If I want to forecast growth over several years, is a trend model the best option?

A: Both have uses. Trend models assume no environmental change and work for 3–5 years. Explanatory models allow the inclusion of geopolitical shifts, infrastructure changes, etc. The right choice depends on your goals. The trend model is a pure prediction of what will happen and the explanatory model is how can this be influenced.

Q: So for a 5-year outlook, use a trend model and note potential impacts?

A: Correct. Trends show expected development if the environment stays stable.

Q: The literature considers collaboration between ports and logistics service providers essential for reliable forecasts. You indicate that its influence is unknown. Is this something that could be incorporated into future analyses?

A: Yes, more data sharing helps both forecasting and real-world efficiency. But quantifying that effect is difficult.

Conclusion and Additional Factors

Q: In your responses, you mention bridge heights, river navigability, and the containerization of goods as additional factors not explicitly mentioned in the literature. Could you explain why these factors are important for inclusion in forecasts?

A: They define hinterland connectivity. If a container can't pass a bridge or waterway, the port loses utility. These can only be included in explanatory models.

Q: You mention the availability of infrastructure, liner services/shuttles, vessel classes, and empty containers as key factors for forecasts. How well are these factors currently incorporated into models?

A: Varies. We know quite a bit about infrastructure. But shuttle services, for example, are hard to map or predict. When is someone going to provide a shuttle service and when are people going to use it?

Q: Relevant only for explanatory models?

A: Yes.

Q: So, not suitable for a trend model?

A: Correct. Unless then you assume current services continue, which is a fair assumption for short-term forecasts.

Q: What are the most important variables for a trend model?

A: GDP, population growth, import and export. In 3 to 5 years, infrastructure won't change dramatically it will probably affect the attractiveness of the ports, however, I wouldn't overcomplicate it.

Q: If I include those variables and highlight potential influences, would that yield a good forecast?

A: Yes.

Q: Would you be willing to participate in a short follow-up interview to discuss my forecasting model results?

A: Absolutely, I'd be happy to.

End of Interview

Appendix 3.1 Questionnaire Answered Before the Interview Bart Kuipers

Introduction

1. Can you please state your name, job title, and briefly describe your role within the company?

   Bart Kuipers, port economist. I conduct policy research, teach port economics, and supervise students with their theses and dissertations.

2. How many years of experience do you have in the container transport sector?

   As a researcher: 35 years.

3. Can you briefly introduce yourself and describe your experience and expertise in the container transport sector?

   - Modal shift research: barriers to shifting to water and rail transport
   - Economic impact of containers on the Dutch economy
   - Forecasting studies
   - Role of China in European seaports
   - Container congestion
   - Research on economies of scale (currently ongoing): Are ships getting larger?
   - Research on vertical integration/carrier haulage (currently ongoing)

4. Do you work with forecasting models for container transport? If so, how are these models used in your work?

   Mainly critical analysis of existing forecasts and providing advice on how to improve forecasting models.

Core Questions

Macro-Economic Factors

5. Which macroeconomic factors, such as GDP, import/export, or population growth, do you consider to have the greatest impact on the growth of container transport?
   Consumer spending. Trade barriers. General economic growth of GDP (relation to consumer spending). The link between container growth and GDP is becoming increasingly complex.

6. Are there specific economic indicators that you see as key drivers for forecasting container flows**?**

   Consumer spending. Increase in trade barriers due to tariffs. Specific policies: dumping by China led to growing flows of solar panels, batteries, and chemicals for example.

Operational Factors

7. How important are transit speed and port capacity in predicting container transport?
   Not very important. However, they are factors that influence the competitiveness of individual ports.

8. What role do fuel prices and other transport costs play in decision-making regarding container transport volumes?

   Not very important: developments are absorbed through slow steaming and economies of scale. They do have a dampening effect. When demand is high, vessels sail faster than when demand is low. Tariffs play a more important role.

9. Are there specific bottlenecks in infrastructure or the logistics chain that significantly impact the growth of container transport?

