The environmental impact of Philips' airfreight logistics and improvements using transport mode shift

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The environmental impact of Philips' airfreight logistics and improvements using transport mode shift

Master's Thesis

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Abstract

In this Master Thesis, a generic calculation methodology is presented to calculate the emissions in carbon dioxide equivalent (CO_2e) of freight transportation. This methodology is applied as a case study to Philips' airfreight shipments to determine the CO_2e impact of each shipment. In 2019, Philips' total operational carbon footprint comprised for 71.4% of logistics emissions of which 65.1% can be attributed to airfreight. Reducing airfreight emissions and implementing sustainable alternatives depends on the trade-off between costs, emissions, and service level. Several sustainable improvement directions are discussed, of which transport mode shift is handled in-depth. A mathematical model is set up that handles this trade-off between costs, emissions and service levels of logistics processes in a multi-modal multi-item setting. The model is solved using Lagrangian relaxation, where the multi-item problem can be decomposed in multiple single-item problems. This model solves the Transport Mode Selection Problem (TMSP) of which transport mode should be assigned to which shipments. The TMSP model is applied as a case study to the most impactful lanes of Philips' airfreight shipments. Using the single-item solutions, an efficient frontier is created which reflects the trade-off between total CO_2e emissions and total costs. Results show that a win-win situation can be obtained, reducing transport emissions with 53.8% while reducing costs with 18.0%. It is recommended that Philips applies transport mode shifts from air to ocean on the selected lanes to reduce CO_2e emissions in a cost-effective way.

Executive summary

Introduction

Over the last few decades, topics like global warming, carbon emissions and sustainability have received increasing attention. One of the important contributors to climate change is transportation. In Europe, around 23% of all carbon dioxide (CO_2) emissions can be attributed to the transport sector. Within the global transport sector, road transport is by far the transport mode with the highest emissions, accounting for about two-thirds of all Greenhouse Gas (GHG) emissions (European Commission, 2017). GHG emissions refer to a collection of gases among which are carbon dioxide, methane and chlorofluorocarbons (CFCs) often expressed in the aggregated measure carbon dioxide equivalent (CO_2e) (Hoen, Tan, Fransoo & van Houtum, 2014a). Air transport is the transport mode with the highest carbon intensity, thus the highest emissions per transported unit (Dekker, Bloemhof & Mallidis, 2012; Hoen, Tan, Fransoo & van Houtum, 2014b; van den Akker, te Loo & Schers, 2009). Companies exert increasing effort on reducing CO_2e emissions, either due to voluntary commitment or as a response to emission regulations (Hoen et al., 2014a). This Master Thesis project considers the possibility to reduce CO_2e emissions by selecting transport modes with lower carbon intensity.

Problem definition

This Master Thesis project is performed in cooperation with the company Royal Philips, referred to as Philips. Philips has the ambition to become fully carbon neutral in its operations, and to source all its electricity usage from 100% renewable sources by the end of 2020. On top of this, Philips aims for 4 to 6% comparable sales growth and an Adjusted EBITA margin improvement of around 100 basis points (Royal Philips, 2019b). In 2019, overall CO_2e emissions from logistics represent 71.4% of the total operational carbon footprint. It can be concluded that within Philips the emissions for the transport mode air are by far the highest, accounting for 65.4% of the total logistics emissions in 2019. Philips wants to implement sustainable improvements, such as transport mode shifts, in transport to decrease the environmental impact of airfreight. However, the company has no clear insights into the current environmental impact of every product shipment and how CO_2e reductions can be obtained best. An analysis is required to get an overview of the current state of logistics emissions and the corresponding costs. This is the starting point of this research.

Research methodology

For the purpose of sustainability, this research aims to analyze and visualize global logistics processes of Philips' airfreight and aims to introduce actionable improvements for sustainability. Based on the defined problem and research goal for this research project, the research question is defined as follows:

What is the current environmental impact of Philips' logistic processes for airfreight and which sustainable improvements can be introduced to drive CO_2e emission reductions?

To answer this research question, three sub-questions have been stated:

1. How to define a method that can accurately calculate the current environmental impact of Philips' logistic processes for airfreight?
2. How to develop a general decision making model that provides a trade-off between emissions, costs and service level indicators?
3. Which improvements can be made for the logistics planning process to include more sustainable transportation alternatives for the most impactful products/lanes?

To answer the first research sub-question, a methodology is described to calculate the CO_2e emissions of transporting goods, based on the Network for Transport Measures (NTM) methodology. This methodology is, with some small adjustments, applied as a case study to Philips' airfreight logistics data. The project scope contains all global airfreight shipments of Philips' products in the time period January 2017 up to October 2019. The scope of reported CO_2e emissions is well-to-wheel (WTW), which is the total use of energy including fuel production, distribution and combustion (NTM, 2018b). After analyzing all airfreight logistics, this project continues to the second research sub-question. Here, a mathematical model is developed that minimizes the total costs under an emission constraint. This model takes the factors costs, emissions and service levels into account in deciding the best way of transport mode selection for several products and lanes. The model is solved using Lagrangian relaxation, where the multi-item problem can be decomposed in multiple single-item problems. Next, this model is applied as a case study to a subset of the most important lanes in Philips' logistics data to discover the improvement potential using transport mode shift. Finally, to answer the third research sub-question, directions for improvement towards more sustainable logistics are presented. These improvements are based on insights generated by the emission calculation and the Transport Mode Selection Problem (TMSP) model.

Carbon emission calculation methodology

In order to reduce the CO2e emissions of logistics, the first step is to measure the current emissions that occur during transport of goods. This Master Thesis describes a general methodology to calculate the CO_2e emissions of airfreight logistics. The first step of this method is the distance calculation, in which the Great Circle Distance (GCD) is used to calculate the flight distance. Additionally, distances are taken into account for detours during take-off and landing, and for the road shipments from the airport to the final destination. The second step includes the weight calculation, where the actual weight is the weight in kilograms of everything loaded into the plane. The volumetric weight is the actual weight, taking into account a minimum density of 167 kg/m^3. For calculating emissions the chargeable weight should be used, which is then defined as the maximum of the actual weight and the volumetric weight. The third step takes into account the vehicle type that is used. Often this vehicle type is connected to the shipment itself, e.g. airfreight shipments of 10,000 kilometers use an intercontinental plane with a certain maximum load and fuel usage. Depending on these vehicle characteristics, the emission factor (EF) is determined. In the final step, the emission calculation is performed. Here, the distance and weight are converted into tonne-kilometers and multiplied with the EFs to get the CO2e emissions. Finally the output can be aggregated into any form, in order to report emissions e.g. per shipment lane or per time period.

The described methodology is applied to all Philips' global airfreight shipments between January 2017 and October 2019. In order to implement the methodology to Philips' data, some adjustments are required. The data is cleaned based on the aspects: origin/destination, weight and cost. The CO_2e emissions are calculated for two scenarios, based on the aircraft type: Scenario (1) uses the limited aircraft data available at Philips; and Scenario (2) uses industry-average aircraft data. The second scenario is considered most representative and results in total WTW CO_2e emissions of 1,192 million kg. Comparing this result to Philips' reported emissions over the same scope, leads to an increase of 18.2%. This increase is, among other things, a result of the emission factor source, the pure freighter aircraft type assumption and the reporting scope.

Transport Mode Selection Problem (TMSP) optimization model

Modelling and optimizing logistics choices is highly complex, since there are many criteria to take into account. It is the objective to combine carbon measurement with carbon management, in order to select lanes that are most suitable for implementing improvements, decreasing the total amount of carbon emissions. This multi-criteria problem takes into account the costs, carbon emissions and service levels of logistics shipments. A mathematical model is stated to solve the Transport Mode Selection Problem (TMSP) of which transport mode should be assigned to which shipments. The purpose of the TMSP model is to minimize the overall transportation and inventory costs, while taking into account an emission constraint in a multi-modal multi-item setting. This model is developed for a company to decide on a tactical level which lanes are most suitable for a transport mode shift. The model is solved using Lagrangian relaxation, where the multi-item problem can be decomposed in multiple single-item problems.

The TMSP model is applied as a case study to a subset of the 20 most important lanes of Philips' shipments data. Unfortunately, many of the required data inputs cannot be obtained. For this reason, all input parameters are estimated with the help of existing data, Philips' analysts and literature. Because the leadtime (variability), demand distribution and warehouse inventory policy are unknown, it is decided to use simulated data to apply the TMSP optimization model. It is concluded that running the model against zero emission penalty cost, results in a win-win decreasing emissions with 53.8% while reducing costs with 18.0% as opposed to Philips' initial situation. This win-win situation at zero emission cost is found with a proposed transport mode shift to ocean for 11 of the 20 lanes in scope. Then, the order in which the other 9 lanes can be shifted from air to ocean transport in a cost-efficient way is tested and results in an efficient frontier of solutions, which reflects the trade-off between total CO_2e emissions and total costs. The total emission reduction potential is calculated to be 96.5% against a cost increase of 31.8%.

Recommendations

Firstly, it is recommended to Philips to substantiate its decisions for the CO_2e calculation scope and to reconsider its current assumptions and EFs. Secondly, the most important recommendation to Philips is to apply transport mode shift from air to ocean for the shipment lanes that are deemed most suitable. It is recommended to start the transport mode shifts for the 11 lanes that resulted in the win-win solution. The next 2 lanes that shift from air to ocean still have a cost below "Philips' initial situation" but do incur additional costs as opposed to the "zero emission penalty" situation. Therefore, it is recommended to switch these 2 lanes in a later stage. The other 7 lanes in scope shift at increasing additional costs, due to which these lanes are less suitable for transport mode shift. Next to transport mode shift, also general recommendations are provided that can help to include more sustainable transportation alternatives. Here, the collaboration with 3PLs is mentioned, to e.g. decrease the contracted minimum weight of a shipment; apply transport consolidation; use cleaner fuels or vehicles; or increase load factors. Furthermore, improvement directions related to Philips' data collection are described. Obtaining relevant data is crucial to improve the calculation accuracy of research sub-questions 1 and 2. Improved accuracy is important when Philips wants to act upon results in order to have reliable expectations for costs of e.g. a transport mode shift.

Implementations

Many aspects of this Master Thesis project are implemented at Philips and integrated in their current way of working. This Master Thesis project contributes to Philips' airfreight logistics CO_2e reporting on several aspects. First, the cleaning of input data of the origin and destination locations with IATA-codes is implemented. This implementation leads to accurate distances for an additional 5% of the shipments compared to Philips' original method. Second, the data cleaning method for weights has also been implemented, which includes cleaning for minimum weight, missing weight values, and maximum weights. Third, the distance calculations have been implemented fully, which consists of the Great Circle Distance (GCD), the detour distances, and the road distance percentage. This implementation enables automated distance calculations instead of using a lookup table for each shipment. All these components are implemented in Philips' CO_2e calculation method, process flow and in Philips' annual report of 2019 (Royal Philips, 2019c). For the process flow, a BPMN tool is built such that everyone can follow the performed calculations and also apply the methodology in the future. Furthermore, a dashboard tool in Qlik Sense is built such that it can easily be seen on which lanes, segments, and periods emissions occur. It is an interactive tool in which a person can select e.g. the origin or destination country or the period and then the selected lanes are shown on a world map. When selecting specific lanes, also the corresponding emissions, costs, and the number of shipments are shown. The final implementation of this project is the implementation of the TMSP model as a case study on a subset of Philips' logistics data. This tool is built in R, which is Philips' preferred programming language and this enables Philips to use the TMSP model on a wider scope in the future. It is also possible to extrapolate current conclusions for the limited scope to a wider scope. This option is a solution that Philips likes to implement in a short-term while starting the in-depth supply chain investigations and additional data collection. This implementation is currently being developed and the first proposal is expected to be finished in April 2020.

Preface

This Master Thesis marks the end of my graduation project conducted at Royal Philips and my Master program Operations Management and Logistics at Eindhoven University of Technology (TU/e). This project took place for seven months from September 2019 to April 2020, at Philips' Group Sustainability in Eindhoven, Netherlands. I would like to devote this page to thank the people who have contributed to this Thesis.

First of all, I would like to thank my first supervisor Tarkan Tan for his contribution to this project. Tarkan, thanks for all your time and constructive feedback which guided me throughout this project. At moments that I was stuck or did not know how to proceed, you always provided me several ideas while also giving me a feeling of trust in my own decisions. I liked having our biweekly team sessions, in which I also got support of Isabelle, Mert and Hakan. Additionally, I would like to thank my second supervisor Virginie Lurkin for your transport related knowledge and your always fast replies. It was nice that you also put emphasis on the good things about my work while helping me improve further.

Within Philips, I would like to express my gratitude towards Siebe Trompert and Simon Braaksma. Siebe, you're one of the most positive and enthusiastic persons that I have ever met. You guided my way at Philips and together we implemented several improvements for Philips' airfreight emissions reporting. Thank you for being open to new ideas and for helping me make a true impact within Philips. Simon, many thanks to you as team leader, for your interest in my well-being and in this graduation project. Additionally, I would like to thank my colleagues who provided me a welcome workplace. I would like to thank Wilma in specific, for all the good days at the office together.

Furthermore, I would like to thank my family and friends for giving me unlimited support and cheerful moments. To my parents and sisters, thank you for all time shared with me during the weekends, as well as your support and faith in me. You always helped me relax and listened to my stories. There are some friends who I would like to thank in specific. Yvon, you were literally always available to answer my programming questions, help me decide how to make the best graphs or just to eliminate my concerns. Joyce, thanks for reading through my complete thesis and providing me tips to improve my writing. Aimee, thanks for always taking care of me when I was stressed and for all the projects that we did together throughout our Masters. Also a big thanks to my friends from Animo, for making my student life unforgettable, fun and full of personal development. There are of course many more people who I appreciate for their support, but too many to mention them all. At the end, thanks to you, reader. If you are reading this line after the others, you at least read one page of my thesis. Thank you!

Sophie Stalpers

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List of Abbreviations

3PL	Third Party Logistics provider
BPMN	Business Process Model and Notation
CO_2	carbon dioxide
CO_2e	carbon dioxide equivalent
EF	emission factor
GCD	Great Circle Distance
GHG	Greenhouse Gas
GLEC	Global Logistics Emissions Council
GSCM	Green Supply Chain Management
i.i.d.	independent and identically distributed
IATA	International Air Transport Association
LSP	Logistics Service Provider
NTM	Network for Transport Measures
SCM	Supply Chain Management
SSC	Sustainable Supply Chain
TMSP	Transport Mode Selection Problem
TTW	tank-to-wheel
TU/e	Eindhoven University of Technology
WTW	well-to-wheel

List of Definitions

Chargeable weight	The shipment weight (kg), being the maximum of the actual and volumetric weight, over which emissions for transport are calculated (NTM Air, 2015)
CO_2 equivalent	The term CO_2e refers to carbon dioxide equivalent units, a measure that allows for aggregating all GHG emissions into one measure (Hoen, 2012)
Emission factor	Activity-based conversion factor for carbon emissions (Boukherroub, Bouchery, Corbett, Fransoo & Tan, 2017)
Extrapolation	An estimation of the dependent variable for values of the independent variable that are located outside the set of observations (Dodge, 2008a)
GHG emissions	GHG emissions refer to a collection of gasses among which are carbon dioxide, methane and chlorofluorcarbons (CFCs) (Hoen et al., 2014a)
IATA-code	A three-letter geocode designating airports around the world, defined by the International Air Transport Association (IATA, 2020)
Lagrange relaxation	A technique to solve constrained optimization problems (Joachim Arts, 2018)
Leadtime	The total transportation time of a product between leaving the origin address and arriving at the destination address
Portfolio effect	To compensate costly emission reductions on one lane with less costly reduction on another lane, to achieve emission reductions at an overall lower cost (Hoen et al., 2014b)
Tank-to-Wheel	The use of energy in transportation, starting from combustion within the vehicle (UK Department for Environment Food and Rural Affairs, 2019)
Well-to-Wheel	The total use of energy in transportation, including fuel production, distribution and combustion (NTM, 2018b)
Winsorizing	Converting the values of data points that are outlyingly high to the value of the highest data point that is not considered to be an outlier (Reifman & Keyton, 2010)

Chapter 1

Introduction

Over the last few decades, topics like global warming, carbon emissions and sustainability have received increasing attention. One of the important contributors to climate change is transportation. In Europe, around 23% of all carbon dioxide (CO_2) emissions can be attributed to the transport sector. This makes the transport sector the second-biggest contributor after the energy sector (Hoen et al., 2014b; European Commission, 2017). Each mode of transportation causes air pollution in a different way and intensity. Air pollution results from the emission of gases, solids and/or liquid aerosols, when they occur in volumes above the capacity of the atmosphere itself to dissipate or dispose them. Air pollution has negative effects both on human health and on the existence and integrity of material goods (D'Agosto, 2019). The increase in emissions is a result of the increase in demand for transportation, and the existing trend in increased energy efficiency is not (yet) sufficient to balance this (Hoen et al., 2014a).

Within the global transport sector, road transport is by far the transport mode with the highest emissions, accounting for about two thirds of all Greenhouse Gas (GHG) emissions (European Commission, 2017; Smart Freight Centre, 2018). GHG emissions refer to a collection of gases among which are carbon dioxide, methane and chlorofluorcarbons (CFCs) (Hoen et al., 2014a). Road transport is the transport mode with overall highest emissions, since road transport is easy to use in short-distance or intermodal logistics. However, air transport is the transport mode with the highest carbon intensity, thus the highest emissions per transported unit (Dekker et al., 2012; Hoen et al., 2014b; van den Akker et al., 2009).

1.1 Company description

This Master Thesis project is performed in cooperation with the company Royal Philips, referred to as Philips. Philips was founded in Eindhoven in 1891 as a manufacturer of electric incandescent light bulbs. In 1918, Philips began with its healthcare department and introduced a medical X-ray tube (Royal Philips, 2019b). Nowadays, Philips is a leading health technology company focused on improving people's health and enabling better outcomes across the health continuum from healthy living and prevention, to diagnosis, treatment and home care. Philips leverages advanced technology and deep clinical and consumer insights to deliver integrated solutions. The company is a leader in diagnostic imaging, image-guided therapy, patient monitoring and health informatics, as well as in consumer health and home care. Philips has sustainability incorporated in its company strategy. The company embraces sustainability to benefit the society and because it believes this is a driver for economic growth (Royal Philips, 2019a). Philips strives to make the world healthier and more sustainable through innovation, with the goal to improve the lives of 3 billion people a year by 2030.

At Philips, each segment has its own supply chain structure and resources. This leads to a decentralized structure with business units that control its own operations with its own resources (Koc, 2010). Products are produced in and shipped to countries all around the world and each department has its own decision making criteria for logistics processes. In 2019, Philips generated sales of 19.5 billion. Additionally, Philips employs approximately 78,000 employees and has sales and services in more than 100 countries (Royal Philips, 2019a).

1.2 Problem definition

Philips has the ambition to become fully carbon neutral in its operations, and to source all its electricity usage from 100% renewable sources by the end of 2020. On top of this, Philips aims for 4-6%

comparable sales growth and an Adjusted EBITA margin improvement of around 100 basis points (Royal Philips, 2019b). In line with the sustainability goal, Philips already increased its global renewable electricity usage in 2019 to 95% (Royal Philips, 2019c). This results in low CO_2e emissions from manufacturing and non-industrial operations, as can be seen as 'Sites' in Figure 1.1. In 2019, overall CO_2e emissions from logistics represent 71.4% of the total operational carbon footprint (see 'Logistics' in Figure 1.1). The remaining part of the operational carbon footprint is allocated to 'Business travel'. The emissions from logistics already decreased by 11.9% in 2019 as compared to 2018 (Royal Philips, 2019c). This decrease has been realized by using multi-modal shipments, a transition from air to ocean freight and a stricter airfreight policy. However, even with this decrease, the category of logistics is by far the biggest contributor to the operational carbon footprint. Therefore, we have to look deeper into this category in order to improve the total operational carbon footprint.

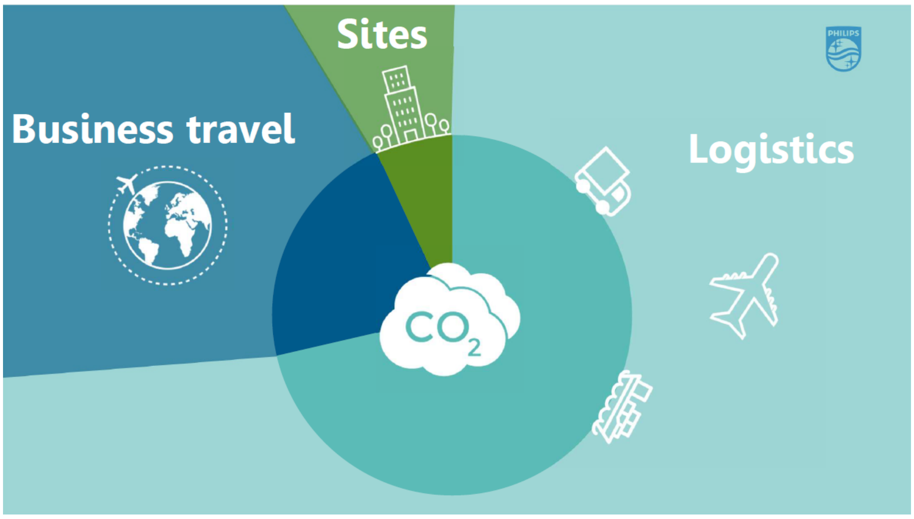

Figure 1.1: Visualization of Philips' total operational carbon footprint in 2019

As discussed above, logistics is the largest category of emissions in the overall operational carbon footprint of Philips. Table 1.1 shows the operational carbon footprint of Philips' logistics over the years 2015 until 2019 in kilotonnes CO_2-equivalent. From this table, it can be concluded that within Philips the emissions for the factor 'Air transport' are by far the highest, accounting for 65.4% of the total logistics emissions in 2019. The factor 'Road transport' that is displayed here, only contains the shipments that are fully transported by road transport. The shipments that are performed by air or ocean transport also include a portion of road transport, where the product is transported from the warehouse to the port/airport. However, this road transport is included in the emissions for air and ocean transport respectively.

Table 1.1: Operational carbon footprint of Philips logistics 2015-2019 in kilotonnes CO_2e (Royal Philips, 2019c)

	2015	2016	2017	2018	2019
Air transport	309	361	491	393	328
Road transport	65	67	67	70	75
Ocean transport	68	63	83	109	101
Total Philips Group	**460**	**491**	**641**	**572**	**504**

The carbon footprint reduced from 2017 to 2019. However, Philips requires more insights in its logistics processes to improve even further. In Table 1.1 is shown that about two thirds of the logistics emissions can be attributed to airfreight. The company wants to implement improvements, such as modal shifts, in transport to decrease the environmental impact of airfreight, but has no clear insights in what the current impact is of every product shipment and where most impact can be gained.

This impact might e.g. depend on the number of times that Philips uses a specific lane; on product characteristics such as value or weight; or on environmental factors such as accessibility. The problem arises that the company has no clear overview of where to implement more sustainable alternatives, such as modal shifts, first. The implementation of more sustainable alternatives also depends on the costs that are attributed to this change. Furthermore, the service levels that Philips currently offers to its customers has to be maintained. An analysis is required to get an overview of the current state of logistics emissions and the corresponding costs. In order to reduce the operational carbon footprint of Philips' logistics, the large factor of 'Air transport' should be investigated in-depth. This is the starting point of this research.

1.3 Research questions and methodology

For the purpose of sustainability, this research aims to analyze and visualize global logistics processes of Philips' airfreight and aims to introduce actionable improvements for sustainability. Based on the defined problem and research goal for this research project, the research question is defined as follows:

What is the current environmental impact of Philips' logistic processes for airfreight and which sustainable improvements can be introduced to drive CO_2e emission reductions?

To answer this research question, three sub-questions have been stated:

1. How to define a method that can accurately calculate the current environmental impact of Philips' logistic processes for airfreight?

To answer the first research sub-question, a methodology is described to calculate the carbon dioxide equivalent (CO_2e) emissions of transporting goods, based on the Network for Transport Measures (NTM) methodology. Then this methodology is, with some small adjustments, applied as a case study to Philips' airfreight logistics data. After having analyzed all airfreight logistics, this project continues to the second research sub-question:

2. How to develop a general decision making model that provides a trade-off between emissions, costs and service level indicators?

To answer the second research sub-question, a mathematical model is developed that minimizes the total costs under an emission constraint. This model takes the factors costs, emissions and service levels into account in deciding the best way of transport mode choice for several products and lanes. The model is solved using Lagrangian relaxation, where the multi-item problem can be decomposed in multiple single-item problems. This model solves the Transport Mode Selection Problem (TMSP) of which transport mode should be assigned to which lanes. Next, this model is applied as a case study to a subset of the most important lanes in Philips' shipments data to discover the improvement potential. Then, the final research sub-question is formulated:

3. Which improvements can be made for the logistics planning process to include more sustainable transportation alternatives for the most impactful products/lanes?

To answer this third research sub-question, directions for improvement towards more sustainable logistics are presented. These insights are based on insights generated by the emission calculation and the TMSP model. The research methodology is summarized in Figure 1.2. This Figure shows how the research questions depend on each other and on external data or literature.

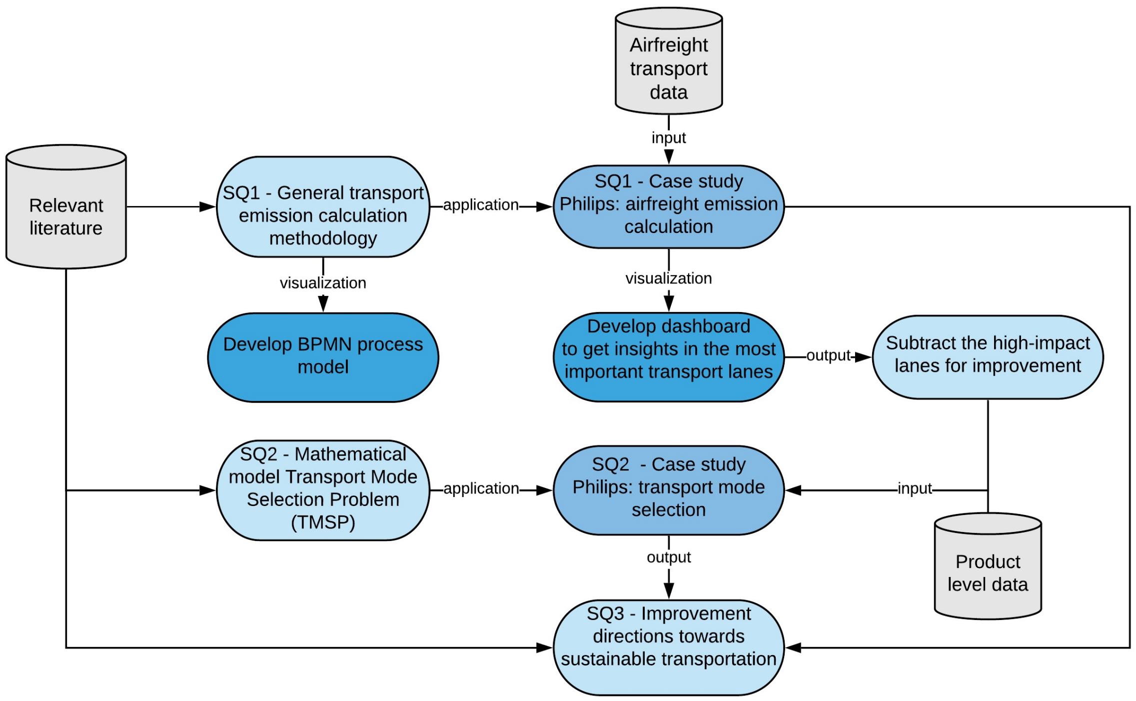

Figure 1.2: Research methodology overview

1.4 Research scope

The scope of this research project contains the carbon dioxide equivalent (CO_2e) emissions of global logistics processes for airfreight shipments of Philips' products in the time period January 2017 up to October 2019. The scope of reported emissions is well-to-wheel (WTW), which is the total use of energy including fuel production, distribution and combustion (NTM, 2018b). The emissions are calculated in CO_2e, which is a measure that allows for aggregating all GHG emissions. The reason for this aggregation notation is that CO_2 emissions have by far the largest impact on global warming of all emissions of Greenhouse Gas (GHG) (van den Akker et al., 2009). Every shipment refers to a combination of an origin and destination location and a product type. Only air shipments that Philips is financially responsible for (that Philips has paid or will pay for), are included in scope.

Figure 1.3 provides a visualization of the general transport chain that is used for shipping one product by air transport. The transport chain starts at a warehouse or production location and is shipped with transport mode road towards a transhipment center. In this transhipment center, the product is loaded from the truck into the aircraft. It is estimated that about 90% of the emissions for logistics and transport activities are due to freight transportation, and 10% for operating logistics buildings (Marklund & Berling, 2017). Since the impact is relatively small, carbon emissions for e.g. electricity or heating of this transhipment centre are out of scope. After the flight the product is again loaded into a truck at the transhipment centre and transported by road transport to the final destination. Only shipments of which reliable data is available can be considered in the analysis. The analysis results in an overview of carbon emissions of all global air shipments within scope, after which a general comparison selects the most impactful shipments or lanes. Subsequently, for these selected lanes a deep-dive case study is conducted to analyze the options for transport mode shift and provide specific recommendations for improvement.

Figure 1.3: Transport chain visualization

1.5 Thesis outline

The remainder of this Master Thesis is structured as follows. Chapters 2 and 3 tackle the first research sub-question. Chapter 2 describes the general calculation method that is designed to calculate the total CO_2e emissions of airfreight logistics. Then, Chapter 3 puts this methodology into practice, applying it as a case study to Philips. Chapters 4 and 5 handle the second research sub-question. Chapter 4 describes the general Transport Mode Selection Problem (TMSP) optimization model on a mathematical level. Thereafter, Chapter 5 applies this model as a case study to Philips' logistics data. Chapter 6 tackles the third research sub-question of sustainable improvement directions. Chapter 7 shows the implementations of this Master Thesis project at Philips. Finally, Chapter 8 provides conclusions and a discussion with directions for future research.

Chapter 2

Carbon emission calculation method

This chapter describes the calculation method that is designed for determining the CO_2e emissions of airfreight shipments. Each subsection describes one step in the calculation in order to provide a clear overview and enable reproduction of results. This chapter provides a general answer to the first research question:

1. How to define a method that can accurately calculate the current environmental impact of Philips' logistic processes for airfreight?

Section 2.1 introduces the concepts of emission calculations for freight logistics. Then, Section 2.2 describes the method that is used for calculating the distances of airfreight shipments. Section 2.3 describes the method that is used for determining the chargeable weight of airfreight shipments. Then, Section 2.4 describes the CO_2e emission calculation method. Finally, Section 2.5 summarizes the chapter and provides an overview of the complete methodology. This chapter contributes to the logistics carbon measurement literature by describing a step-by-step methodology to calculate emissions for global airfreight transport shipments.

2.1 Introduction to logistics emission calculations

In order to reduce the CO_2e emissions of logistics, the first step is to measure the current emissions that occur during transport of goods. Two methods can be applied to calculate CO_2e emissions of logistics processes: energy-based calculations or activity-based calculations (Boukherroub et al., 2017). With energy-based calculations, the Logistics Service Provider (LSP) measures the actual fuel being used. This method is potentially the most accurate one. However, the amount of fuel combusted is generally not directly monitored. With activity-based calculations, an estimation of emissions is made based on shipment characteristics such as distance and product weight. The activity information is used to derive carbon emissions by using emission factors. Such an emission factor (EF) is a calculated ratio relating carbon emissions to a proxy measure of activity at an emissions source (Boukherroub et al., 2017). While emission calculation should always depend on the data available, this chapter proposes a method for activity-based carbon calculation of airfreight.

A literature review investigated several existing activity-based CO_2e emission calculation methodologies and their EF sources. There is not one best method to calculate transport emissions. Instead, different research methods and tools exist to determine CO_2e emissions. All of these methods and tools have different scopes, backgrounds and results (van den Akker et al., 2009). For example, ARTEMIS is a European project focused on getting better understanding of differences in model predictions and to address uncertainties in emission modelling (Boulter & Mccrae, 2007). Since ARTEMIS only focuses on Europe and since it does not provide a lane-specific calculation method, ARTEMIS is not considered very relevant for this Master Thesis. STREAM is a study on emissions of both freight and passenger transport and focuses on comparisons of intermodal transport based on Dutch vehicle and vessel fleets (Otten, Hoen & den Boer, 2016). Since this Master Thesis includes intercontinental transport routes, STREAM is not considered to be very relevant either. The Greenhouse Gas (GHG) Protocol is a standardized step-by-step approach to help firms understand their full value chain emissions impact. It is a calculation method on a high aggregation level, taking into account only the vehicle type, fuel type and distances (Greenhouse Gas Protocol, 2011). A framework with a more detailed calculation level is the NTM framework (NTM, 2019). This method provides a higher level of detail than the GHG Protocol by providing a separate calculation method per transport mode.

Further, NTM provides estimates for transport parameter values that might be unknown to a company or 3PL. The latest update of the default and benchmark transport data of NTM in 2018 shows also global figures, which makes the method applicable on a global scale (NTM, 2018b). Finally, the GLEC framework contains global industry guidelines for emission calculation, reporting and reduction of emissions (Smart Freight Centre, 2018). The GLEC framework is accredited by the GHG Protocol and aligns with a growing number of other methodologies and industry standards. The GLEC Framework is not an independent method that can be seen as an alternative to GHG Protocol or NTM Framework, since it combines several input factors together in one practical overview. However, it provides separate formulas and EFs, thus it is considered as a separate choice. An overview of the emission factors per transport mode for the relevant methodologies can be found in Appendix A.1. Note that the list of logistics carbon measurement methods and corresponding EFs is not exhaustive and includes only the most relevant methods.

In literature, five criteria are described for evaluating carbon footprint tools: (1) Breadth - the scope of activities included in the measurement; (2) Depth - the range of direct and indirect emissions included in the measurement; (3) Precision - the level of detail provided by the measurement; (4) Comparability - the degree with which measurements can be compared across time and organizations; (5) Verifiability - the degree of assurance in the results and methodology (Craig, Blanco & Caplice, 2013). The first three criteria together capture how relevant a measure is for decision-making. The other two criteria provide a measure of how well suited the tool is for external use to faithfully represent the actual performance. In the literature study of Stalpers (2019), the GHG Protocol, NTM framework and GLEC framework are scored based on these five criteria. The result of this can be seen in Table 2.1. After this thorough literature research, it is decided to base the calculation method on the Network for Transport Measures (NTM) methodology (NTM, 2019). This is the preferred methodology, due to the high level of detail and the possibility of adding and changing parameters and values. The full literature study can be found clicking HERE.

Table 2.1: Criteria scores of emission calculation methods and corresponding EFs

Method	(1) Breadth	(2) Depth	(3) Precision	(4) Comparability	(5) Verifiability
GHG	High	Low	Low	High	Low
NTM	High	High	High	Moderate	High
GLEC	High	High	Moderate	Moderate	Moderate

2.2 Description of calculation method for distances

In this section, the calculation methodology for distances is described. First, Subsection 2.2.1 describes the method to calculate distances of flights. Thereafter, Subsection 2.2.2 discusses the method to calculate additional distance for detours along the route. Finally, Subsection 2.2.3 describes the method for determining the road distance for transport from and towards the airports.

2.2.1 Distance calculation of flights

The distance calculation of an airfreight shipment is required in order to know the total CO_2e emissions that occur during the flight. The emissions of airfreight are mostly calculated with an emission factor (EF) that represents the kg of CO_2e emissions per tonne-kilometer. The tonne-kilometer then represents the movement of one tonne (1,000 kg) weight over a distance of one kilometer. Thus, in order to calculate the emissions, it is required to know the distance of each shipment.

In order to calculate the distance of an air shipment, the Great Circle Distance (GCD) formula is applied. The GCD, also known as direct distance or ‘as the crow flies’, defines the shortest distance between two points on the surface of a sphere. It is a common method for calculating distances in the aviation industry (Greene & Lewis, 2019). This distance can be calculated using the geographical coordinates of the origin and destination (NTM Air, 2015). According to Mahmoud and Akkari (2016), Haversine is the appropriate method for this type of shortest path calculation. Therefore, the Haversine GCD method is used in this methodology, see Equation 2.1.

$$d = 2 \cdot r \cdot \arcsin(\sqrt{\sin^2(\frac{lat2 - lat1}{2}) + \cos(lat1) \cdot cos(lat2) \cdot \sin^2(\frac{long2 - long1}{2})}) \quad (2.1)$$

Where d is the total distance in km; r is the radius of the earth (equals 6378.137 km) (Wikipedia, 2019a); *lat1* and *lat2* are the latitude of origin and destination respectively (in radians); and *long1* and *long2* are the longitude of origin and destination respectively (in radians).

2.2.2 Additional detour distance

The Great Circle Distance (GCD) is the shortest distance between the start and end point of a flight. This would be the ideal flight route between two airports but in practice there may be many deviations, particularly at take-off and landing. Each flight needs to take into account the uplift distance of the flight during take-off and landing. To compensate for this, the total route distance should also include a 'detour' distance. With this detour distance, also emissions of stacking, traffic and weather-driven corrections are included (NTM, 2019; ICAO, 2017). Using the NTMCalc 4.0 online tool (NTM, 2019), the detour distances are determined for each GCD interval of 1,000 kilometers. The additional detour distance in kilometers for the GCD in 1,000 kilometers is displayed in Table 2.2.

Table 2.2: Detour distances (NTM, 2019)

GCD (*1000 km)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Detour (km)	63	87	105	120	133	144	155	164	173	182	190	197	205	211	218	224	230

Using these distances, the underlying trend could be identified with an Excel tool (see Appendix A.2). The result of this can be seen in Equation 2.2. Here, the GCD is expressed in 1,000 kilometers and the detour in kilometers. This function should be applied to every Great Circle Distance (GCD) flight length. Then, the total flight distance (in kilometers) is the sum of the GCD of Equation 2.1 and the detour distance of Equation 2.2.

$$\text{detour (km)} = 63.472 * \text{GCD}^{0.4564} \quad (2.2)$$

2.2.3 Additional road distance

The transport chain of an air shipment consists of a multi-modal road-air-road combination. Until now, only the origin and destination airports were considered and the travel from the warehouse/production site towards the airport and back was neglected. In order to calculate the additional road distance from the production/warehouse to the airport and from the destination airport to the final location, it is required to know the exact locations. Between the origin/destination location and origin/destination airport, the road distance has to be calculated. This is a bit more complex than air distance, since one has to take into account the positioning of the roads. The NTMCalc 4.0 online emission calculation tool is capable of calculating this specific route distance, also for different stops along the route (NTM, 2019). However, this tool is only suitable for calculating specific routes one by one. When it is required to calculate road distances for many shipments at the same time, then the 'osrm' package offered by R is recommended to use (Giraud, Cura & Viry, 2019). Note that this package requires either an address or coordinates with longitude and latitude to calculate road distances.

Further, taking into account the road type (motorway, rural or urban) and the road gradient, which is a measure for driving uphill and downhill, improves the accuracy of emission calculation. Also the positioning of a truck before transport should be included in the distance per shipment. NTM Road (2015) recommends to use an additional factor of 20% of the transport distance as the positioning distance. The emissions related to empty running after delivery of the cargo is not considered by the NTM method.

2.3 Description of calculation method for weights

Next to the distances, also the weight of an airfreight shipment is required in order to determine the total CO_2e emissions that occur during the flight. In air transport, weight is an essential and delimiting factor defining total environmental performance. It is assumed that shipment transports are undertaken in a shared transport system where the capacity of a vehicle (or set of vehicles) can be shared between multiple shipments (NTM, 2019). The *actual weight* of a shipment is the total actual physical weight of everything loaded onto the plane. The weight of containers, pallets and other cargo handling and securing devices must be included in this calculation (NTM Air, 2015). Emission calculation of airfreight often takes into account a *volumetric weight*, e.g. by a minimum density for air transport (Hoen et al., 2014a). This is done, because there is limited space in an airplane. When performing calculations only with the actual weight, while e.g. transporting a huge bag of air, too little emissions would be attributed to this specific shipment. For this reason the volumetric weight is used, which is the volume (in m^3) multiplied with the minimum density. The minimum density for airfreight is set to 167 kg/m^3 which is in coordination to the literature (NTM Air, 2015; Hoen et al., 2014a). The emission calculation and allocation is performed based on the *chargeable weight*, which is the maximum of the actual weight and the volumetric weight (NTM Air, 2015). For the purpose of emission calculation, the chargeable weight in kilograms should be divided by 1,000 to be expressed in tonnes, since an emission factor (EF) is normally expressed in kilograms of CO_2e per transported tonne-kilometer.