   There are alternative ports within port ranges. If there is an infrastructure bottleneck at one port, an alternative is chosen. Low water levels, for example, impact the use of inland container shipping. Bottlenecks in the Suez and Panama Canals. But the system is flexible. COVID-19 had a major impact due to port closures.

Market Dynamics and Regulations

10. To what extent do regulatory changes and environmental policies influence the development of container transport?
    Limited. Growth is only slightly dampened by emissions trading and higher fuel costs.

11. What is the impact of geopolitical developments (e.g., trade conflicts, Brexit, sanctions) on container transport volumes?

    This can have a significant impact (as mentioned above).

12. Are there technological advancements (e.g., digitalization, automation) that are increasingly playing a role in forecasting container flows?

    - Development of smart containers (modal shift from air to sea)
    - Better forecasting through AI
    - Digital handling via port community systems shortens port time
    - DIL/BDI: more insight into ETA/ATA

Seasonal Influences and External Shocks

13. How significant is the influence of seasonal patterns (e.g., peak periods around holidays) on container transport volumes?
    Fairly significant. Chinese New Year is very important. Sales for the holiday season (e.g., Christmas) are very important. Fruit seasons determine reefer flows.

14. How can unforeseen events such as pandemics, natural disasters, or strikes affect the predictability of container transport?

    Definitely: COVID-19 is a key case study. It led to a total disruption of the container system, and predictability dropped dramatically. A strike in a major country like the U.S. is also highly disruptive. Additionally: what if the Houthis stop and the current overcapacity returns to the market? Invasion of Taiwan by China?

Demand and Supply Developments

15. How do shifts in consumer behavior and e-commerce affect the demand for container transport?
    Very important influence: clearly observable during the COVID-19 period. E-commerce also gave a strong boost. These are very important indicators for me, with a significant derived demand for container capacity: effect on global value chains.

16. To what extent do changes in supply chain strategies, such as nearshoring or reshoring, impact the forecasting of container flows?

Not yet clearly materialized. These forecasts are not yet visible in the statistics but could become relevant in the future.

Port and Logistics Performance

17. Which port performance indicators (e.g., waiting times, efficiency, digitalization) do you consider important to include in a forecasting model?
    - Time at berth per ship
    - Average crane productivity per terminal
    - Modal split of hinterland transport
    - Terminal capacity
    - Terminal dwell time
    - D&D volumes per port

18. How crucial is collaboration between ports, shipping companies, and logistics service providers in improving the predictability of container transport?

    What is meant by a port? A terminal? There is a trend toward vertical integration, where shipping lines are becoming integrated logistics providers and manage the entire chain. A key variable is reliability, but shipping lines are developing their own strategic solutions for this (Gemini vs MSC).

Conclusion

19. Are there any other factors we haven't discussed but that you consider essential for forecasting container transport growth?
    The container system has become increasingly susceptible to disruptions: it's more vulnerable.

20. What are the most important factors that should be included in forecasting models for container transport?

    Consumer spending.

21. Do you have any recommendations for sources and/or databases that could be valuable for my research?

I think most sources and databases are well-known but costly (Dynamar, Drewry, Alphaliner). UNCTAD's Review of Maritime Transport is useful. CBS and Eurostat as well.

Appendix 3.2 Interview Protocol Bart Kuipers

Interview with Bart Kuipers

Objective of the Interview:

This interview is part of a study investigating the key factors influencing the growth of container transport. The interviews are structured as guided discussions, systematically comparing expert insights with findings from existing literature.

Participants receive a questionnaire in advance and are asked to submit their written responses at least two days before the scheduled interview. During the interview, these responses are analyzed in conjunction with academic research to explore similarities, differences, and underlying explanations in greater depth.

Welcome and Purpose

- Thank you for participating in this interview. The goal of this discussion is to compare expert insights with existing literature on forecasting container transport growth.
- Your input will help refine forecasting models by identifying key factors and understanding potential differences between academic research and practical applications.

Confidentiality and Consent

- Your responses will not be anonymized unless you explicitly request otherwise.
- The interview will last approximately 30 minutes. Please feel free to elaborate on your answers where necessary.
- This interview will be recorded with consent.

Macro-Economic Factors

1. In the literature, the growth of container transport is often linked to macroeconomic indicators such as GDP, import/export, and population growth. However, you indicated that consumer spending and trade barriers are more important indicators. Could you explain why, in your view, these factors play a more significant role?

2. The literature describes GDP as an important predictor of container volumes, whereas you stated that the relationship between container transport and GDP is becoming less clear. What, in your opinion, are the causes of this changing relationship?

Operational Factors

3. According to the literature, dwell time and port capacity play a crucial role in the growth of container transport. However, you indicated that these factors mainly affect the competitiveness of individual ports rather than directly influencing total container flows. Could you elaborate on this?
4. The literature identifies fuel prices and transport costs as important predictors of container flows, while you stated that slow steaming and economies of scale offset these effects. To what extent do you believe that fuel prices could still have a significant impact in extreme situations, such as during a sudden price spike?
5. Are there any specific bottlenecks in the Brabant region that I should take into account or mention as potentially affecting the accuracy of predictions?

Market Dynamics and Regulation

6. Regulations and environmental policy are frequently mentioned in the literature as important factors influencing container flows. However, you indicated that the impact of such regulations is limited. Could you explain why you believe regulation plays a less significant role?
7. The impact of geopolitical developments, such as trade conflicts and sanctions, is described as significant both in the literature and in your responses. Are there specific examples you observe in practice? To what extent can forecasting models account for such developments?
8. Technological developments such as digitalization and automation are increasingly mentioned in the literature as determining factors for container flows. You mentioned innovations such as smart containers and digital processing via port community systems. To what extent do you see these developments as game-changers for the predictability of container transport?

Seasonal Influences and External Shocks

9. The literature states that seasonal patterns, such as peak periods around holidays, play a major role in container transport. You confirmed this and specifically mentioned holidays like Chinese New Year and Christmas, as well as the impact of fruit seasons on reefer flows. Do you think that seasonal patterns will continue to affect the predictability of container flows in the future?
10. The literature describes how unforeseen events, such as pandemics and strikes, can severely disrupt container flows. You cited the COVID-19 pandemic as an important case study. Are there other disruptive events that you believe are not sufficiently covered in the literature? Given the unpredictability of these events, should they be excluded from forecasting models and instead only be flagged as potential risks, in your view?

Demand and Supply Developments

11. The literature highlights the impact of changing consumer behavior and e-commerce on container transport. You indicated that these factors have a highly significant influence. In what ways do these factors affect container transport and its forecasting?
12. Nearshoring and reshoring are often cited as trends that could influence container flows. You mentioned that the impact of these developments is not yet visible in the statistics. What signs do you observe that suggest these trends may play a role in the future?

Port and Logistics Performance

13. The literature emphasizes various performance indicators for ports, such as waiting times, efficiency, and digitalization. You specifically mentioned indicators such as berth time per vessel, crane productivity, and hinterland transport modal split. Could you elaborate on the differences between the indicators you consider important and those commonly highlighted in the literature?
14. Collaboration between ports and logistics service providers is considered essential in the literature for improving the predictability of container flows. You pointed to the trend of vertical integration, where shipping lines increasingly gain control over the

supply chain. How do you believe this development will affect the predictability and efficiency of container transport?

Conclusion and Additional Factors

15. You identified consumer spending as the most important factor for forecasting models related to container transport. If I want to forecast future growth using a trend model, is this the only factor I should include? What are your thoughts on incorporating population growth and import/export data to generate a more accurate forecast?

Closing

Thank you for participating in this interview. Your responses will contribute to a better understanding of the differences between academic literature and practical insights and help improve container transport forecasting models.