2.4 Emission calculation

This section combines all input parameters into the emission calculation. In this calculation method, CO_2e emissions are derived from activity information by using conversion factors. These factors are calculated ratios relating carbon emissions to a proxy measure of activity. Such an activity-based conversion factor is often referred to as emission factor (EF) (Boukherroub et al., 2017). Different values for EFs are defined for each mode of transport, see Appendix A.1. Ranking the transport modes from highest to lowest emission factor, results in: air, road, rail and water transport (Dekker et al., 2012; Hoen et al., 2014b; van den Akker et al., 2009). Subsection 2.4.1 describes the use of EF for air transport, followed by Subsection 2.4.2 which describes the EFs for road transport. Finally, Subsection 2.4.3 describes how to convert the distance, weight and EF into CO_2e emissions.

2.4.1 Emission factors for transport mode air

The NTM methodology presents emission factors for carbon calculation. All EFs are based on the aircraft type and the load factor of the plane. When calculating aircraft emissions care needs to be taken in choosing the right aircraft or type of aircraft, since environmental performance varies both with aircraft/engine configuration and the type of aircraft. Calculations on for example belly freight, taking into consideration that more of the aircraft's volume and weight is used for the passengers, show approximately 30% higher emissions for belly freighters as compared to pure freighters (NTM, 2018a). This is due to the higher tare weight (or unladen weight) of a belly freighter.

Table 2.3: Average airfreight emission factors (NTM, 2018b)

Aircraft range	Distance range (km)	Aircraft type	WTW CO2e (kg/tkm)
Regional	< 785	Freight	2.10
Continental	785 - 3,600	Freight	0.92
Intercontinental	$> 3,600$	Freight	0.58
Regional	< 785	Belly	2.10
Continental	785 - 3,600	Belly	1.10
Intercontinental	$> 3,600$	Belly	1.10

Table 2.3 presents an example overview of the NTM airfreight emission data per distance range. The table shows the well-to-wheel (WTW) emission factors, which is the total use of energy including fuel production, distribution and combustion. The aircraft type is specified, dividing between regular

freight aircrafts and belly aircrafts (passenger aircrafts carrying additional cargo) (NTM, 2018b). For each of the aircrafts, an average load factor of 65% is assumed (NTM, 2019). Note that the choice of emission factors is an important factor determining the final output of the CO_2e emissions. There is not one single standard that is used consistently in industry or literature. However, as long as the assumptions of using a methodology are defined clearly, it cannot be stated that one method is better than another method.

2.4.2 Emission factors for transport mode road

The emission factors of a road vehicle depend on the size of the vehicle, as well as the energy efficiency, load factor, road type and road gradient (NTM Road, 2015). The road gradient describes the road topography as this has an influence on fuel consumption (NTM, 2018b). Besides, the average emission factors differ per region of the world. For example, it can be concluded that the average emission factors for the US are slightly higher than the EFs for the EU (NTM, 2018b). The NTM method provides clear averages for the EU, US, Asia, South America as well as global averages.

Whenever actual data for vehicles, route, load factor or road gradient is not present, it is an option to work with industry averages. Since road transport in this setting is used for transport from e.g. a warehouse to an airport, it is most likely that an average rigid truck is used. For this reason, it can be assumed that the truck type is a rigid truck (20-26 tonnes). This truck size has a typical capacity of 15 tonnes (NTM, 2019). NTM (2018b) uses an average road gradient of 2% and an average load factor of 50% for a truck. Here, the default load factor (%-weight) includes empty positioning of truck. Table 2.4 shows an overview of the emissions of CO_2e including fuel production, distribution and the combustion (WTW) under these assumptions. Again, the emissions are expressed in kg of CO_2e per shipped tonne-kilometer. If the country under consideration is not mentioned in Table 2.4, the world averages can be used instead. The impact of the truck size on the emission factors is shown in A.1.

Table 2.4: Average road emission factors per region (NTM, 2018b)

Transport region	WTW CO2e (kg/tkm)
Europe	0.130
United States	0.136
Asia	0.160
South America	0.130
World averages	0.139

2.4.3 Emission calculation

Until now, the method for calculating shipments' distances and weights has been described as well as the use of emission factors. Using these input variables, the emissions of a shipment can be calculated as in Equation 2.3. Here, it is assumed that I={1,2,...,n} ($i \epsilon I$) denotes the set of available transport modes. In this calculation, only the transport modes air and road have been used. Further, J={1,2,...,m} ($j \epsilon J$) denotes the set of lanes to which certain products are shipped. Each shipment consists of a product type, an origin location and a destination location. Note that the emissions should be calculated separately per transport mode (e.g. air or road) and can be added afterwards.

$$e_{i,j} = w_j \cdot EF_{i,j} \cdot \delta_{i,j} \tag{2.3}$$

Where the emissions ($e_{i,j}$) are expressed in kilograms of CO_2e; the total distance ($\delta_{i,j}$) for air shipments is the distance of GCD Equation 2.1 plus Detour Equation 2.2 in kilometers; the total distance ($\delta_{i,j}$) for road shipments as explained in Section 2.2.3; the chargeable weight (w_j) is expressed in tonnes; the emission factor ($EF_{i,j}$) is expressed in kg CO_2e/tonne-kilometer. Note that the emission factor depends on several factors, such as the distance of the shipment, the vehicle type and the (average) load factor of the vehicle. For this reason, the emissions have to be calculated for every single shipment separately and can then be summed afterwards.

2.5 Summary emission calculation method

Figure 2.1 provides an overview of the calculation method that has been described throughout this chapter. The first step is the distance calculation, in which the Great Circle Distance (GCD) is used to calculate the flight distance. Additionally, distances are taken into account for detours during take-off and landing, and for the road shipments from the airport to the final destination. The second step includes the weight calculation, where the actual weight is the weight in kilograms of everything loaded into the plane. The volumetric weight is the actual weight, taking into account a minimum density of 167 kg/m^3. For calculating emissions the chargeable weight should be used, which is then defined as the maximum of the actual weight and the volumetric weight. The third step takes into account the vehicle type that is used. Often this vehicle type is connected to the shipment itself, e.g. airfreight shipments of 10,000 kilometers use an intercontinental plane with a certain maximum load and fuel usage. Depending on these vehicle characteristics, the emission factors are determined. In the final step, the emission calculation is performed. Here, the distance and weight are converted into tonne-kilometers and multiplied with emission factors to get the CO_2e emissions. Finally the output can be aggregated into any form, in order to report emissions e.g. per shipment lane or per time period.

Figure 2.1: Calculation method overview CO_2e emissions

The methodology described throughout this chapter contains some aspects for discussion. One of the biggest challenges in the topic of carbon measurement and disclosure is non-comparability, because there is no internationally agreed standard or authoritative guidance for benchmarking and measuring GHG emission levels (Hartmann, Perego & Young, 2013; Bouman, Lindstad, Rialland & Strømman, 2017). Section 2.1 discusses several methodologies for logistics emission calculations and evaluates the most relevant methods based on five criteria. The NTM methodology is selected as the most promising methodology for this Master Thesis. However, even within one methodology, the choices to be made to get a final CO_2e result are not straightforward. For example, Table 2.3 assumed higher EFs per tonne-kilometer for belly freighters as compared to pure freighters (NTM, 2018b). However, this depends on the allocation method of CO_2e emissions of a flight over freight and passengers. That this allocation is not straightforward can also be concluded from the words of a NTM representative: *"Allocation in NTM (2018b) is done by pure weight. The common discussion is to set passenger (including luggage) at 100 kg. One could also argue that seats, galley, toilets and flight attendants should be allocated to passenger. On the other hand the flight would not exist if there were no passengers."* This qualitative difference for allocation methodologies occurs with every methodology and is important to consider when drawing conclusions. Another factor that remains a bottleneck in practice is the availability of correct and complete data about shipments, load factors and vehicle types which is required input to perform emission calculations. It is the objective to combine carbon measurement with carbon management, in order to select lanes that are most suitable for implementing improvements, decreasing the total amount of carbon emissions.

The discussed methodology can be applied to any data set of airfreight shipments, including at least the variables: year and month; origin and destination airport; origin and destination address; the actual and/or chargeable shipment weight; shipment volume. Variables that make the calculation more accurate include (among other things): exact vehicle types (full freighter/ belly freight aircraft); fuel consumption and load factors of airplane; packaging size and weight. Chapter 3 implements this methodology as a case study using Philips' logistics data to determine the total emissions of its airfreight logistics.

Chapter 3

Case Study Philips: Emissions

This chapter describes the methodology for calculating the carbon emissions related to Philips' airfreight logistics. It is an application of the methodology as described in Chapter 2. Thus, this chapter answers the first research question:

1. How to define a method that can accurately calculate the current environmental impact of Philips' logistic processes for airfreight?

Section 3.1 describes both the data that is used as input for the calculations as well as the data cleaning steps that are performed. Section 3.2 describes the method that is used for calculating the distances of airfreight shipments. Thereafter, Section 3.3 describes the method that is used for determining the chargeable weight of airfreight shipments. Section 3.4 describes the CO_2e emission calculation for air and road transport that is applied to every shipment in scope. The final section of this chapter, Section 2.5, presents and discusses the final result. All calculations are performed in programming language R.

3.1 Description of input data

3.1.1 Data input description airfreight shipments

This calculation method is set up to determine the emissions of Philips' airfreight logistics. The flight data is provided by the Forwarding and Distribution department of Philips. This department has an overview of all flights that Philips used and paid for over the past years. All global flights within the time frame January 2017 up to October 2019 are included in the calculations. Table 3.1 shows some aggregated data characteristics.

Table 3.1: Airfreight shipments characteristics

Year	Months	Number Flights	Shipped weight (kg)
2017	Jan-Dec	97,984	62,030,207
2018	Jan-Dec	99,024	53,711,004
2019	Jan-Oct	82,766	42,346,040
Total		**279,784**	**158,087,251**

For the input data, the following characteristics are included: segment, year, month, origin airport, destination airport, origin country, destination country, shipper name, shipper city, receiver name, receiver city, and chargeable weight. However, for some shipments, data is incomplete, incorrect or unreliable. Working with any database, the possibility of wrong or missing entries has to be taken into account. All noise, such as missing values or outliers have to be handled (Márquez & Lev, 2019). The airfreight shipments data has been cleaned on the aspects: origin/destination, weight and cost.

Data cleaning origin and destination

The input of the origin and destination airports has been cleaned first. In total twenty types of wrong entries have been identified for the IATA-code of origin and destination airports. These IATA codes are three-letter geocodes designating airports around the world, defined by the International

Air Transport Association (IATA, 2020). Appendix B.1 provides an explanation of the IATA code rectification process that has been applied to the input data, in order to change the incorrect codes to official IATA-codes on all shipment lines. This cleaning step greatly contributes to the distance calculation, by providing a higher availability of origin and destination locations. This is also be explained with the distance calculation, see Section 3.2.1.

Data cleaning of costs

As a second step, the airfreight shipments have been cleaned based on their transport cost value. The airfreight shipments data is first cleaned from negative values for costs. These are shipments that are paid for initially, but that were cancelled. Further, the data contains shipments having no cost value, which is denoted as NA in the input file. One of the reasons for this, is that recent shipments still have to be paid for in the next month. To fill in estimated cost values, it was tested whether the costs depend on the weight and/or the distance of a shipment. Unfortunately, no clear relation between the cost and chargeable weight or between the cost and distance could be identified (see Appendix B.2). For this reason, it is decided to fill in the average cost of that specific year-month combination. Next to the negative and NA cost values, outliers on both the lower and upper side of the costs have to be cleaned. An outlier is defined as an observation in a set of data that is inconsistent with the majority of the data (Sheskin, 2010). Since no clear relation could be identified between the cost and the chargeable weight of a shipment, or between the cost and distance of a shipment, this cannot be used to identify outliers. However, outliers need to be removed, since these values can exert a disproportionate influence on statistical analyses (Reifman & Keyton, 2010). One method to clean out data outliers for one variable, not taking into account other variables, is winsorizing. To winsorize data, one converts the values of data points that are outlyingly high to the value of the highest data point that is not considered to be an outlier. Then, the outlying values are reduced in magnitude to a value that is still at the high end of the distribution, but not as extreme (Reifman & Keyton, 2010). This way, the information that a case had among the highest (or lowest) values in a distribution remains, but the data is protected against some of the harmful effects of outliers. The absolute and relative changes due to data cleaning of shipments costs are provided in Appendix B.3.

Data cleaning of weights

As a next step, the airfreight shipments are cleaned based on their chargeable weight. The chargeable weight is defined as the total shipment weight in kg, including the weight of containers and pallets, corrected for the minimum density of airfreight shipments. According to Philips' Sustainability and Forwarding and Distribution analysts, the minimum chargeable weight for a shipment is 30 kg. This is a fixed agreement with the 3PLs. Note that this might lead to an overestimation of the emissions, since the actual chargeable weight of these shipments can be below 30 kg. Next to shipments having a minimum weight, there is also a maximum weight to a shipment. The maximum load of an airplane is limited, depending also on the type of airplane and distance range (see Table 3.2). According to Philips' analysts, all shipments in the data are separate shipments and no aggregation takes place. Therefore, the chargeable weight of a shipment is considered an outlier when it exceeds the maximum load for the airplane type. These outliers are deleted from the data set.

Table 3.2: Freight aircraft characteristics (NTM, 2018b, 2019)

Freight aircraft	Distance range (km)	Maximum load (kg)
Regional	< 785	5,327
Continental	785-3,600	41,146
Intercontinental	$> 3{,}600$	91,937

Missing values for chargeable weight have to be handled as well. When the chargeable weight of a shipment is missing, the best estimate has to be filled in. It is preferred not to delete the shipments without a chargeable weight, since these shipments are most likely real shipments with emissions. Until now, Philips applied a policy in which they used a column called 'volumetric weight' for the missing chargeable weights. However, according to Philips' data analysts, this data input is very unreliable, because filled in volumes of shipments are often wrong. Instead, in this Master Thesis project it is chosen to fill in the average chargeable weight of that specific year-month combination. This is considered as the best estimate and results in a chargeable weight for every shipment. The absolute and relative changes due to data cleaning of shipment weights are provided in Appendix B.3.

3.1.2 General airport data

Next to Philips' specific airfreight logistics data, also several general input data sources are being used. The first data input source is a data hub for all the world airport codes (Codes, 2019). Since only the ISO-country codes and the IATA-codes of the origin/destination airport are provided in Philips' airfreight data, an external source was needed to find the corresponding city and country names. With this external source all the city and country information has been filled in for each IATA-code that is used by Philips. The second data input source being used is a data download of the longitude and latitude coordinates of all airports worldwide (OurAirports, 2019). Latitude is a geographic coordinate that specifies the north-south position of a point on the Earth's surface and longitude specifies the east-west position. This information is required to calculate the distances between airports. Also for this data set, the wrong or missing values have to be checked. The coordinates in the airport file have been cross-referenced with Google Geohack database, in order to ensure reliable data input. This file included originally a total of 9,039 airports worldwide. After sorting out the IATA-codes that Philips uses, and checking the correctness of the corresponding coordinates, there are twelve IATA-codes for which no coordinates are found. These IATA-codes had to be added manually to the input file. An overview of the missing IATA coordinates is given in Appendix B.4.

3.2 Description of calculation method for distances

To calculate GCD for airfreight, Equation 2.1 has been applied to all lanes in Philips' airfreight logistics. Each lane consists of an origin airport IATA and a destination airport IATA. In total there are 4,392 unique combinations of origin and destination airports, using 434 unique airports. Figure 3.1 shows an overview of all the airports worldwide that are used by Philips. The majority of the airports is located either in Europe, Asia or in the United States.

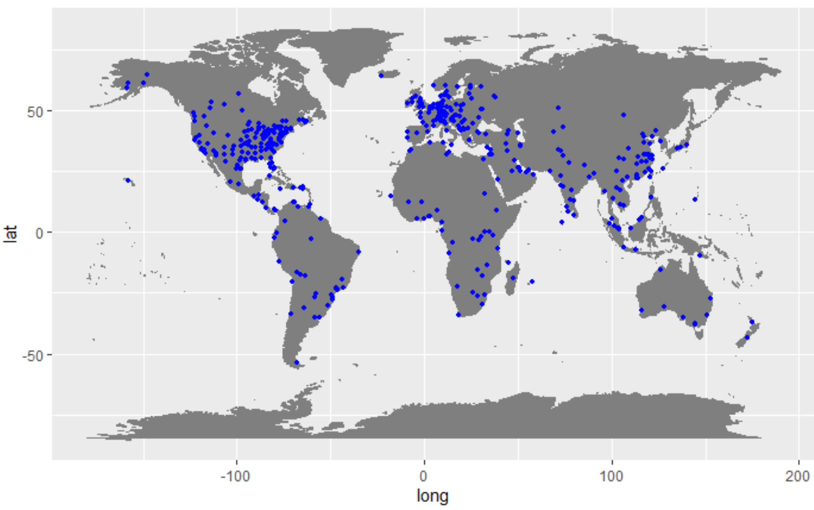

Figure 3.1: Worldwide airports used by Philips

3.2.1 Discussion of results distance calculation

This subsection discusses the results of the former distance calculation method that was used by Philips and the new method as is described in Subsection 2.2.1. Firstly, both methods are compared based on their availability of distances. For availability, the results of both methods are compared using two measures: (1) the percentage of flights for which a distance is found, and (2) the total shipped weight for which a distance is found. Secondly, the correctness of the newly calculated values are checked by comparing it with Philips' distance file.

Availability of distances

The former method of Philips for distances used a fixed database of origin-destination combinations with distances between these locations. It is unknown with which calculation method this database is constructed, but it assumed that the distances are (approximately) correct. Applying Philips' distance database to the airfreight flights resulted in flight distances for 92.73% of the number of flights, corresponding to 92.03% of the shipped weight. Using the method as described in Subsection 2.2.1 for calculating distances, with the longitude and latitude coordinates corresponding to each IATA-code, a higher percentage of distances is found than with Philips' method. After applying the rectifications as explained in Appendix B.1 and Appendix B.4, this methodology could calculate a distance for 97.76% of the flights. This corresponds to 97.59% of the total shipped weight. It can be concluded that the new distance calculation method results in 5.03% more distances (for 14,088 shipments) than Philips' original method.

For the remaining shipments without a calculated distance, it is often the case that either the origin IATA-code or the destination IATA-code is missing or cannot be identified as any specific airport. For these cases, Philips' method uses a weighted average of country-to-country distances. It is assumed that this method is indeed the most accurate method when specific IATA or city information is missing. The method works as follows: For every shipment lane with a calculated distance, the average is determined on a country-to-country level. This means that e.g. all shipments within the United States have an average distance of 1594 kilometers. For the percentage of flights where distances are missing, this number is filled in for all flights with origin country and destination country the US. After this step a distance is determined for 99.96% of the flights. Note that the lanes with an average country-to-country distance cannot be used for direct improvements or deep-dive study of transport, since the lacking city information is crucial for this point of view. Therefore these airfreight shipments are be handled separately, but their emissions are added to the total CO_2e impact.

Correctness of distances

Until now, only the percentages of available distances have been compared. The next step is to investigate the correctness of the distance calculations, by comparing the calculated distance values in kilometers with Philips' distance values. Note that this can only be done for the lanes that were already in the distance file of Philips. Philips' distance values have been compared with the distance values of the calculation as described in Subsection 2.2.1. On average, the calculation method as described in Subsection 2.2.1 results in distances of 7.48 kilometers longer than Philips's reported distances. This corresponds to 0.086% of the total average flight length. The lanes for which the percentage difference was the largest are discussed in Appendix B.5. Overall, it is concluded that the new method performs well in terms of accuracy and is therefore a reliable calculation method. With this method, distances could be calculated for 97.76% of the total airfreight shipments. By improving the distance calculation method, the accuracy of the emission calculation is also be improved.