Appendix 4.1 Interview Protocol Johan Visser

Interview with Johan Visser

Objective of the Interview:

This interview is part of a study investigating the key factors influencing the growth of container transport. The interviews are structured as guided discussions, systematically comparing expert insights with findings from existing literature.

Participants receive a questionnaire in advance and are asked to submit their written responses at least two days before the scheduled interview. During the interview, these responses are analyzed in conjunction with academic research to explore similarities, differences, and underlying explanations in greater depth. However, the questionnaire has not been completed in time, therefore the duration of the interview may be extended to ensure the same level of depth is achieved.

Welcome and Purpose

- Thank you for participating in this interview. The goal of this discussion is to compare expert insights with existing literature on forecasting container transport growth.
- Your input will help refine forecasting models by identifying key factors and understanding potential differences between academic research and practical applications.

Confidentiality and Consent

- Your responses will not be anonymized unless you explicitly request otherwise.
- The interview will last approximately 30-45 minutes. Please feel free to elaborate on your answers where necessary.
- This interview will be recorded with consent.

Introduction

1. Can you please state your name, job title, and briefly describe your role within the company?

2. How many years of experience do you have in the container transport sector?
3. Can you briefly introduce yourself and describe your experience and expertise in the container transport sector?
4. Do you work with forecasting models for container transport? If so, how are these models used in your work?

Macro-Economic Factors

5. Which macroeconomic factors, such as GDP, import/export, or population growth, do you consider to have the greatest impact on the growth of container transport?
6. Are there specific economic indicators that you see as key drivers for forecasting container flows?

Operational Factors

7. How important are transit speed and port capacity in predicting container transport?
8. What role do fuel prices and other transport costs play in decision-making regarding container transport volumes?
9. Are there specific bottlenecks in infrastructure or the logistics chain that significantly impact the growth of container transport?

Market Dynamics and Regulations

10. To what extent do regulatory changes and environmental policies influence the development of container transport?
11. What is the impact of geopolitical developments (e.g., trade conflicts, Brexit, sanctions) on container transport volumes?
12. Are there technological advancements (e.g., digitalization, automation) that are increasingly playing a role in forecasting container flows?

Seasonal Influences and External Shocks

13. How significant is the influence of seasonal patterns (e.g., peak periods around holidays) on container transport volumes?
14. How can unforeseen events such as pandemics, natural disasters, or strikes affect the predictability of container transport?
15. Because unforeseen events and geopolitical changes are so unpredictable, it is difficult to integrate them into the forecasting models. This can only be done by using scenarios. Do you agree with this?
16. What do you expect to happen in the coming years that I should take into account in the scenarios with regard to unforeseen events and geopolitical changes?

Demand and Supply Developments

17. How do shifts in consumer behavior and e-commerce affect the demand for container transport?
18. To what extent do changes in supply chain strategies, such as nearshoring or reshoring, impact the forecasting of container flows?

Port and Logistics Performance

19. Which port performance indicators (e.g., waiting times, efficiency, digitalization) do you consider important to include in a forecasting model?
20. How crucial is collaboration between ports, shipping companies, and logistics service providers in improving the predictability of container transport?

Conclusion and Additional Factors

21. Are there any other factors we haven’t discussed but that you consider essential for forecasting container transport growth?

22. What do you think are the most important factors that should be included in the forecasting models if the growth trend for container transport is to be considered for the coming years as a basis? And which factors should be included in describing scenarios?

23. Are there any other things I should take into account regarding the scenarios and what might or could happen in the coming years that could impact the forecast?

Closing

Thank you for participating in this interview. Your responses will contribute to a better understanding of the differences between academic literature and practical insights and help improve container transport forecasting models.

Appendix 5.1 Interview Protocol Bas Turpijn

Interview with Bas Turpijn

Objective of the Interview:

This interview is part of a study investigating the key factors influencing the growth of container transport. The interviews are structured as guided discussions, systematically comparing expert insights with findings from existing literature.