3.2.2 Additional detour distance

The Great Circle Distance (GCD) is the shortest distance between the start and end point of a flight. This would be the ideal flight route between two airports but in practice there may be many deviations, particularly at take-off and landing. To compensate this, the total route distance should also include a 'detour' distance, as described in Subsection 2.2.2. The detour Equation 2.2 is applied to the airport-to-airport distances and to the country-to-country distances and added to the GCD to get the total flight distance. For the ten lanes that are used most often by Philips, the calculated detour percentages can be seen in Appendix A.2.

Before this Master Thesis project, Philips used a detour percentage of 0.81% of the flight length. It is unknown by Philips' current employees where this number was based on. However, after application of the detour calculation in this Master Thesis, it can be concluded that Philips' detour percentage is too low. The application of the detour method as displayed in Equation 2.2 results in a detour corresponding to 1.80% of the flight length. Since all transport is outsourced, there is no reason to assume that Philips has a lower detour percentage than the worldwide average. Therefore, a detour of 1.80% of the flight length is applied in Philips' logistics emission calculation.

3.2.3 Additional road distance

As discussed in Subsection 2.2.3, it is required to obtain data of the exact origin and destination location of shipments in order to calculate the additional road distance. Until now, only the origin and destination airports were considered and the travel from the warehouse/production site towards the airport and back was neglected. In order to estimate this distance, Philips used a fixed percentage of 3.79% of the air distance on each shipment lane, corresponding to 1.90% for the first and for the last leg respectively. However, no documentation exists on the calculation method for this percentage. Unfortunately, no data could be obtained specifying the exact origin and destination location of shipments. This lack of data makes it impossible to calculate the exact distances of the road transportation part. For most of the shipments, a 'shipper city' and 'receiver city' are specified, giving an indication of the final destination. Note, however, that this data field is also sometimes left blank or can state the city of the person booking the shipment, instead of a location where the freight has been. Due to the lacking data, it is decided to calculate the road distance for a portion of the shipments and translate this distance as a percentage of the flight distance. Then, this distance can be extrapolated over the other shipments. Extrapolation is defined as an estimation of the dependent variable for values of the independent variable that are located outside of the set of observations (Dodge, 2008a).

Sample size

In order to randomly calculate the distances for a subset of the data, it is required to know the minimum sample size for statistically valid extrapolation. For this purpose, three criteria have to be specified: the level of precision, the level of confidence or risk, and the degree of variability (Israel, 1992). The *level of precision* is the range in which the true value of the population is estimated to be. This is often expressed in percentage point, e.g. a precision rate of 5% reflects that the result can be either 5% higher or lower than the reported number. The *confidence level* is based on ideas emcompassed under the Central Limit Theorem. A confidence level of 95% means that 95 out of 100 samples will have the true population value within the specified range of precision. The *degree of variability* refers to the distribution of attributes in the population. A proportion of 0.5 indicates the maximum variability in the population, and is thus often used in determining a more conservative sample size (Israel, 1992).

For this sampling study, a precision rate of 10%, a confidence interval of 95%, and a degree of variability of 0.5 are used. The precision level is set to 10%, such that the output of this sampling study should reflect the real road distances up to 10% accurate. Decreasing this percentage is considered not to be very useful, since the location data is only accurate up to city level. Then, Equation 3.1 is used to find the sample size (Israel, 1992).

$$n = \frac{N}{(1 + N * e^2)} \tag{3.1}$$

Where n is the sample size, N is the population size (equals 434 airports) and e is the level of precision (equals 0.1). Equation 3.1 results in a sample size of 82 unique airports.

Method and assumptions for road distances

Using a random generator, random unique integers are sampled which numbers correspond to the 434 airports that Philips uses. An airport can have several origin or destination cities. For each of these airports, the origin and destination cities are written down and the distances from airport to this city are calculated using the NTMCalc 4.0 tool (NTM, 2019). Then, also the number of times that this specific airport-city combination is used is written down. The sampling of new random sets continues, until the sample size of 82 airports has been reached.

To make calculating road distances possible with limited data quality, some assumptions have to be made. The first set of assumptions handles with the unavailability of city locations and the mistaken city data. First, it is assumed that if the road distance is equal to or higher than 1,000 kilometers, the city name is incorrect and therefore this distance cannot be calculated. This assumption is considered as valid since all locations are within 1,000 kilometer radius from an airport. Additionally, it is not efficient to drive more than 1,000 with road transport. Secondly, for a similar reason, it is also assumed that the road distance cannot exceed the flight distance. Thus, whenever the road distance is equal to or greater than the flight distance, the city name is assumed to be incorrect. Note that it is chosen to have both an absolute and a relative target on the road distance, since the flight distances differ greatly. Further, it is chosen to handle these city mistakes and the blank city fields as 'lost samples', meaning that they do not add up to the minimum samples that should be taken to reach the stated precision level. Note that these wrong entries are included in the data, since there is no automatic way to clean wrong entries, but they are not included in the sample size. Thus, it can be concluded that the actual precision of the sample is most probably higher than the 10% as stated in the last section. The third assumption is made to define a distance whenever there are several cities with the same name. In this case, the city closest to the airport is assumed to be the destination location. The last assumption holds in the case that the IATA-code of the airport is the same as the city. Since there are no final addresses in the data, no distance can be calculated from and towards the same city. Therefore, it is assumed that if the IATA-code city is the same as the destination city, the distance is equal to 25 kilometers. This assumption is made to apply an average within-city distance. Note that this assumption is an educated guess and that it is hard to justify this number, since every city has a different size and street mapping. A sensitivity analysis has been applied to test the impact of this assumption (see Appendix B.6).

Results for road distances

The results of the sampling study for road distances are presented in Table 3.3. The road distance percentages stated in Table 3.3 are applied to the Great Circle Distance (GCD) of Philips' shipments. The sum of the road distance percentages of a shipment corresponds on average to 1.38% of the GCD. As discussed in Section 2.2.3, an additional pre-positioning distance of 20% should be included on every shipment lane (NTM Road, 2015). Adding the additional 20% results in the total average distance percentage of 1.66% of the GCD. This road percentage is used to determine CO_2e emissions for the road legs of airfreight shipments.

Table 3.3: Sampling results for road distance

Description	Amount	Percentage
Sample size first leg	155,178 shipments	55.5% of shipments
Sample size last leg	67,684 shipments	24.5% of shipments
Total sample size	222,862 shipments	39.8% of shipments
Average flight distance	8,234 km	-
Average distance first leg	60.20 km	0.73% of GCD
Average distance last leg	53.84 km	0.65% of GCD
Sum distances legs	114.04 km	1.38% of GCD
Total average road distance	**136.85 km**	**1.66% of GCD**

3.3 Description of calculation method for weights

As discussed in Section 2.3, the weight of an airfreight shipment is required in order to calculate the total CO_2e emissions that occur during the flight. The described method of Section 2.3 states that the chargeable weight should be calculated using the actual weight and the volume of the shipment. Unfortunately, according to Philips' Forwarding and Distribution data analyst, the volume data of shipments is completely unreliable. This specialist states that often commas are misplaced, leading to large outliers. This can also be concluded from the data, leading to volumetric weights up to 1.7 million kilograms. The chargeable weight input data is considered as the most reliable shipment weight data and is thus being used for the emission calculations. This chargeable weight data is obtained from the databases of the 3PLs.

3.4 Emission calculation

3.4.1 Emissions with transport mode air

Section 2.4 discusses the use of emission factors and its role in calculating activity-based CO_2e emissions. When selecting a specific emission factor source, the underlying assumptions have to be clear and have to fit the purpose and scope of reporting. Further, the importance of the aircraft type (freighter/belly) was pointed out in Section 2.4. Aircraft data is not standardly captured in the database of Philips' shipments, and thus had to be requested. Some data could be obtained through Philips' biggest 3PL Expeditors. The aircraft type data was obtained for 3.5% of the shipments in scope, which is only a very small portion. This is a random sample of shipments that is captured in one specific data system that stores aircraft specific information. It appeared that 14.9% of the shipped chargeable weight is transported using a pure freight aircraft. The other 85.1% of the shipped chargeable weight is transported as belly freight. Since the aircraft type information is limited, it might be more reliable to work with industry-averages. According to NTM Air (2015), on average 51% of the freight logistics is transported using a full-freighter and 49% using a belly-freighter. These numbers are based on industry-wide average freight traffic data.

In order to work with the different aircraft options, two scenarios are defined and calculated. The first scenario is based on Philips' limited data for aircraft types and the second scenario is based on industry-average aircraft types. For both scenarios, an average load factor of 65% is assumed (NTM, 2019).

Scenario 1: Philips aircraft data

In this scenario, it is assumed that the obtained aircraft data is representative for all flights of Philips. It is chosen to extrapolate the aircraft outcomes over all shipments of all 3PLs. This means that the aircraft type percentages are multiplied with the EFs of Table 2.3 to form a 'combined' representative aircraft. Table 3.4 provides an overview of these weighted emission factors that are applied to Philips' airfreight data. Note that specific aircraft data on all shipments of all 3PLs would greatly improve the accuracy of the emission factor calculation.

Table 3.4: Emission factors for Philips (Scenario 1)

Aircraft range	Distance range (km)	Aircraft type	WTW CO2e (kg/tkm)
Regional	< 785	Combined	2.10
Continental	785 - 3,600	Combined	1.073
Intercontinental	$> 3,600$	Combined	1.023

Until now, Philips assumed that all airfreight shipments are delivered using a full-freighter aircraft with EFs of UK Department for Environment Food and Rural Affairs (2019). It can now be concluded that this assumption results in the application of too low emission factors, especially for intercontinental shipments. Applying the variable emission factors of Table 3.4, together with the distance and weight data into Equation 2.3, the CO_2e emissions per shipment are calculated. The total WTW CO_2e emissions for the airfreight shipments within scope sum up to 1,445 million kg. An overview of CO_2e emissions on a shipment-level is provided in Table 3.5.

Table 3.5: Result of emission calculation (1) (kg CO_2e)

Minimum	1rst Quartile	Median	Mean	3rd Quartile	Maximum
0.00	302.7	1,335.2	5,167.3	4,138.5	1,048,548.9

Scenario 2: Industry-average aircraft data

In this scenario, it is assumed that the available aircraft data of Philips is too limited, since it only reflects 3.5% of the total available data in scope. This percentage is statistically too low to extrapolate over the whole population (Dodge, 2008a). Therefore, the industry-wide averages for aircraft types are applied to the emission factors of Table 2.3. Table 3.6 provides an overview of the emission factors that would be applied under this scenario.

Table 3.6: Emission factors for Philips (Scenario 2)

Aircraft range	Distance range (km)	Aircraft type	WTW CO2e (kg/tkm)
Regional	< 785	Combined	2.10
Continental	785 - 3,600	Combined	1.00
Intercontinental	> 3,600	Combined	0.84

Comparing Table 3.4 and Table 3.6, the most noticeable difference lies in the intercontinental distance range. This difference can result in high differences of calculated emissions, when the amount of intercontinental shipments is high. Applying the emission factors of Table 3.6, together with the distance and weight data into Equation 2.3, the final emissions per shipment are calculated. The total WTW CO_2e emissions for the airfreight shipments within scope sum up to 1,189 million kg. An overview of emissions on a shipment-level is provided in Table 3.7.

Table 3.7: Result of emission calculation (2) (kg CO_2e)

Minimum	1rst Quartile	Median	Mean	3rd Quartile	Maximum
6.9	250.9	1108.6	4,254.1	3416.4	860,978.6

3.4.2 Emissions with transport mode road

Next to the emissions that are released with the airfreight shipment itself, there are also CO_2e emissions for transportation towards and from the airport. In this calculation, it is assumed that separate shipments are consolidated within trucks, such that trucks meet the average 50% load factor. Besides, when the load of a shipment exceeds the maximum weight (15 tonne) of a typical rigid truck (NTM Road, 2015), it is assumed that a shipment can be divided over several trucks and that this does not affect the average load factor. Applying the emission factor calculation of Equation 2.3 and the emission factors of Table 2.4 to the road legs of Philips' shipments, results in a total of 3.35 million kg CO_2e over all shipments in scope. Table 3.8 provides an overview of the road emission calculation on a shipment-level. It can be concluded that on average, the road emissions of a shipment are 0.28% of the air emissions of a shipment.

Table 3.8: Result of emission calculation road (kg CO_2e / tonne-km)

Minimum	1rst Quartile	Median	Mean	3rd Quartile	Maximum
0.01	0.69	3.06	11.98	9.60	2,518.2

3.5 Conclusion and discussion

This last section presents the conclusions of the emission calculation method that has been applied to Philips' airfreight shipments within scope. The total CO_2e emissions of Philips' airfreight are defined as the sum of the airfreight emissions, plus the road emissions for the first and last leg of the shipment. Due to the limited amount of Philips' airplane type data, it is chosen to calculate the total emissions based on two scenarios, as described in Section 3.4. Scenario 2 is expected to be the most representative one, based on industry-wide averages for the division between full freighter airplanes and belly freighter airplanes. In this scenario, the total CO_2e emissions for all Philips' shipments within scope add up to 1,192 million kg CO_2e, which is on average 4,266 kg CO_2e per shipment.

The final output of CO_2e emissions of this calculation method for Scenario 2 are 18.2% higher than the emissions that Philips reported over the same scope. This significant difference can mainly be attributed to the fact that Philips uses EFs of DEFRA with different underlying assumptions. The methodology of this Master Thesis based on NTM EFs is considered to be an improvement as opposed to Philips' method with DEFRA EFs. This is the case, because the EFs of DEFRA are not clearly defined for use outside of the UK (Downie & Stubbs, 2012). DEFRA defines three different emission factors: (1) domestic, to/from UK, (2) short-haul up to 3,700 km and (3) long-haul flights over 3,700 km (UK Department for Environment Food and Rural Affairs, 2019). Currently, Philips applies the UK domestic EF to all global shipments within a distance range of 1,500 km; the short-haul for global flights between 1,500-4,000 km; and the long-haul for flights over 4,000 km, which is considered to be incorrect. Additionally, the EFs of DEFRA only include tank-to-wheel (TTW) emissions, while the methodology of this Master Thesis reports well-to-wheel (WTW) emissions. WTW reporting is recommended, since it includes the total use of energy including fuel production, distribution and combustion (NTM, 2018b). Reporting the full WTW CO_2e impact is relevant for Philips in their ambition to become fully carbon neutral in its operations.

Using the methodology as described in Chapter 2 and Chapter 3 makes emission calculation more transparent by following a clear and coherent set of assumptions. The added value of this Master Thesis method over Philips' former method, can e.g. be seen in the improved distance calculation for the Great Circle Distance (GCD), detour distances and road distances, being more accurate. Besides, many data preparation steps lead to better data quality e.g. by removing outliers and filling in data gaps. These improvement steps are already applied to Philips' official carbon calculation methodology and reporting, which is also discussed in Chapter 7. However, several data gaps are faced when implementing the CO_2e calculation methodology. The biggest issues come up with the lack of specific shipment data, such as the exact route of a shipment and its final address (Section 3.2), the volume of a shipment (Section 3.3), and the vehicle type and its load factor (Section 3.4). These data issues result in the fact that the methodology of Chapter 2 cannot be implemented right away. The assumption with the highest impact is the aircraft type, being either a full freighter or a belly freight aircraft. A high level overview of which data would ideally be used and which data was actually available is presented in Section 6.2.3. Here is also discussed how data gaps are filled in and recommendations for Philips are stated.

Philips states that implementing the complete CO_2e calculation method depends on the target setting and the industry norms for reporting. It is expected that additional costs arise for Philips related to the implementation of the full carbon calculation methodology. When Philips decides to change the emission factors for reporting, the overall emissions increase. Since Philips has an internal carbon price and wants to become carbon neutral in its operations, this would mean that there are more costs incurred with reporting higher emissions. Here, the most important aspect is that Philips is aware of the fact that its current assumptions of TTW reporting and EFs might not be representative. It is recommended that Philips substantiates the decisions for carbon calculations and reconsiders the current assumptions. This has been discussed in formal meetings with the manager of Sustainability Reporting team, and Philips will consider taking the next implementation steps in 2020.

Chapter 4

Transport Mode Selection Problem optimization model

Modelling and optimizing logistics choices is highly complex since there are many criteria to take into account. It is the objective to combine carbon measurement with carbon management, to select lanes that are most suitable for implementing improvements, decreasing the total amount of carbon emissions. This multi-criteria problem takes into account the costs, carbon emissions and service levels of logistics shipments. This chapter describes the general optimization model that can be used for decision-making in logistics processes. Specifically, the model solves the Transport Mode Selection Problem (TMSP), where a decision is made on the transport mode to select for each specific shipment lane. The second research question is be answered:

2. How to develop a general decision-making model that provides a trade-off between emissions, costs and service level indicators?

First, Section 4.1 describes related literature. Then, Section 4.2 discusses the goal and assumptions of the optimization model. In Section 4.3, the model parameters are presented and the mathematical problem is formulated. Section 4.4 analyzes the mathematical model with Lagrange relaxation. Then, Section 4.5 states the conclusions and provides an overview of the trade-offs within the model. Finally, Section 4.6 states directions for future research.

4.1 Related literature

Both the operations management and transport literature, and specifically literature that incorporates carbon emissions, are related to this research. A short introduction to these topics is presented in this section, in order to position the model of this Master Thesis project into the existing literature.

Within the operations management field, literature on Green Supply Chain Management (GSCM) is connected to this work. GSCM is defined by Srivastava (2007) (p. 54-55) as: *'Integrating environmental thinking into supply-chain management, including product design, material sourcing and selection, manufacturing processes, delivery of the final product to the consumers as well as end-of-life management of the product after its useful life'.* The field of GSCM including carbon emissions is rapidly extending to include green inventory models that link inventory, ordering behavior and emissions of e.g. packaging, waste and locations (Bonney & Jaber, 2010). Further, the study of Benjaafar, Li and Daskin (2013) illustrates how carbon emission concerns could be integrated into operational decision-making with regard to procurement, production, and inventory management. Operations research has and will bring important contributions to the environment, but it is quite often implicit and without a clear end-point (Dekker et al., 2012; Bouchery, Corbett, Fransoo & Tan, 2017). Although these papers incorporate carbon emissions in inventory decisions, the transport modality is assumed to be an external parameter.

Several studies have been performed on the topic of transport mode selection or shift, taking into account the environmental effect of transportation. One category of studies considers passenger transport. The article of Bigazzi (2019) evaluates the difference between average and marginal energy and emission factors for passenger transport modes, concluding that policies for increasing or decreasing passenger travel on certain transport modes will have smaller environmental impacts than suggested by average emission factors. The article of Zhang, Liu, Li and Yu (2013) studies the effects of low-carbon constraints on the route and mode choices of trip makers in a network composed of buses and private cars. Further, in this category there are models considering the influence of travel time, travel cost and emissions simultaneously on route selection problems. For example, the article of Nagurney, Dong and Mokhtarian (2002) develops a multi-criteria traffic network equilibrium model with an explicit environmental criterion and solves it for a numerical example where members of a class of traveler perceive their generalized cost as a weighting of travel time, cost and emissions generated. Besides, there are models that discuss environmental constraints to control transport in order to not exceed the corresponding environmental capacity or emission permit (A. Chen, Zhou & Ryu, 2011).

Next to the category of passenger transport, the category of freight transport is especially relevant for this model. Some studies incorporate different carbon emission regulations, such as carbon tax and emission caps, in their decision model for transport modes. The article of Wang, Liu, Choi and Yue (2015) shows that imposing a carbon-emission tax on the product with a higher production cost, a bigger product volume, or a bigger product density can increase the probability of improving social welfare through emission reductions. The article of X. Chen and Wang (2016) studies a retailer's ordering and transportation mode selection problem using stochastic customer demand and investigates the optimal ordering and transportation mode selection decisions under different carbon emission reduction policies. The analytical results reveal that there are some important transportation mode shifting thresholds under different carbon emissions reduction policies.