Participants receive a questionnaire in advance and are asked to submit their written responses at least two days before the scheduled interview. During the interview, these responses are analyzed in conjunction with academic research to explore similarities, differences, and underlying explanations in greater depth. However, the questionnaire has not been completed in time, therefore the duration of the interview may be extended to ensure the same level of depth is achieved.

Welcome and Purpose

- Thank you for participating in this interview. The goal of this discussion is to compare expert insights with existing literature on forecasting container transport growth.
- Your input will help refine forecasting models by identifying key factors and understanding potential differences between academic research and practical applications.

Confidentiality and Consent

- Your responses will not be anonymized unless you explicitly request otherwise.
- The interview will last approximately 30-45 minutes. Please feel free to elaborate on your answers where necessary.
- This interview will be recorded with consent.

Introduction

1. Can you please state your name, job title, and briefly describe your role within the company?
2. How many years of experience do you have in the container transport sector?

3. Can you briefly introduce yourself and describe your experience and expertise in the container transport sector?
4. Do you work with forecasting models for container transport? If so, how are these models used in your work?

Macro-Economic Factors

5. Which macroeconomic factors, such as GDP, import/export, or population growth, do you consider to have the greatest impact on the growth of container transport?
6. Are there specific economic indicators that you see as key drivers for forecasting container flows?

Operational Factors

7. How important are transit speed and port capacity in predicting container transport?
8. What role do fuel prices and other transport costs play in decision-making regarding container transport volumes?
9. Are there specific bottlenecks in infrastructure or the logistics chain that significantly impact the growth of container transport?

Market Dynamics and Regulations

10. To what extent do regulatory changes and environmental policies influence the development of container transport?
11. What is the impact of geopolitical developments (e.g., trade conflicts, Brexit, sanctions) on container transport volumes?
12. Are there technological advancements (e.g., digitalization, automation) that are increasingly playing a role in forecasting container flows?

Seasonal Influences and External Shocks

13. How significant is the influence of seasonal patterns (e.g., peak periods around holidays) on container transport volumes?
14. How can unforeseen events such as pandemics, natural disasters, or strikes affect the predictability of container transport?
15. Because unforeseen events and geopolitical changes are so unpredictable, it is difficult to integrate them into the forecasting models. This can only be done by using scenarios. Do you agree with this?
16. What do you expect to happen in the coming years that I should take into account in the scenarios with regard to unforeseen events and geopolitical changes?

Demand and Supply Developments

17. How do shifts in consumer behavior and e-commerce affect the demand for container transport?
18. To what extent do changes in supply chain strategies, such as nearshoring or reshoring, impact the forecasting of container flows?

Port and Logistics Performance

19. Which port performance indicators (e.g., waiting times, efficiency, digitalization) do you consider important to include in a forecasting model?
20. How crucial is collaboration between ports, shipping companies, and logistics service providers in improving the predictability of container transport?

Conclusion and Additional Factors

21. Are there any other factors we haven't discussed but that you consider essential for forecasting container transport growth?

22. What do you think are the most important factors that should be included in the forecasting models if the growth trend for container transport is to be considered for

the coming years as a basis? And which factors should be included in describing scenarios?

23. Are there any other things I should take into account regarding the scenarios and what might or could happen in the coming years that could impact the forecast?

Closing

Thank you for participating in this interview. Your responses will contribute to a better understanding of the differences between academic literature and practical insights and help improve container transport forecasting models.

Appendix 6.1 Interview protocol Follow-up interview Monique van den Berg

Welcome and Purpose

Thank you for participating in this interview. This interview aims to gather expert insights on how data characteristics, such as frequency, volume, historical range, and external influences, affect the performance of predictive models for port container throughput. Your input will contribute to the interpretation and contextualization of modeling outcomes in the thesis.

Confidentiality and Consent

- Your responses will not be anonymized unless you explicitly request otherwise.
- The interview will last approximately 30-45 minutes. Please feel free to elaborate on your answers where necessary.
- This interview will be recorded with consent.