The TMSP optimization model that is presented in this Master Thesis is mainly based on Hoen et al. (2014a) and Hoen et al. (2014b). The model considers and optimizes for transport modality decisions and inventory simultaneously, where the transport cost and emissions are modelled as a function of product characteristics. Whereas Hoen et al. (2014a, 2014b) presents two separate models, one single-product setting with stochastic demand and one multi-product setting with deterministic demand, this Master Thesis model combines the two into a multi-product stochastic demand setting. Combining these two models ensures that the realistic applicability for a company is improved, since companies most likely have multiple products and face stochastic demand. Another difference between the two models of Hoen et al. (2014a, 2014b) and this Master Thesis model lies in the scope of application. Whereas the studies of Hoen et al. (2014a, 2014b) focus on a European scope, this study focuses on a global scope. This has implications for the transport network to which the model is applied (see Chapter 5).

4.2 TMSP model goal and assumptions

4.2.1 Model goal

The goal of this model is to gain insights in the relationship between costs, carbon emissions and service level of logistics. It can be a reoccurring trade-off for companies to pick the transport mode that balances these three factors. Some companies might just pick the easy and fast option of air transport, while other options might as well meet their service requirements at lower cost and/or emission levels. The model is designed to select specific routes for transport mode shift that have the highest positive impact in terms of cost and emissions. The model has a tactical decision level, which means that the results correspond to longer term choices in transportation. The model can be reconsidered e.g. every year; or when it is known that changes occurred in the transportation of certain lanes; or when the emission reduction target changed. The model solves the Transport Mode Selection Problem (TMSP): which transport mode to use for shipments to each of the locations in order to meet a predetermined emission target for all products together, while minimizing the overall costs. The costs that are taken into account in this model include: transportation costs, holding costs for items in transportation and in stock, penalty costs for not fulfilling customer demand and emission penalty costs.

The study considers a company that ships products to customers worldwide using only airfreight. The company wants to reduce the emissions related to transport of the products by shifting to less polluting transport modes. In this situation, multiple products are taken into account to satisfy one overall emission constraint. With this, the company makes use of the portfolio effect. The purpose of the portfolio effect is to compensate costly emission reductions on one lane with less costly reduction on another lane to achieve emission reductions at an overall lower cost (Hoen et al., 2014b). This decision model is useful when it is given that the overall emissions of a product portfolio should decrease to reach a specific target, but it is unknown which products or lane(s) to select for modal change. Thus, this model represents a multi-item multi-modal logistics trade-off.

4.2.2 Model assumptions

This subsection describes the assumptions that are made in relation to the optimization model. As a first step, the assumptions regarding transportation are stated. First, in this model it is assumed that the company can determine which transport mode to use for all shipments to a specific customer. This assumption corresponds with a situation in which the producer agrees with the customer a service level regarding the delivery of products (Hoen, 2012). Secondly, it is assumed that the model is generically applicable to several transport modes, e.g. air, road, rail and ocean. It is assumed that within one shipment, only one of the options air, rail or ocean can be chosen. All transport modes use a multi-modal combination with the transport mode road, except for the case when only the mode road is being used. If it is undesirable or infeasible that a particular transport mode is used, e.g. because of network restrictions, then the transport cost is set to infinite. Thirdly, it is assumed that the transport activity is outsourced and executed by a 3PL. If transport would be executed by company-owned vehicles, a modal shift may in fact be a capital investment decision. The assumption that transport is outsourced has implications for the cost function and emissions structure. Namely, only a variable cost component per shipped unit or shipped weight is considered. Fourth, it is assumed that transport consolidation can be used on every shipment lane. In practice, this means that a large shipment can fill up an entire vehicle, or a small shipment can be consolidated with other small shipments in a vehicle. This results in the fact that every vehicle is filled up to the average load percentage.

As a next step, some assumptions about the scope are stated. First, only shipments that have a warehouse as final destination are within the scope of this model. This scope is set, in order to be able to measure the service level of a shipment and to make general comparisons. Secondly, it is assumed that no lateral transshipments take place between warehouses. Demand can only be fulfilled by sending a new order from the production site to the specific warehouse. Thirdly, this model only considers shipment decisions and not production decisions. This is a valid assumption when the buffer stock at the production site is enough to always fulfill a shipment. Finally, it is assumed that demand is fulfilled using a first-come-first-serve policy. All demand that cannot be fulfilled directly from stock is backordered and has to be fulfilled before any new demand can be fulfilled.

4.3 TMSP model description

The problem to solve is which transport mode to use for shipments to each of the customers to meet a predetermined emission target for all customers together while minimizing the total costs. This problem is solved as a variant of the famous knapsack problem, where each shipment should be assigned to a transport mode (Fisher, 1981).

4.3.1 Model parameters

This subsection describes the parameters that are being used in the model. Let I={1,2,...,n} ($i \epsilon I$) denote the set of available transport modes. Let J={1,2,...,m} ($j \epsilon J$) denote the set of shipments. Each shipment consists of a product type, an origin location, which is a warehouse or a production site, and a destination location, a warehouse. In the remainder of this section the term 'shipment' is used to denote one transportation of products to this specific warehouse. Table 4.1 provides an overview of the parameters that are used in the TMSP optimization model.

Transportation equations

The transportation cost ($t_{i,j}$) depends on the transportation cost rate of a shipment ($f_{i,j}$), the distance of a shipment ($\delta_{i,j}$) and the weight of a shipment (w_j), as shown in Equation (4.1). Note that the distance of a shipment depends on the transport mode that is being used.

$$t_{i,j} = \delta_{i,j} \cdot f_{i,j} \cdot w_j \tag{4.1}$$

Table 4.1: TMSP optimization model parameters

Parameter	Description
$\mathrm{w_j}$	The chargeable weight of a shipment (tonne)
$\delta_{\mathrm{i,j}}$	The distance (km) of a shipment j with a specific mode i
$\mathrm{k_j}$	The value density of a shipment (€/tonne)
$\mathrm{l_{i,j}}$	Lead time for shipment j using mode i
$\mathrm{f_{i,j}}$	The transportation cost rate of a shipment (€/tonne-km)
$\mathrm{EF_{i,j}}$	Emission factor (kg CO_2e/tonne-km) for transport mode i and shipment j
$\mathrm{h_c}$	Holding cost rate (€)
$\mathrm{p_c}$	Penalty cost rate (€)
ϵ	Emission reduction target (%)
$\mathrm{h_{i,j}}$	Holding costs (€) of a shipment j using mode i
$\mathrm{t_{i,j}}$	Transport costs (€) of a shipment j using mode i
$\mathrm{e_{i,j}}$	Unit emissions (kg CO_2e) of shipment j using mode i
$\mathrm{s_{i,j}}$	Holding costs (€) over inventory in destination j using mode i
$\mathrm{p_{i,j}}$	Penalty costs (€) for insufficient inventory in destination j using mode i
$\mathrm{d_j}$	Stochastic demand at shipment j's destination

Holding cost is the cost associated with physically having inventory in stock. Such a cost arises due to the capital invested in the inventory (capital cost) and to rent/write-offs on warehouses, salaries to staff etc. (Berling, 2008). The same principle holds for inventories that are caught up in transportation. Holding costs ($\mathrm{h_{i,j}}$) do in this model depend on the total weight ($\mathrm{w_j}$) of a shipment; the transport leadtime ($\mathrm{l_{i,j}}$); the shipment value density ($\mathrm{k_j}$) and the holding cost rate ($\mathrm{h_c}$). It is assumed that holding costs are paid over each day that has been used (partially). The holding cost calculation can be seen in Equation (4.2).

$$h_{\mathrm{i,j}} = h_{\mathrm{c}} \cdot k_{\mathrm{j}} \cdot l_{\mathrm{i,j}} \cdot w_{\mathrm{j}} \tag{4.2}$$

The emissions associated with transporting one shipment j using mode i are denoted by $\mathrm{e_{i,j}}$. The total CO_2e emissions of a shipment can be the sum of multiple transport modes, e.g. multi-modal with road when using air or ocean transport. In this situation, the emissions are calculated separately per mode and summed afterwards. The calculation for the emissions is based on the NTM methodology (NTM, 2018b) (see Chapter 2). The emissions are denoted by Equation (4.3).

$$e_{\mathrm{i,j}} = w_{\mathrm{j}} \cdot EF_{\mathrm{i,j}} \cdot \delta_{\mathrm{i,j}} \tag{4.3}$$

Inventory equations

As stated above, holding cost is the cost associated with physically having inventory in stock. Holding costs are incurred for each unit of stock in a warehouse at the end of a period, and the average is denoted with: $E\left[IL_i^+\right]$ in tonnes. Note that the underscore i denotes that the expected inventory at the end of a period depends on the transport mode being used. A slower transport mode would typically require higher stocks to cover the demand during the leadtime. Then, the inventory holding cost of the total inventory in a specific warehouse depends on the holding cost rate ($\mathrm{h_c}$), the value density of a product ($\mathrm{k_j}$) and the expected inventory ($E\left[IL_i^+\right]$) as. This relation is denoted in Equation (4.4).

$$s_{\mathrm{i,j}} = h_{\mathrm{c}} \cdot k_{\mathrm{j}} \cdot E\left[IL_i^+\right] \tag{4.4}$$

Penalty cost, also known as the shortage cost or the stock-out cost, is the cost of not having sufficient stock on hand to satisfy demand when it occurs (Nahmias, 2014). Such a cost arises due to unfulfilled demand and potentially losing customers to competitors. The average number of units of unfulfilled demand at the end of a period is denoted by: $E\left[IL_i^-\right]$ in tonnes. Since all unfulfilled demand is backordered, this is equal to the expected number of backorders. Then, the penalty cost depends on the penalty cost rate ($\mathrm{p_c}$), the value density of a product ($\mathrm{k_j}$) and the expected backorders ($E\left[IL_i^-\right]$). This relationship is denoted in Equation (4.5).

$$p_{\mathrm{i,j}} = p_{\mathrm{c}} \cdot k_{\mathrm{j}} \cdot E\left[IL_i^-\right] \tag{4.5}$$

The values for $E\left[IL_i^+\right]$ and $E\left[IL_i^-\right]$ denote the expected inventory and expected backorders at the end of a period respectively. When deriving the expected values for inventory and backorders at the end of a period, one could make use of the equations of Hoen (2012), Chapter 2. The only differences between Hoen (2012) and this model are that: (1) this model expresses demand per shipment per period, whereas the single-product model of Hoen (2012) defined demand as a function of the leadtime and (2) in this model the holding costs and penalty costs do not depend on an emission cost. Let $\mathrm{d_j}(\mu, \sigma)$ denote the demand for shipment j during one period, which is independent of the transport mode used. Demands in different periods are assumed to be independent and identically distributed (i.i.d.). Let $f_i(x)$ and $F_i(x)$ denote the probability density function and cumulative distribution function of demand during a period. Additionally, S_i is defined as the order-up-to level for inventory in the destination warehouse using transport mode i. This order-up-to level can be determined by application of the single-period newsvendor problem or can be a given input parameter based on warehouse capacity and demand characteristics in the supply chain. Then, the expected inventory and expected backorders at the end of a period can be derived using equations (4.6), (4.7) and (4.8).

$$G_i(y) = \int_y^\infty (x-y) f_i(x) \mathrm{d}x \tag{4.6}$$

$$E\left[IL_i^-\right] = G_i(S_i) \tag{4.7}$$

$$E\left[IL_i^+\right] = S_i - \mu + G_i(S_i) \tag{4.8}$$

4.3.2 Mathematical problem formulation

This section states the mathematical model formulation. The purpose of the model is to minimize the total costs while meeting a specific emission reduction target (ϵ). It is assumed that the sales price and quantity are fixed for all products, selecting a suitable transport mode based on historical data. The average number of products shipped per period is equal to the average demand μ_j. The total costs per time unit for transport mode i and shipment j are denoted by Equation (4.9).

$$C_{i,j} = p_{\mathrm{i,j}} + s_{i,j} + \mu_j (h_{i,j} + t_{i,j}) \tag{4.9}$$

It is assumed that the starting inventory levels are known and that the historical shipments are transported in sufficient amounts such that demand is being met against a desirable service level. Further, the total emissions per time unit are denoted by Equation (4.10).

$$E_{\mathrm{i,j}} = \mu_j \cdot e_{\mathrm{i,j}} \tag{4.10}$$

Let $\mathrm{x_{i,j}}$ ($\mathrm{x_{i,j}} \epsilon \{0,1\}$) denote whether mode i is used for shipment j. Note that only one transport mode i can be chosen for each shipment j. This is the transport mode that is always used to transport this specific product on this specific lane. The mathematical formulation of the Problem (P) can be stated as:

Minimize:

$$C(\mathrm{x}) = \sum_{j \epsilon J} \sum_{i \epsilon I} x_{i,j} \cdot C_{ij}$$

Subject to:

$$E(\mathrm{x}) = \sum_{j \in J} \sum_{i \in I} x_{i,j} \cdot E_{ij} \leq \epsilon$$

$$\sum_{i \epsilon I} x_{i,j} = 1 \ \forall j \epsilon J$$

$$x_{ij} = \begin{cases} 1 & \text{if } i \text{ assigned to } j \\ 0 & \text{otherwise} \end{cases}$$

The objective function minimizes the overall costs over all shipments j and all transport modes i. The first constraint ensures that the emission reduction target is met, whilst the second and third constraints ensure that one (and only one) transport mode i is assigned to each shipment j.

4.4 TMSP model solution

4.4.1 Mathematical analysis

The constrained minimization Problem (P) is solved using Lagrangian relaxation. With Lagrangian relaxation, the multi-item problem can be decomposed in multiple single-item problems. A useful property of Lagrangian relaxation is that all solutions that are generated are efficient, i.e. there is no solution with higher profits given that emission target, but not all efficient solutions are generated. This mathematical analysis is based on cost-minimization case in the work of Hoen (2012), Chapter 3. The main difference between this work and Hoen (2012) lies in the definition of total costs $\mathrm{C_{i,j}}$. This work includes both transport and inventory costs in the model, whereas the model of Hoen (2012) excluded the effect of demand, inventory costs and penalty costs. However, solving the constrained minimization problem using Lagrangian relaxation here follows the exact same steps as in Hoen (2012) Chapter 3.

In Lagrange relaxation, a penalty cost is introduced for violation of the constraint, in this case the emission target (ϵ). This means that the first constraint of Problem (P) is relaxed. It is not a hard constraint anymore, but the emission penalty ensures that the end-result comes as close as possible to the target. The Lagrangian function for Problem (P) is defined as in Equation (4.11).

$$L(\mathbf{x}, \lambda) = \sum_{j \in J} \left(\sum_{i \in I} x_{i,j} C_{i,j} \right) - \lambda \left(\sum_{j \in J} \left(\sum_{i \in I} x_{i,j} E_{i,j} \right) - \epsilon \right), \tag{4.11}$$

where $\lambda \geq 0$ is the Lagrange multiplier. As λ increases, it reduces the emissions by charging a higher penalty. Since the costs and emission function are separable in j as is the implicit constraint $((x) \in (X))$, the Lagrangian is also. Hence the Lagrangian can be written as:

$$L(\mathrm{x}, \lambda) = \sum_{j \in J} L_j \left(\mathrm{x}_j, \lambda \right) + \lambda \epsilon, \tag{4.12}$$

where

$$L_j \left(\mathbf{x}_j, \lambda \right) = \sum_{i \in I} x_{i,j} C_{i,j} - \lambda \sum_{i \in I} x_{i,j} E_{i,j} \tag{4.13}$$

is the *decentralized Lagrangian* for shipment j. See Appendix C.1 for clarification steps on Lagrange relaxation. Note that the Lagrangians are only connected by a single multiplier λ of the emission constraint. For a given value of λ there is a solution $\mathrm{x}^*(\lambda) = (\mathrm{x}_1^*(\lambda), \ldots, \mathrm{x}_m^*(\lambda))$ that minimizes the Lagrangian. If $\epsilon = E(\mathrm{x}(\lambda))$, then, by the Everett result (Everett, 1963) , $\mathrm{x}(\lambda)$ is the optimal solution to the mathematical Problem (P) and the constraint will be met with equality. See Appendix C.2 for clarification on the Everett result. By varying the value of λ, different optimal solutions to the mathematical problem for specific values of ϵ are obtained. Note that this technique is not in general certain to produce solutions for all interesting constraint levels. It follows from Theorem 1 of Everett (1963) that these solutions are efficient solutions for the unconstrained multi-criteria Problem (Q):

$$\min_{\mathrm{x}\in \mathrm{X}} C(\mathrm{x})$$

$$\min_{x\in X} E(\mathrm{x})$$

The advantage of having an unconstrained Problem (Q) is that it can be solved by only applying minimization techniques. The decentralized Lagrangian can be separated further in mode i, because it is separable and only connected by the implicit constraint $(x_j) \in (X_j)$). We denote this function by

$$L_{i,j}(\lambda) = C_{i,j} + \lambda E_{i,j} \tag{4.14}$$

The decentralized Lagrangian can then be rewritten as follows, which follows from Equation (4.13) :

$$L_j(\mathbf{x}_j, \lambda) = \sum_{i\in l} x_{i,j} L_{i,j}(\lambda) \tag{4.15}$$

Applying Equations (4.10), (4.11) and (4.13) to Equation (4.15), the following result is obtained:

$$L_j(\mathbf{x}_j, \lambda) = \sum_{i\in l} x_{i,j}(\mathrm{p_{i,j}} + s_{i,j} + \mu_j(h_{i,j} + t_{i,j} + \lambda e_{i,j})) \tag{4.16}$$

This can be rewritten in the final decentralized Lagrangian function:

$$L_j(\mathbf{x}_j, \lambda) = \sum_{i\in I} x_{i,j} z_{i,j}(\lambda) \tag{4.17}$$

where

$$z_{ij}(\lambda) := \mathrm{p_{i,j}} + s_{i,j} + \mu_j(h_{i,j} + t_{i,j} + \lambda e_{i,j})$$

represents the inventory cost and logistics cost including emissions. Minimizing the decentralized Lagrangian over $x_j \in X_j$ is equivalent to selecting the mode that minimizes $z_{i,j}(\lambda)$. For this model, the Lagrangian is decreasing in λ. Note that for a given λ, only the value of $z_{i,j}(\lambda)$ determines the differences in the values of $L_j(\lambda)$ for different modes of shipment j. This is true since the mean demand μ_j is stable and $x_{i,j}$ is the decision variable. This implies that if the values of $z_{i,j}(\lambda)$ for the two modes are equal, then the model is mathematically indifferent between selecting a mode with lower cost and higher emissions, and higher cost and lower emissions. Note that the overall goal of this model is emission reduction, so in this case the most sustainable mode is selected.

4.4.2 Model output

After the transport mode allocation is performed, the total emissions, logistics cost and inventory cost of this allocation can be calculated. The total emissions $\mathrm{E}(\mathbf{x})$ are equal to the sum of emissions $(\mathrm{e_{i,j}})$ of all shipments, which depend on the transport mode being used per lane $(\mathrm{x_{i,j}})$. Here, $(\mathbf{x})$ denotes an allocated transport mode for each of the shipment lanes $\mathrm{x}^*(\lambda) = (\mathrm{x}_1^*(\lambda), \ldots, \mathrm{x}_m^*(\lambda))$. Then, the total costs of this solution $\mathrm{x}^*(\lambda) = (\mathrm{x}_1^*(\lambda), \ldots, \mathrm{x}_m^*(\lambda))$ are the sum of the logistics costs and inventory costs, $C_{ij}(\mathbf{x})$. This can be calculated over every time unit, e.g. per month or year. Note that this cost also reflects the service level, since the cost for not fulfilling demand is higher than the cost for having inventory. A low service level is reflected in high penalty costs. For different values of λ a different solution can be obtained when a lane shifts between transport modes. Every obtained solution is an efficient solution, in the sense that no solution has both lower emissions and lower costs.

4.5 Conclusion

The mathematical TMSP optimization model as presented in this chapter is able to solve the second research sub-question generically. It can be applied to any product mix, route and transport mode, as long as all required input parameters are available (see Table 4.1). The purpose of the model is to minimize the overall transportation and inventory costs, while taking into account an emission constraint. This model is developed for a company to decide on a tactical level which lanes are most suitable for a transport mode shift. When specific lanes are selected for a transport mode shift, an in-depth investigation of the required changes in the supply chain structure is needed. These required changes might concern production capacity, warehouse capacity, or increased handling costs of freight. A company can rerun this model e.g. every year to select new lanes for transport mode shift. Also when it is known that changes occurred in the transportation of certain lanes; or when the emission reduction target changed the solution can be reconsidered. The case study of Chapter 5 applies this TMSP model to a subset of Philips' freight logistics.

4.6 Directions for future research

In the current model, the service level is only taken into account indirectly by charging higher costs for missing demand. It is also an option to set a service level constraint and use this as an additional constraint in the Lagrange optimization model. A similar method would apply as for the emission constraint in Problem (P). Then, there would be two Lagrangian multipliers λ_k ($\lambda > 0$), where each λ_k can be interpreted as a penalty cost for violating the k-th constraint. This can be useful when it is observed that the current penalty cost for not fulfilling demand is not high enough to ensure satisfying service levels.

Another useful addition to this model could be to implement the option for a transport mode mix. Then, the model would not necessarily pick one transport mode per shipment, but could indicate which percentage is performed by one mode or the other. For example, one shipment lane could be on default transported with ocean, but 10% of the shipments could be performed by air. This addition can be implemented mathematically by changing the last constraint of Problem (P), which states that $\mathrm{x}_{\mathrm{i,j}}$ can only get the integer values 0 and 1. This constraint can be changed such that each mode gets a ratio score which represents the percentage of shipments allocated to this transport mode. The second constraint $\sum_{i\epsilon I} x_{i,j} = 1 \; \forall j\epsilon J$ ensures that the sum of the modes is equal to 1. Then, at each moment in time, one could consider the current inventory levels and the inventory in transit, and decide whether the next shipment can use a slower and more sustainable transport mode, or needs the faster and more polluting mode. This is useful when demand variability is high or demand can only be forecasted on short notice. Implementing this additional feature would shift the level of the model from tactical to a more operational level.

Furthermore, future research can be performed on how this model with single echelon perspective can be extended to a supply chain perspective. Currently, it is assumed that production always meets the amounts that should be transported. However, this assumption might not hold in reality, leading to logistics planning issues. When production is late, it is tempting for companies to use a faster but more polluting transport mode to still meet targets for customer service levels. Supply chain cooperation and communication is required in order to solve this issue. As a final point of discussion, the current model does not take into account the trade-off between increasing inventory capacity or shipping more frequently. This is a relevant trade-off when shifting to a transport mode with higher leadtimes and higher leadtime variability, since this requires higher stock levels. This could e.g. be done mathematically by incurring a cost for increasing warehouse capacity.

Chapter 5

Case study Philips: TMSP

The purpose of this chapter is applying the methodology described in Chapter 4 to Philips' data as a case study. This shows the potential of the model and how it can be used in practice. This chapter functions as an implementation of the second research question:

2. How to develop a general decision making model that provides a trade-off between emissions, costs and service level indicators?

Section 5.1 describes the scope of the application and the subset of data that is being used. Section 5.2 describes all input parameters. Then, Section 5.3 shows how the model is applied to Philips' data by using a simulation model. It is chosen to implement the Transport Mode Selection Problem (TMSP) optimization model with the help of simulate data, due to data restrictions. In this section, the pseudo-code for implementation is given, as well as a description how leadtimes, demand and inventory are simulated. Section 5.4 presents the simulation results. Section 5.5 presents the sensitivity analyses. Finally, Section 5.6 states the conclusions and provides a discussion.

5.1 Data subset

In order to apply the mathematical TMSP model of Chapter 4, scoping of the original problem is required. The main reason why a selection of lanes is required for this application, is unavailable data about which items are being shipped. Therefore, product type and value estimation needs to be done manually with the help of a specialist at Philips. It is decided to implement the TMSP model on the lanes that have the highest CO_2e impact for Philips. The Commodity Manager of Philips Forwarding and Distribution department states that the lane with highest CO_2e emissions recently shifted from airfreight to ocean freight. Thus, it is expected that this lanes' emissions strongly decrease in the coming year. For the following 20 lanes, there is no transport mode shift or changes in the policy for the coming year as opposed to the years 2017-2019. Therefore, these 20 lanes have been selected as scope. These lanes together account for 25.6% of all logistics emissions within Philips. The time period over which these shipments occurred is January 2017 until October 2019.

Table 5.1 provides an overview of the 20 lanes in scope and their shipment characteristics such as segment, average weight and estimated value. The origin, destination and segment data have been coded to ensure confidentiality. Here, the location codes consists of a world region and a number, where every replication of the same location gets the same code. The world regions are shown on a map in Appendix D.1. The average shipment weight could directly be calculated from the available data, and therefore represents the true shipped amount. The average value per shipment is estimated, by taking for each segment an estimated value density (€/kg) and multiplying with the average weight. To obtain this value density, both the weight and the value of one product had to be estimated. Multiple sources and specialists have been consulted per segment, in order to estimate the average product value and average product weight. Here, the origin location is taken into account as well as the product mix produced at this specific production site. Then, a weighted average is taken over the product weight and value in order to estimate an 'average' product that is transported (see Appendix D.2). Note that it is difficult to state the accuracy of the estimations, since the exact contents of shipments are unknown. However, this is the best product value estimation that could be obtained in order to show the implementation and relevance of the model.

Table 5.1: Overview of shipment characteristics of the 20 lanes in scope

Lane	Origin	Destination	Segment	# shipments	Avg. weight (kg)	Avg. value (€)
1	NAM1	APAC2	A	1,214	3,175	12,065
2	NAM2	EUR1	A	1,390	8,185	31,103
3	EUR1	APAC3	B	3,267	1,142	151,886
4	EUR1	APAC2	B	1,837	1,817	241,661
5	NAM3	EUR1	C	8,387	640	153,600
6	APAC1	EUR2	A	1,017	1,777	6,753
7	EUR1	APAC4	B	2,702	1,276	169,708
8	NAM1	EUR2	A	1,710	1,763	6,699
9	NAM3	EUR3	D	5,520	733	76,232
10	NAM2	APAC3	A	299	7,859	29,864
11	APAC3	EUR1	C	2,868	761	182,640
12	APAC4	NAM4	E	454	2,665	44,506
13	EUR1	APAC5	B	978	2,122	282,226
14	NAM1	APAC3	A	701	2,002	7,608
15	EUR1	NAM5	B	1,276	1,617	215,061
16	EUR1	APAC1	B	1,876	992	131,936
17	NAM5	APAC6	F	893	986	8,184
18	NAM5	EUR1	F	1,157	1,612	8,544
19	EUR1	APAC6	B	1,434	800	106,400
20	APAC1	NAM3	A	699	1,600	6,080

All calculations related to the implementation of the TMSP optimization model are performed using an estimated shipment value. This is obtained by multiplying the actual shipment weight with the estimated product value density. The scope of this case study is set to the use of two transport options only: a combination of air-road or a combination of ocean-road. This decision has been made, because of the fact that no route within scope is suitable for road transport due to the long distances, and because Philips never uses rail transport. Therefore, no data could be obtained about the potential train network to use, its distances, leadtimes or costs.

5.2 Input parameters model

This section describes the input parameters as being used in the numerical application and analysis of the multi-item multi-modal optimization model of Chapter 4. Each of the parameters of Table 4.1 is handled in this section. Note that the weight of a shipment (w_j) is provided by Philips. The cost of a product is estimated using the value density (k_j) as described in Section 5.1.

5.2.1 Holding cost rate (h_c)

Holding cost is the cost associated with physically having inventory in stock. The holding costs are most commonly obtained by taking a percentage of the product value, the holding cost rate (h_c), multiplied with the amount of inventory on hand. This holding cost rate is often in the range of 12 to 34% depending on the industry (Berling, 2008). Hoen (2012) assumes a holding cost rate of 25% per year. Since this model has similar application and the cost rate falls in the middle of the range as described by Berling (2008), the 25% rate is also used in this case study. This would result in a holding cost rate of 0.0048 per week, or 0.00068 per day. Here, it is assumed that transport can occur 365 days a year. Holding costs are calculated over items that are in transportation and over items that are in the warehouse inventory. To find the total holding costs, this cost rate is then multiplied with the product value and weight, following Equations 4.2 and 4.4.

5.2.2 Penalty cost rate ($\mathbf{p_c}$)

Penalty cost is the cost associated with having not enough inventory to fulfill demand. When demand cannot be fulfilled from stock immediately, a customer can be lost and go to a competitor. The other option is that a backorder is placed, and that the customer waits until the next batch of products arrive to fulfill demand later. This last option is assumed in this model, which comes with a cost that represents reduced customer satisfaction. The cost of not fulfilling demand is higher than the cost of having these items on stock. Hoen et al. (2014a) assumes in their model that the penalty cost rate (p_c) is 10 times higher than the holding cost rate (h_c). This assumption is also applied to the model in this Master Thesis, which results in a penalty cost rate of 0.0068 per day. The impact of this assumption is tested with a sensitivity analysis in Section 5.5.

5.2.3 Distance per transport mode ($\delta_{\mathbf{ij}}$)

In this subsection, the distances per transport mode are discussed. The methodology for distances of air transport has been discussed elaborately in Chapters 2 and 3. This calculated distance is therefore also used in this model. For all shipments within scope the methodology is able to calculate an air distance.

Next, the distances for ocean transport have to be calculated. Since there are only 20 lanes in scope, the distances could be calculated manually using an online tool that calculates distances between sea ports (Sea-distances.org, 2020). It is assumed that a shipment always uses the port that is closest to the origin and destination. Afterwards, the ocean distance in nautical miles has been converted to ocean distance in kilometers by multiplying with 1.852 (Wikipedia, 2019b). In order to calculate the first and last leg of every shipment, a similar methodology is applied as in Section 2.2.3. The NTMCalc 4.0 tool has been used in order to calculate the road distance between the port and the origin/destination city (NTM, 2019). Here, it was again assumed that the within city distance is on average 25 kilometers. This means that when the port is in the same city as the origin/destination, then a road distance of 25 km is applied. Further, it is again assumed that there is always a 20% detour on road distances as opposed to the optimal route. Then, these road distances are added to the specific shipment when the transport mode ocean is being used. Appendix D.3 provides an overview of the distances per transport mode and their corresponding road distances.

5.2.4 Leadtime per transport mode ($\mathbf{l_{ij}}$)

The leadtime is defined as the total transportation time of a product between leaving the origin address and arriving at the destination address. This time depends on the transport mode being used, but also on the origin and destination locations. It is assumed that there are three phases in each transport: pre-carriage, transport and post-carriage. The carriage stages exist in order to move the product to the right (air)port and to load the product(s) in and out of the vehicle. Data of the contracted transportation leadtimes for both air and ocean could be obtained of 3PLs. Note that these leadtimes are not the actual or realized leadtimes per transport mode but only the planned duration.

Applying the contracted country-to-country ocean leadtimes to the shipment lanes, results in an available leadtime for 93.4% of the shipments with an average leadtime of 28.7 days. This means that for 6.6% the country-to-country connection did not exist in the data file. In order to fill in the best estimate, multiple regression analysis is performed. In simple linear regression, the model shows how the mean of variable Y depends linearly on the value of a predictor variable X; this relationship is expressed as the conditional expectation $E(Y|X) = b_0 + b_1 * X_1$ where b_0 is a constant and b_1 is the regression coefficient (Krzywinski & Altman, 2015). To determine the prediction accuracy the coefficient of determination (R^2) can be used. The R^2 is calculated as the squared correlation between the actual and the predicted values of the dependent variable. Moreover, the R^2 can have a value between 0 and 1, where $R^2 = 1$ means a perfect prediction, and $R^2 = 0$ means no prediction. When more than one variable predicts the outcome, the simple linear regression becomes a multiple linear regression. To expand the simple regression equation, the independent variable with the greatest predictive power should be added. The equation becomes as follows: $Y = b_0 + b_1 \cdot X_1 + b_2 \cdot X_2 + \epsilon$ where ϵ is the prediction error. Every time a variable is added, the R^2 increases. Therefore the *adjusted* R^2 is introduced, which prevents over-fitting, and does not increase every time you add another variable (Hair, Black, Babin & Anderson, 2014).

A multiple linear regression model for ocean leadtime includes the variables distance, origin region and destination region of a shipment. The different regions that are used by Philips in this data set are discussed in Appendix D.4. Each of the relations in the model is significant and the prediction scores $R^2 = 0.62$. This means that 62% of the variation in ocean leadtimes is explained by this multiple linear regression model. An overview of the multiple regression model can be found in Appendix D.5.

For air transport leadtimes, a similar methodology has been applied. First, the country-to-country air leadtimes have been applied to the shipments file. It appears that for 69.5% an air leadtime was found and for the remaining 30.5% the country-to-country connection did not exist in the data file. Unfortunately, the linear regression model methodology did not work well for the air leadtimes. The air leadtime could not reliably be predicted by any (combination) of the other variables in the data. Therefore, the missing air leadtimes are filled in based on a region-to-region data mapping. Again, Appendix D.4 provides an overview of the leadtime per region that is used and Appendix D.5 shows the air leadtime overview. The mean contracted leadtime for air transport is equal to 6.4 days.

Now the leadtimes from (air)port-to-(air)port have been filled in, the leadtimes by road for the first and last leg need to be determined. Since there is no data available about the actual road transport, it is assumed that the speed of a truck equals 400 km/day (Hoen et al., 2014a). Then, with the help of the road distances (see Appendix D.3), this can be easily calculated towards the expected leadtimes. An overview of the road leadtimes per transport mode is given in Appendix D.5.

5.2.5 Transportation costs ($\mathbf{f_{ij}}$)

In this subsection, the costs per transport mode are discussed. Since the subset of data that is used for this model consists of air shipments, the total transport costs for the transport mode air are a known input for each shipment.

The costs for transport mode ocean have to be estimated. Data is obtained from Philips' 3PLs with the total costs per container on a country-to-county lane base. It is assumed that freight is transported in the standard container size of 20 feet. The maximum payload of such a container is 25,000 kg (DSV Global transport and logistics, 2020). This is used to allocate a portion of the costs of each container to a shipment. As stated in Chapter 5, it is assumed that a shipment can be spread over multiple containers and/or transport consolidation is assumed. Due to this assumption, the average load factor of a container is equal to 70% (NTM Sea, 2015). The total transport cost of a container is then estimated using Equation 5.1, filling in the country-to-country container costs (€).

$$\text{Cost ocean shipment (€)} = \text{cost container (€)} \cdot \frac{\text{weight shipment (kg)}}{\text{load factor \%} \cdot \text{container capacity (kg)}} \tag{5.1}$$

After this calculation, there is an ocean transport cost calculated for 93.4% of the shipments. For the remaining 6.6% of the shipments, the country-to-country transportation cost did not exist in the input file. Therefore, again multiple linear regression is applied in order to build a prediction model. According to Equation 4.1, the transportation cost of a shipment is linearly increasing in weight and distance. The multiple linear regression model for transport cost, based on ocean distance and the weight of a shipment, results in a reliable prediction model with $R^2 = 0.97$. The variables in the model were log-transformed in order to prevent negative cost predictions. Appendix D.6 provides an overview of the model and the results for ocean transport costs.

5.2.6 Remaining transport parameters

Finally, this subsection defines the general transport parameters that are used. This includes the transport mode, the region where the vehicle is used, the vehicle capacity, the average load factor, and the emission factor (EF) per transport mode (see Table 5.2). For the transport mode air, the assumptions of Scenario 2 hold (see Section 3.4). This means that an industry-average aircraft is used, where 51% of the flights use a full-freighter and 49% uses a belly-freighter aircraft. For the transport mode road, the EF per specific region is used if applicable, otherwise the world average for road transport is used.

Table 5.2: Transport parameters per mode (NTM, 2018b)

Mode	Region	Average load	Vehicle capacity	EF (kg CO2e/tkm)
Air	Regional (< 785 km)	65%	5,327 kg	2.10
Air	Continental (785-3,600 km)	65%	41,146 kg	1.00
Air	Intercontinental (> 3,600 km)	65%	91,937 kg	0.84
Road	Europe	50%	Rigid truck 20-26 tonne	0.130
Road	United States	50%	Rigid truck 20-26 tonne	0.136
Road	Asia	50%	Rigid truck 20-26 tonne	0.160
Road	South America	50%	Rigid truck 20-26 tonne	0.130
Road	World average	50%	Rigid truck 20-26 tonne	0.139
Ocean	Intercontinental	70%	6,000 - 12,000 TEU	0.0159

5.3 TMSP implementation

This section states all steps that are performed in order to implement the generic TMSP model to Philips' data as a case study. Unfortunately, no data could be obtained about the exact shipment contents, their leadtimes, demand variation or stock levels. Therefore, data had to be simulated in order to implement the TMSP model and show its potential. For this purpose, some assumptions about the leadtime variability (Subsection 5.3.1), demand variability (Subsection 5.3.2) and starting inventory levels (Subsection 5.3.3) have to be made. Note that, even though these assumptions are made as realistic as possible, they are always simplifications as opposed to reality. A high level overview of which data would ideally be used and which data was actually available is presented in the next chapter, Section 6.2.3. Here is also discussed how data gaps are filled in and recommendations for Philips are stated. Subsection 5.3.4 states how the service level of the simulation can be calculated. Finally, Subsection 5.3.5 states the pseudo-code of the implementation of the TMSP model to simulated data. With this pseudo-code, the methodology can always be replicated for other applications inside or outside Philips.

5.3.1 Leadtime variability

In Subsection 5.2.4, the contracted transport leadtimes per mode are discussed. However, in reality, the actual transportation is not always as planned and delays may occur. The actual transportation time may for example depend on the route, shipping mode, and period of the year (Freightos, 2020). Unfortunately, there is no data available at Philips that states the realized leadtimes for shipments by air or ocean transport. Therefore, these values need to be estimated in order to simulate a system that is as close as possible to the real world. For this purpose, several sources have been consulted and the best estimate is filled in. A leadtime variability is only applied to the air and ocean part of the shipments, and not to the first and last road leg. This decision has been made, since the first and last leg only make up a small percentage of the total transportation distance and time.

Using the online freight transit time calculation tool of Freightos (2020), an interval of transportation times (in days) for each of the transport lanes can be generated. For ocean transport is the leadtime variability about 25 days. This is the interval between the minimum transport time and the maximum transport time. Here, every day within the interval is equally likely to be the actual transport time. Then, it is being checked where the contracted leadtimes of Philips fall in the interval generated by Freightos (2020). In total 8 out of 20 lanes have a contracted leadtime that is at the minimum range as given by the online tool. None of the lanes have a higher contracted leadtime than the maximum range. As a next step, several interviews have been held with supply chain specialists of several sectors. These supply chain specialists all indepenently stated that the contracted ocean leadtimes are unreliable and that shipments arrive mostly later than contracted. Taking into account these sources, it is decided to use a combination of Philips' insights and Freightos (2020) data, where the leadtime is most probably higher than Philips' contracted leadtimes. Therefore, the ocean leadtimes in the simulation are random samples drawn from a uniform distribution, with a minimum of the contracted leadtime minus 5 days and a maximum of the contracted leadtime plus 20 days.

For air transport, the transportation time variability within scope is smaller than with ocean, on average 4 days (Freightos, 2020). Here, it could be observed that all Philips' contracted leadtimes were within the generated interval of Freightos (2020), of which some are on the lower side. For this reason, it has been decided to apply a similar method to air leadtimes as was done to ocean leadtimes. Therefore, the air leadtimes in the simulation are random samples drawn from a uniform distribution, with a minimum of the contracted leadtime minus 1 day and a maximum of the contracted leadtime plus 3 days. In Section 5.5, the impact of the uniform distribution assumption is tested by also running the TMSP model under the assumption that leadtimes follow a Gamma distribution.

5.3.2 Demand simulation

For the demand simulation per product and shipment lane, historical shipment data is being used. Here, it is assumed that the total historical shipments reflect the total historical demand. For simulation purposes it is chosen to express time in days, because in reality it is often possible to send shipments every day with the use of a 3PL and customers can place orders every day. The historical shipment patterns have been analyzed in cooperation with an analyst at Philips. It is concluded that there is large variation on some lanes, but that no clear pattern or seasonality could be identified. Thus, demand in different periods are assumed to be independent and identically distributed (i.i.d.). A normal demand distribution is assumed. The total demand is summed and a mean and standard deviation of demand per day is calculated, under the assumption that demand can occur 365 days per year. Appendix D.7 provides an overview of the mean and standard deviation of demand per day over the total time in scope. To simulate demand, every day in every warehouse gets a non-negative demand with the normal demand distribution (μ_X, σ_X) assigned. It is assumed that demand and leadtime of shipments are uncorrelated.