Interview Questions

Data Frequency

To what extent do you think the difference in data frequency (monthly data for Moerdijk versus quarterly data for the other ports) has influenced the performance of the models?

Historical Time Span

Could the shorter historical period available for Moerdijk (starting from 2017) explain why more complex models perform better there compared to the baseline model?

Data Volume

In your view, how does the volume of data (number of observations) affect the robustness and reliability of model forecasts?

Historical Depth for Moerdijk

Do you think that with a longer historical dataset for Moerdijk, the model results would be more consistent with those for Rotterdam and Antwerp?

Sensitivity to External Fluctuations

Could it be that Moerdijk, being a smaller port, is more sensitive to external fluctuations (such as fuel prices), and therefore benefits more from models with multiple variables?

Alternatively, could Rotterdam and Antwerp align more closely with Moerdijk if reliable data on such external factors were available?

Port-Specific Characteristics

Might the type of cargo transported or the market position of the port influence which variables are predictive?

Scale and Specialization

Do you think the scale or specialization of a port plays a role in determining which variables are relevant for forecasting?

Model Complexity

Why do you think a model with more variables does not necessarily perform better in every situation?

External Data Reliability

How do the availability and reliability of external data (e.g., global trade indicators, fuel prices) affect model performance for different ports?

Weight in Hybrid Models

How can we explain that in some cases, the best-performing individual model does not carry the most weight in the hybrid model?

Model Selection Trade-off

If you had to choose a model to predict future container transport growth, would you prefer a model that occasionally makes large errors but performs reasonably well on average, or a model that consistently has small errors but never performs exceptionally well? Why?

Trend Assumptions

To what extent do you think the assumption of a linear versus exponential trend influences model performance?

Could it be that some ports perform better under exponential models due to rapid market growth, while others benefit from linear models due to more stable throughput figures?

Closing

Is there anything else you would like to add that might help us better understand the relationship between port characteristics, data quality, and model performance?

Thank you for participating in this interview.

Appendix 7 Interview Protocol Terminal Challenges in Brabant

1. Introduction

- Introduce the interviewer and explain the purpose of the research.
- Mention that the interview will take approximately 30 minutes.
- Ask for consent to record the interview and whether the responses should be reported anonymously.

2. General Information

- How long have you been active in the sector?
- What is your experience with container transport in Brabant?

3. Current Capacity and Terminal Usage

- On what basis do you currently calculate terminal capacity? What factors are involved? (e.g., square meters, stacking height, required clearance space, etc.)
- How would you describe the current capacity of your terminal(s)?
- What are the main bottlenecks you are currently experiencing in terms of capacity?
- Are there specific times or seasons when the pressure on the terminal(s) is significantly higher?

4. Expected Growth and Capacity Impact

- According to my research, I do not foresee immediate problems with the total capacity of terminals in Brabant until early 2029 for the flow from the major ports of Rotterdam, Antwerp, and Moerdijk to the province of Brabant. I'm very interested in hearing your perspective on this.
- How realistic do you consider this forecast based on your practical experience?
- What impact would this growth have on the capacity and operations of your terminal(s)?
- Are there specific areas where you expect major challenges? For example: storage space, lead times, personnel, infrastructure, ICT systems, etc.

5. Possible Solutions and Strategies

- What measures are you currently taking to prevent or mitigate capacity issues?
- What structural or innovative solutions do you think could help accommodate the expected growth? (e.g., digitization, infrastructure expansion, collaboration with other terminals, more efficient planning)
- What do you see as the role of governments and other stakeholders in addressing these challenges?

6. Conclusion and Additional Insights

- Do you have any other important insights regarding terminal capacity in Brabant?
- Are there specific policy measures or initiatives you would recommend?
- Do you have any additional comments or anything we haven’t discussed that you think is relevant?

Closing:

- Thank the respondent for their time and contribution.
- Explain how the collected information will be processed.