5.3.3 Starting inventory

Generally, the slower the transport mode, the higher the variability in leadtimes. This leadtime variability can cause low service levels because of increasing stock-outs. Avoiding stock-out occasions needs optimization of the reorder inventory levels. Increasing reorder levels reduces probability of stock-outs whereas it increases inventory holding costs. As discussed in Section 4.3, there are holding and/or penalty costs incurred for positive or negative inventory respectively. This simulation model also incurs these costs on a daily base. Every day the model handles the following subsequent steps: (1) check previous inventory; (2) add new arriving shipments to the inventory; (3) subtract demand of that day; (4) incur holding and/or penalty costs over the inventory. The shipments are simulated using the historical data with a sending date and an assigned leadtime. The demand is simulated as stated above. Since the simulation only uses shipments based on historical data, the inventory policy in each of the warehouses is out of scope. For this reason, the application of this TMSP model does not use an order-up-to level S_i as denoted in Section 4.3. Instead, in order to start the simulation, an assumption is made on the initial inventory level of each of the destination warehouses.

It is assumed that the starting inventory is mode dependent. This means that a slower transport mode usually needs higher stocks, because a slower transport mode usually has higher variability in transport times than faster transport modes (Freightos, 2020) and inventory needs to make up for this variability. An initialization period of one month is applied in the simulation, in order to make up for the fact that the first shipments have a higher leadtime for ocean than for air transport. The single-period newsvendor model is used in order to set the starting inventory levels, taking into account the trade-off between holding costs and penalty costs: $F_i = \frac{p_c}{p_c+h_c}$ (Nahmias, 2014). For the current simulation it was assumed that penalty costs are 10 times the holding costs, thus the result of the newsvendor equation equals 0.909. This score can then be translated to a z-score of the Normal Distribution $F_i^{-1} = 1.33$. Demand during day (t) are independent and identically distributed (i.i.d.) random variables drawn from a normal distribution with mean (μ_X) and standard deviation (σ_X), as discussed in Subsection 5.3.2. For a generic leadtime distribution with mean μ_L and standard deviation σ_L, the demand during the leadtime has mean $M = \mu_L \cdot \mu_X$ and standard deviation $S = \sqrt{\mu_L \sigma_X^2 + \mu_X^2 \sigma_L^2}$ (Silver & Peterson, 1985). Note again that it is assumed that demand and leadtime variability are uncorrelated. Then, using the normal distribution (z-score $= \frac{x^*+M}{S}$), the initial inventory levels can be calculated filling in M and S.

This calculation is applied to all shipment lanes in order to set a starting inventory (x^*) for the simulation model. Note that, since this inventory level is just an initial inventory to start simulation, it is not necessarily the optimal inventory level.

5.3.4 Service level calculation

Service level is defined as the portion of customer demand that is fulfilled directly from stock (Heydari, 2014). This definition of service level is sometimes in literature also referred to as the fill rate (Chopra, Reinhardt & Dada, 2004). In order to calculate the service level of a shipment lane, the demand that is fulfilled directly from stock is summed and displayed as a percentage of the total demand (see Equation (5.2)). Note again that this TMSP simulation model denotes both demand as well as inventory in kilograms of product.

$$\text{Service level (\%)} = \frac{\text{demand directly fulfilled from stock}}{\text{total demand}} * 100\% \tag{5.2}$$

The service level is calculated per day and then the average is taken over all days in the simulation scope. All demand is fulfilled following a first-come-first-serve policy. This means that, when new items arrive at a warehouse and there are backorders from last period, the backordered demands are fulfilled first and the new demands are fulfilled afterwards. This can result in several consecutive days of negative inventory. The total service level can either be denoted per transport mode, by taking the average of all lanes allocated to this specific mode, or as a total service level for all lanes combined. In this latter case, the average service level is calculated over all 20 lanes where each lane lane displays the service level of the allocated transport mode.

5.3.5 Pseudo-code simulation model

Algorithm 1 (see next page) shows the pseudo-code of the implementation of the Transport Mode Selection Problem (TMSP) simulation model. This implementation is based on the mathematical model described in Chapter 4, the input parameters of Section 5.2 and the simulation parameters of Section 5.3. The purpose of this pseudo-code is to provide a clear overview of the steps being taken and to enable others to replicate the model. The TMSP simulation model is made using the programming language R.

5.4 Simulation results

In this section, the simulation results are presented based on three different situations. The first situation that is presented is the current situation of Philips' shipments within scope. This means that every shipment uses the transport mode air. The second output shows the improvement potential without incurring emission penalty costs (win-win situation). The third output presents all other efficient solutions while incurring emission penalties, in order to show the total potential for Philips' improvements. All results in this section are obtained using partially simulated data. Every simulation run gets a stochastic leadtime per shipment and demand per day allocated. A simulation model should be sampled enough times to provide stable predictions of performance (Ritter, Schoelles, Quigley & Klein, 2011). It should be noted that the outcomes of costs and service level provide an indication of the actual values, since the demand, leadtimes and inventory levels are simulated based on assumptions and literature, instead of on Philips' data. The results in terms of CO_2e emissions are quite stable, since these are based on the historical shipments and the emissions calculation methodology of Chapters 2 and 3. The main outcome of this model is which transport mode to use, which is an exact result of the implemented model on the simulated data. This outcome must be stable across several runs for specific settings.

Algorithm 1: Pseudo-code TMSP simulation model

```
Result: Allocated transport mode per shipment
Initialization of all model parameters: product type, shipment value, shipment weight, origin and
  destination, emission factors, holding cost rate, penalty cost rate, transportation costs,
  distances per mode, leadtime distribution (μL, σL), demand distribution (μX, σX), starting
  inventory levels ;
while iterating over λ values do
    if There are new shipments for transportation then
        Allocate a random date when the shipment is put on transit ;
        Simulate a leadtime U(μL, σL) for each shipment and each mode;
        Determine the arrival day of the shipments;
        Calculate t_i,j, h_i,j, e_i,j
    end
    if A new time period is added to the simulation then
        Simulate a demand N(μX, σX) for each shipment and each day
    end
    while at the beginning of a new day t do
        Check the current inventory level on each lane;
        if Shipment(s) j arrive using transport mode i then
            Add the shipment (w_j) to the previous inventory;
            Subtract the demand of that day (d_i,j);
            Determine new inventory levels;
            Allocate holding (s_i,j) and/or penalty (p_i,j) costs for remaining inventory;
            Calculate the service level of day t (% fulfilled demand)
        else
            No shipment j arrives on this lane on day t;
            Subtract the demand of that day (d_i,j);
            Determine new inventory levels;
            Allocate holding (s_i,j) and/or penalty (p_i,j) costs for remaining inventory;
            Calculate the service level of day t (% fulfilled demand)
        end
    end
    Calculate z_i,j(λ) for each shipment lane;
    Decide on the transport mode to use on each shipment lane;
    Calculate the costs, emissions and service level
end
```

Results Philips' initial situation

Table 5.3 provides an overview of Philips' initial situation for the shipments within scope. The project was scoped in such a way that the initial situation contains only airfreight shipments. Thus, Philips' initial situation results from running the TMSP model and choosing transport mode air for every transport lane. This is done, because there is no data available about the actual inventory -, holding -, penalty -, or emission costs that Philips currently faces. These emissions represent the emissions that were incurred by historical shipments, calculated by using the methodology of Chapters 2 and 3. The costs include the total simulated logistics and inventory costs over the time period January 2017 until October 2019, as in Equation (4.17). The service level is determined using Equation (5.2).

Table 5.3: Results after simulation Philips' current situation

Transport mode	% of shipments	CO2e (tonnes)	Costs (million €)	Service level (%)
Air + road	100	272,188	144.4	70.9
Ocean + road	-	-	-	-
Total	100	272,188	144.4	70.9

Results simulation without emission penalty cost

Table 5.4 provides an overview of the results of the TMSP simulation model, without taking into account the emission penalty cost ($\lambda = 0$). This situation can be seen as the optimal starting situation, from which the emission penalty cost are increased to create more efficient solutions. The CO_2e, costs and service level are provided separately for ocean and air transport, for the lanes allocated to each mode. It can be concluded that the model with zero emission penalty results in a proposed transport mode shift for 11 lanes: 1, 2, 6, 8, 10, 12, 14, 15, 17, 18, and 20. Here, a win-win situation can be obtained where transportation by ocean is both cheaper and more sustainable than Philips' initial situation. This results in a situation where the CO_2e emissions are reduced with 53.8% while the costs reduce with 18.0% as opposed to using air transport only. It can be concluded in this situation without emission penalty cost, that all lanes of the segments A, E and F shift towards ocean transport, which are the lanes with products of low value density. One lane of segment B already shifts, while all other lanes from segments with high value density B, C and D do not shift.

Table 5.4: Results after simulation with zero emission penalty cost ($\lambda = 0$)

Transport mode	% of shipments	CO2e (tonnes)	Costs (million €)	Service level (%)
Air + road	32.4	125,076	98.8	90.7
Ocean + road	67.6	4,276	19.7	86.6
Total	100	129,352	118.5	88.4

Validation is done for determining whether a model is an accurate representation of the actual system. In other words, validation is the confirmation of the model's results via the information obtained from real-life (Law, 2015). Here, validation is done by comparing the outputs of the simulation with literature findings. First, a low product value density results in lower holding costs, both in transportation and in warehouses, and vice versa. Therefore, shipment lanes with cheaper products shift easier to ocean transportation in this model than more expensive products. This relationship is also found in literature, see e.g. (Wang et al., 2015; Hoen et al., 2014a). Further, it can be concluded from the model that heavier shipments are shipped with cleaner transport modes. The average chargeable weight of the shipments on lanes that shifted to ocean is about 3 times higher than the lanes that are allocated to air transport. This result can also be confirmed by literature (Hoen et al., 2014a). Additionally, it can be concluded that for larger distances cleaner modes are selected, because the inventory holding and penalty costs are balanced by lower transport (and emission) costs (Hoen et al., 2014a). Here, the top 20% lanes with highest air distance result in a choice for ocean transport. Another observation is that there are also transport mode shifts when both air and ocean distances are low. When the ratio between the ocean distance and the air distance is low, this means that the distance difference is not (very) disadvantageous for ocean. Then, the lower transportation cost rate for ocean (and lower emissions) balance the inventory holding and penalty costs. This can also be seen as the most logical explanation why one lane of segment B was selected to shift to ocean. This observation is not directly found in literature, but follows a similar reasoning as the distance aspect described above.

The win-win situation, improving both costs and emissions, can appear when the transportation costs are considerably lower for ocean than for air, and also lower than the additional inventory costs. The situation where emission reduction can be obtained against relatively low costs, has been concluded more often from literature. For example, Arıkan, Fichtinger and Ries (2013) state that a policy change from cost to emission minimization has low impact on cost, but can have considerably high impact on emissions. This means that little extra costs are incurred by decreasing the transport emissions substantially. Furthermore, Boere (2010) concludes from a case study that a maximum cost savings of 9.5% can be obtained in combination with an emission reduction of 27.9%. Hoen et al. (2014b) conclude from a transport mode selection case study that a 10% emission reduction could be realized at only 0.7% cost increase. This case study was applied to a European scale without the transport mode air, which reduces the emission reduction potential as opposed to the case study in this Master Thesis. Since all findings until now can be substantiated by literature, it is likely that the TMSP model is functioning well.

Results simulations with different emission penalty cost values

The total transport mix and emissions of the solution presented in Table 5.4 are taken as the starting situation for the next simulation step, where emission penalty costs are included. The multi-objective approach in this model allows to define a set of efficient solutions (or a Pareto frontier) which are defined as the set of solutions such that there is no other solution that dominates them, i.e., each solution of the set is strictly better than the rest of the solutions in at least one objective and is not worse than the rest of the solutions in all objectives (Bouchery et al., 2017). For all solutions that are efficient, it holds that if a transport mode has lower emissions than the other mode, then the expected costs are higher for the other mode, i.e. $C^*_{i_1} \leq C^*_{i_2}$ and $e_{i_1} \geq e_{i_2}$ (Hoen, 2012). Choosing one option over the other depends on how a company makes a trade-off between the two objectives. In this simulation model, runs are performed over different λ values, in order to identify all efficient solutions for different emission penalty costs. By increasing the emission penalty, none of the lanes that were ocean in overview Table 5.4 shift back towards air. This is the case since ocean is always the transport mode with lowest emissions, thus increasing the emission penalty cost never leads towards the 'unsustainable mode'. Therefore, only the lanes that had air transport in the initial situation, shift to ocean at a specific level of λ. When a lane shifts to ocean, the costs increase and the emissions decrease. A graph of all efficient solutions is shown in Figure 5.1.

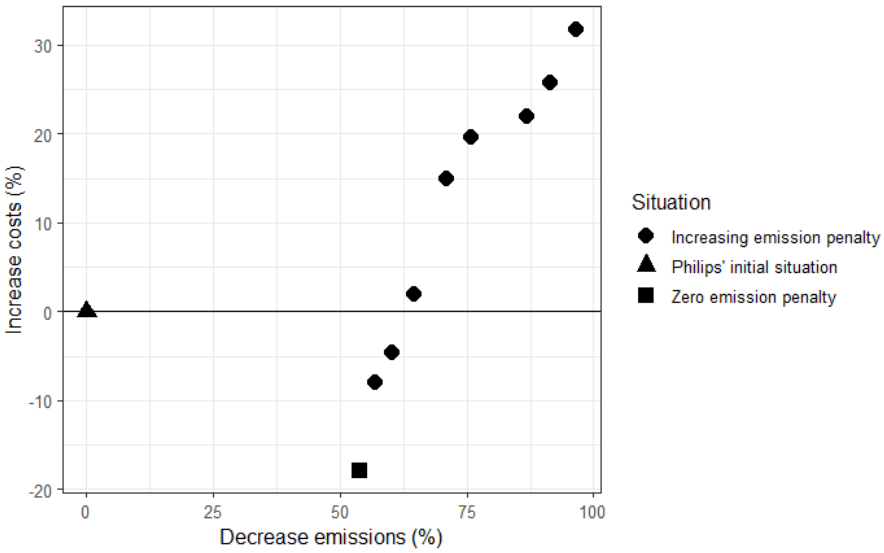

Figure 5.1: Efficient solutions Transport Mode Selection Problem (TMSP)

Several conclusions can be drawn from Figure 5.1. As stated before, it can be seen that the first 53.8% of emissions reductions can be obtained against a cost reduction of 18.0%. This is the gap between the triangle of "Philips' initial situation" (Table 5.3) and the square "Zero emission penalty" (Table 5.4). Philips' initial situation is used as a comparison point for all efficient solutions of the model. Increasing the emission penalty cost, it can be concluded that applying transport mode shift to the other 9 lanes comes with additional costs. However, the first two efficient solutions that incur emission penalty cost, still contain a total cost that is below Philips' initial situation. The first efficient solution that incurs emission penalty costs, increases the total costs ($C_{i,j}$) with 9.9% while leading to an additional emission reduction of 3.0%. No clear pattern between decreasing emissions and increasing costs can be identified from the graph. This might be due to the fact that there are only 20 lanes within scope, of which 11 already pick ocean with zero emission penalty cost. Other explanations can be that some lanes contain much more shipments than others, have highly variable demand, or have a disadvantageous ratio between transportation costs for air versus ocean. Finally, it can be concluded that a total emission reduction potential of 96.5% is identified against a cost increase of 31.8%.

Since the solutions are obtained by simulation and not by exact calculation, it is not possible to determine the specific emission penalty cost per lane where the transport mode shift occurs. However, it is possible to identify the order in which the transport mode shifts occur. In this model, the win-win situation at zero emission cost was found for lanes 1, 2, 6, 8, 10, 12, 14, 15, 17, 18, and 20. As a next step, the emission penalty costs (λ) are increased and the lanes 19 and 16 can also be shifted against a cost level that is below Philips' initial situation. Then, the order in which the other lanes can be shifted from air to ocean transport in a cost-efficient way is: 13, 4, 7, 3 and 9, 11, and 5.

Service level calculation

Next to the cost trade-off for the transport mode selection, also the service level per lane has been simulated and calculated. Service level could be an important measure for Philips, in order to fulfill customer demand from stock and maintain customer satisfaction. The simulation as described in this chapter results in an average service level of 86.6% for ocean and 90.7% for air transport, as denoted in Table 5.4. These service levels are obtained using simulation, and each simulation run results in a different service level value. The service level confidence interval per lane is discussed in Appendix D.8. Depending on the product category, customers and network characteristics, it can be desirable to have a service level of 95% or even higher. As discussed in Chapter 4, service level can theoretically be used as a constraint in the optimization Problem (P) and then handled with Lagrange relaxation in a similar way as the emission constraint. From an operations management point of view, it could make sense to apply different strategies for different lanes or warehouses. Some products or markets may need higher service levels due to customer characteristics than others.

5.5 Sensitivity analyses

Verification is the confirmation of the model's results via the information obtained from sensitivity analyses (Law, 2015). Sensitivity analyses are performed with respect to the assumptions in the TMSP simulation model. In each analysis, one assumption is tested and the impact on the overall result is calculated. The first sensitivity analysis tests the assumption of the holding cost/penalty cost ratio. This is a factor where Philips has influence on, deciding the importance of customer service level versus inventory costs. The second sensitivity analysis tests the assumption of demand variability. This is a factor where Philips has not much influence on, but that can have an impact on the mode of transport to select. The third and last sensitivity analysis tests the assumed leadtime distribution, by applying a Gamma distributed leadtime instead of the uniform distributed leadtime. Here, the same mean leadtime is used but the probability of extreme leadtimes changes. These analyses test several scenarios at zero emission penalty cost, to see the effect on the number of lanes allocated to each transport mode; the service levels per mode; and the logistics and inventory costs per mode.

Sensitivity 1 - Changing the holding cost/penalty cost ratio

In Section 5.2, it was assumed that the penalty cost rate ($\mathrm{p_c}$) for not having inventory to fulfill customer demand directly from stock is 10 times higher than the holding cost rate for inventory ($\mathrm{h_c}$). This assumption was made based on the assumption in a similar research of Hoen et al. (2014a). However, the trade-off between the penalty cost rate and the holding cost rate is not a given ratio. The ratio between the two cost rates depends on the importance that Philips places on the customer service level or on minimizing inventories. A higher penalty cost rate for not fulfilling customer demand directly from stock, results in higher stock levels that Philips keeps. Vice versa, a higher holding cost rate for having inventory in stock results in lower stock levels that Philips keeps. This trade-off was represented in the starting inventory calculation as: $F_i = \frac{p_c}{p_c+h_c}$. This score can then be translated to a z-score of the Normal Distribution, which is used to determine the initial inventory level. This sensitivity analysis tests how the model behaves under different holding cost/penalty cost ratios. Sensitivity analysis is performed to test the scenarios where the penalty cost rates ($\mathrm{p_c}$) are 5, 10, 50, and 100 times higher than the holding cost rate. This corresponds to z-scores of 0.96, 1.33, 2.06, and 2.33 respectively. The holding cost rate ($\mathrm{h_c}$) remains equal to 0.00068€/day. This sensitivity analysis compares the number of lanes per transport mode; the service levels per mode; the logistics costs per mode; and the inventory costs per mode across the different scenarios. Note that the second scenario with a z-score of 1.33 equals the original TMSP simulation.

Figure 5.2 shows the transport mode choice for the 20 lanes within scope at different z-scores. This figure is constructed at the zero emission penalty cost ($\lambda = 0$). It can be concluded that a low penalty cost rate results in more lanes being allocated to the transport mode ocean. This can be substantiated by the fact that service level is less important at a lower penalty cost rate, thus a slower transport mode is chosen more often. Increasing the penalty cost rate from factor 5 to 10 and from factor 10 to 50 has an impact on the transport mode choice of lanes. However, increasing the penalty cost factor from 50 to 100 did not change the final result. Appendix D.9 provides an overview of which lanes are allocated to which transport mode for each of the scenarios. Since it is not realistic that the penalty cost rate is more than 100 times higher than the holding cost rate, these scenarios are not tested. It can be concluded that transport mode selection result is quite robust for moderate to high z-scores.

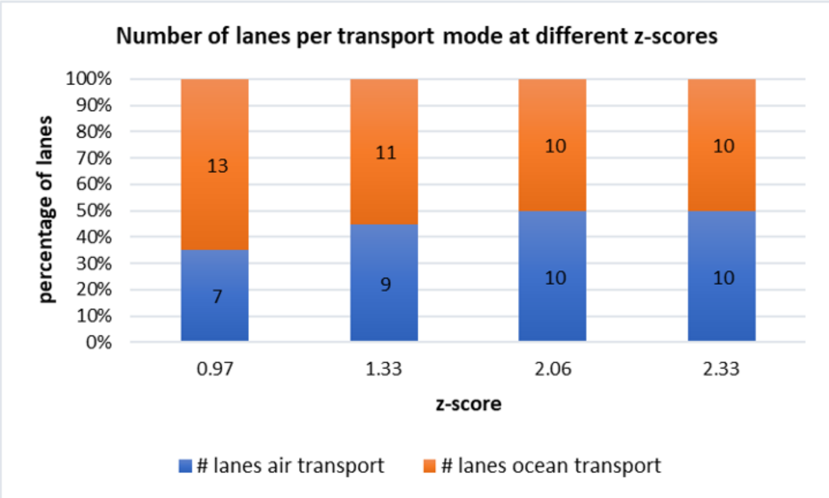

Figure 5.2: Number of lanes per transport mode at different z-scores

Figure 5.3 shows the service level and CO_2e emissions for the TMSP simulation results at different z-scores. The average scores are combined for all 20 lanes, where each lane is allocated to their optimal transport mode, as shown in Figure 5.2. It can be concluded that the service level is increasing in the z-score. This makes sense, since a higher z-score corresponds to higher penalty costs for not fulfilling customer demand directly from stock. These increased penalty costs result in higher initial inventory levels and more lanes being allocated to the faster transport mode. Furthermore, it can be concluded that the CO_2e emissions are increasing in the z-score. This is the case, since a low service level corresponds to more lanes allocated to ocean transport and vice versa. Since there is no change in transport mode allocation between z-scores 2.06 and 2.33, the CO_2e emissions stay the same.

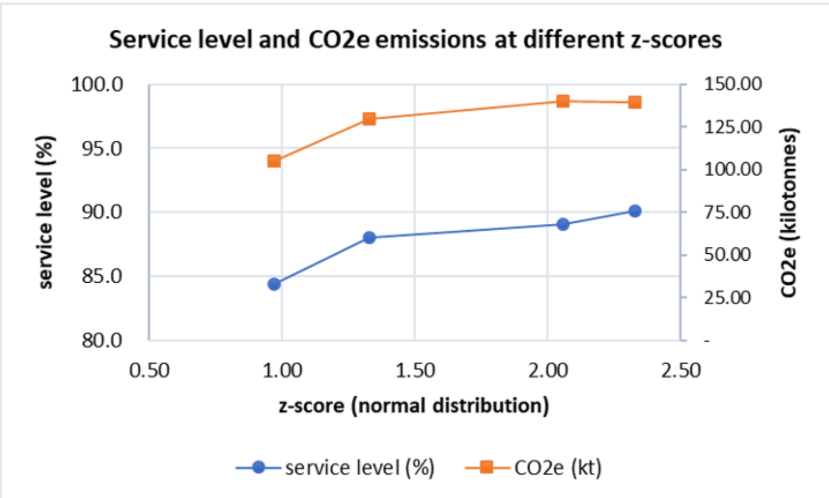

Figure 5.3: Service level and CO_2e emissions at different z-scores

Figure 5.4 shows the inventory costs and the logistics costs for the different z-scores. These are the average costs for all 20 lanes combined, where each lane is allocated to its optimal transport mode, as shown in Figure 5.2. It can be concluded that the logistics costs remain quite stable across different z-score scenarios. Only the scenario with the lowest penalty cost rate has increased logistics costs. This can be explained by the fact that more lanes are allocated to ocean transport and ocean transport incurs higher holding costs during transport than air transport. For the inventory costs, it can be concluded that the cost differences are bigger across the four scenarios. It can be concluded that a low penalty cost rate, which corresponds to low initial inventories, results in higher inventory costs than the TMSP original. These additional costs can be attributed to having reduced service levels and thus increased number of backorders. Further, it can be seen that the inventory costs decrease from z-score 0.97 to 1.33, while the inventory costs increase from 1.33 to 2.33. This increase of inventory costs at higher penalty cost rate can be explained by the fact that unfulfilled demand is more expensive and warehouses hold higher inventory levels. From this can be concluded that there is most likely a minimum in the inventory cost curve.

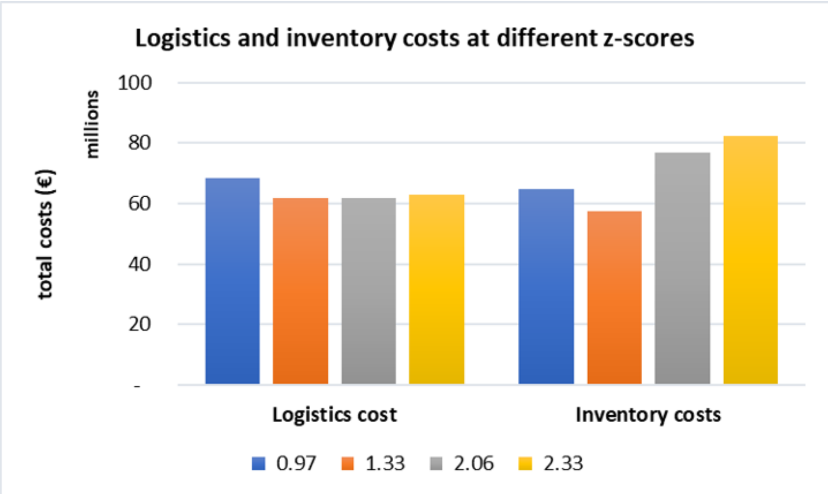

Figure 5.4: Logistics and inventory cost (€) at different z-scores

From this first sensitivity analysis can be concluded that changing the holding cost/penalty cost ratio has high impact on the inventory costs of the simulation and moderate impact on the service level result of the simulation. However, the main result of which lanes are allocated to which transport mode at zero emission penalty costs is quite robust at a moderate to high penalty cost rate.

Sensitivity 2 - Changing the demand variability

This sensitivity analysis concerns the variability of the simulated customer demand at the warehouses. Demand during a day are i.i.d. random variables drawn from a normal distribution with a mean and standard deviation per lane (see Appendix D.7). In this sensitivity analysis, the TMSP model is tested for two scenarios: half of the standard deviation ($\frac{1}{2} \cdot \sigma$) and double the standard deviation ($2 \cdot \sigma$) on each lane. The initial inventory levels in the simulated destination warehouses depend on the mean and standard deviation of demand during the leadtime (see Section 5.3.3). When the standard deviation of demand increases (decreases), the starting inventories also slightly increase (decrease). The mean (M) remains unchanged, whereas the deviation (S) changes into: $S' = \sqrt{\mu_L \left(\mathbf{factor} \cdot \sigma_x\right)^2 + \mu_x^2 \sigma_L^2}$. In this sensitivity analysis, the 'factor' is either $\frac{1}{2}$ or 2. When running this TMSP simulation model, all other input parameters remain unchanged.

Figure 5.5 shows the transport mode choice for the 20 lanes within scope at different demand variability scores. This figure is constructed at the zero emission penalty cost ($\lambda = 0$). Note that demand variability score of 1 equals the TMSP original result. It can be concluded that a high demand variability score results in more lanes being allocated to the transport mode air. This can be substantiated by literature; Hoen et al. (2014a) states that it is expected that when demand variability is high, a faster and more polluting mode is selected to cope with uncertainty. Appendix D.9 provides an overview of which lanes are allocated to which transport mode for each of the scenarios. It can be concluded that transport mode selection result is quite robust for changes in the demand variability.

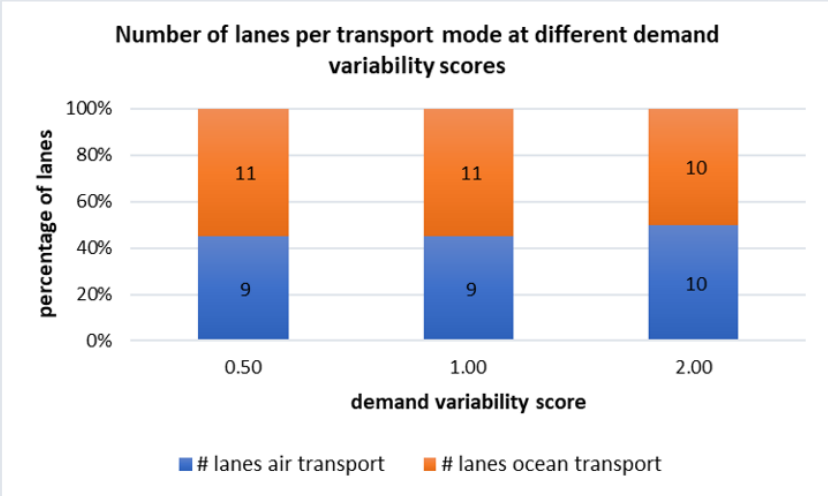

Figure 5.5: Number of lanes per transport mode at different demand variability scores

Figure 5.6 shows the service level and CO_2e emissions for the TMSP simulation results at different demand variability scores. These are the average scores for all 20 lanes combined, where each lane is allocated to its optimal transport mode, as shown in Figure 5.5. It can be concluded that the service level with factor $\frac{1}{2}$ slightly decreases as opposed to the TMSP original. This might be due to the fact that the initial inventories slightly decreased, while the transport mode selection did not change. The service level at doubled demand variability decreases strongly. This makes sense, since a higher demand variability corresponds to more uncertainty thus more frequent stock-outs. Furthermore, it can be concluded that the CO_2e emissions do not change between factors $\frac{1}{2}$ and 1.0 since there is no change in transport mode allocation. There is a slight increase in CO_2e emissions between factors 1.0 and 2.0, due to the fact that one additional lane is allocated to air transport.

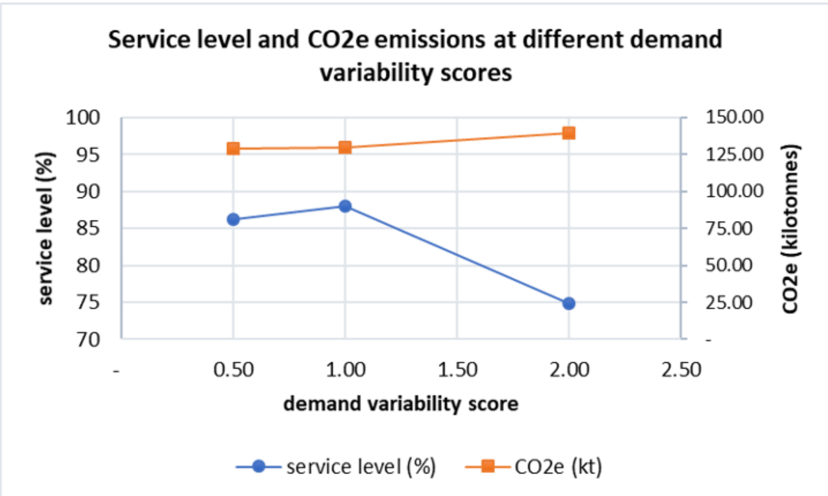

Figure 5.6: Service level and CO_2e emissions at different demand variability scores

Figure 5.7 shows the inventory costs and the logistics costs for the different demand variability scores. These are the average costs for all 20 lanes combined, where each lane is allocated to its optimal transport mode, as shown in Figure 5.5. It can be concluded that the logistics costs remain stable across different demand variability scenarios. For the inventory costs, it can be concluded that the cost differences are bigger across the three scenarios. It can be concluded that a low demand variability score, results in the lowest overall inventory costs and vice versa.

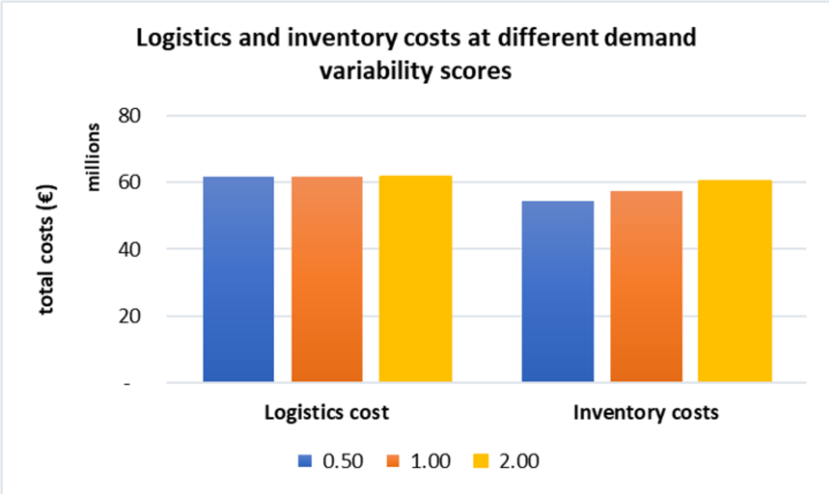

Figure 5.7: Logistics and inventory cost (€) at different demand variability scores

From this second sensitivity analysis can be concluded that changing the demand variability has high impact on the service level and moderate impact on the inventory costs of the simulation. However, the main result of which lanes are allocated to which transport mode at zero emission penalty costs is robust across several demand variability scores. Only at doubled demand variability, one additional lane is attributed to the transport mode air.

Sensitivity 3 - Changing the leadtime distribution

This sensitivity analysis concerns the distribution of the simulated leadtimes for air and ocean shipments respectively. Until now, it was assumed that leadtimes follow a uniform distribution. The ocean leadtimes in the simulation are random samples drawn from a uniform distribution, with a minimum of the contracted leadtime minus 5 days and a maximum of the contracted leadtime plus 20 days. The air leadtimes follow the same distribution, with a minimum of the contracted leadtime minus 1 day and a maximum of the contracted leadtime plus 3 days. This leadtime interval is obtained using the online freight tool of Freightos (2020). This interval implies that the average leadtime for ocean equals the contracted leadtime + 7.5 days and for air equals the contracted leadtime + 1 day. This sensitivity analysis tests the TMSP simulation model using a Gamma distribution instead of the uniform distribution for leadtimes. The mean simulated leadtime for both distributions is equal. Using the Gamma distribution, there is a higher probability that a simulated leadtime is close to the mean than in the uniform distribution, whereas in the uniform distribution every interval is equally likely. Besides, the Gamma distribution is skewed. In a symmetric distribution, the median, arithmetic mean, and mode are in the same central point. This is not true when the distribution is skewed. In this case, the mode is separate from the arithmetic mean, and the median is between two of them (Dodge, 2008b). Since there is no data available about the actual leadtimes, it cannot be stated that one distribution is better than the other. For this example, the contracted leadtime is used as shape parameter and a scale parameter around 1.25 is used to ensure that the mean of the Gamma distribution is equal to the mean of the former uniform distribution. Figure 5.8 shows how the resulting leadtimes per mode are distributed. This figure is constructed for a random example of lane 4 (EUR1-APAC2) within scope. For every other lane within scope, a similar shaped graph can be constructed. When running this TMSP simulation model, all other input parameters remain unchanged.

It can be concluded that changing the leadtime distribution from uniform to Gamma in the TMSP simulation model, the exact same lanes are allocated to transport modes ocean and air as in the TMSP original simulation (see Appendix D.9). Furthermore, it can be concluded that the logistics costs increase with 1.0% and the inventory costs increase with 1.4%. Additionally, the average service level over all 20 lanes decreases with 0.6%. This slight increase in cost and decrease in service level can be due to the fact that some leadtime values are more extreme on the high end, incurring additional holding costs during transport and penalty costs in the warehouse. The total CO_2e emissions decrease with 0.3%. It is expected that this minor change is due to simulation effects.

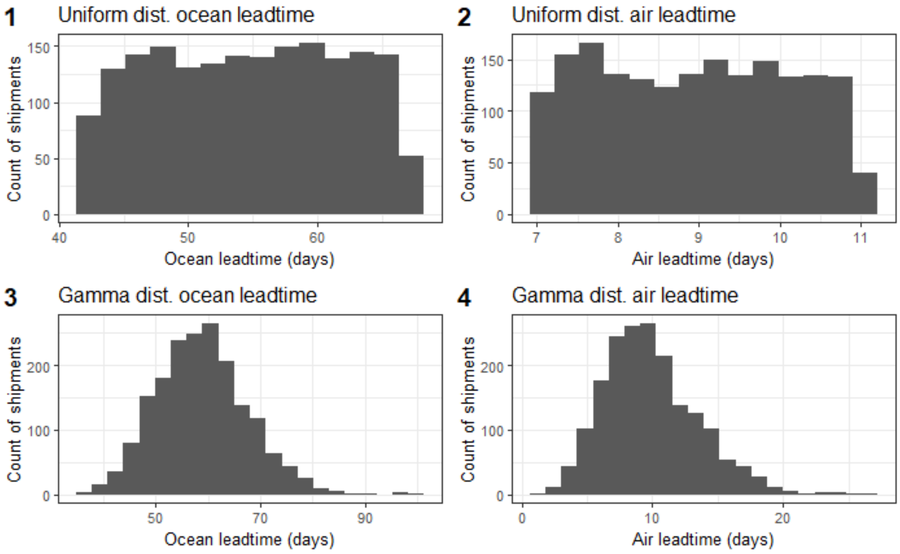

Figure 5.8: Simulated leadtimes per transport mode using uniform and Gamma distribution

5.6 Conclusion and discussion

To our best knowledge, the literature on transport mode selection problems for freight transport did not yet cover a decision model that is applied to intercontinental, multi-item multi-modal freight shipments, to make a transport mode decision based on a trade-off between cost, emissions and service levels. This Master Thesis project contributes to the literature by investigating the relations between cost, emissions and service level of freight transport, taking into account both logistics and inventory costs. The objective of this model is to present a decision-supportive model on a tactical level that can be applied in practice. The mathematical model could not be implemented right away due to data issues. However, with the help of a case study and data simulation, the potential of the model is shown.

As opposed to existing literature, this model has some additional or improved features that potentially enhance realistic results. The model of this Master Thesis takes into account the road distances depending on the transport mode, whereas e.g. Hoen et al. (2014a) and Hoen et al. (2014b) base their decision only on (air)port-to-(air)port routes. However, some locations might be good accessible by air transport but are located far away from an ocean port. Taking into account the positioning of destinations ensures that the routes and leadtimes are realistic. Next to realistic routing, also the emissions of this first and last road leg are determined in the total emission figure. Furthermore, the model is applied on a global scale, whereas existing models were applied only in a specific area. On the other hand, this model also has its shortcomings. For example, this model is applied using two transport modes only: the multi-modal combinations air-road and ocean-road. These two transport modes are selected based on Philips' supply chain network and its available data. It can be interesting in the future to also include the transport mode rail or to use other multi-modal transport combinations. Besides, the TMSP model is only applied as a case study to a limited amount of shipment lanes and does not consider the production side of the supply chain.

For this simulation model, the historical shipments got a shipment date assigned and a variable leadtime, depending on the route and transport mode. Every shipment consists of a product type, origin and destination, where it is assumed that each destination is a warehouse of Philips. In each warehouse there is a demand simulated for each day using the normal distribution, based on historical shipments. Starting inventories are determined using the newsvendor model and the mean and standard deviation of demand during the leadtime. Then, the total costs and emissions are analyzed using different values for the emission penalty cost and the service levels are determined. It is concluded that a win-win opportunity exists for Philips, where they can reduce costs and CO_2e emissions at the same time. This solution applies a transport mode shift to ocean for 11 lanes within scope. The transport mode shift for these lanes together reduces the CO_2e emissions with 53.8% while reducing the costs with 18.0%. For the other 9 lanes within scope, the efficient solutions are obtained in order to show the additional cost that would be incurred by shifting from air to ocean transport. The total emission reduction potential is calculated to be 96.5% against a cost increase of 31.8%.

A sensitivity analysis is performed for three assumptions: (1) the holding cost/penalty cost ratio; (2) the demand variability; and (3) the leadtime distribution. The goal of the sensitivity analysis is to see how robust the TMSP model is and how the results change based on different assumptions. In Sensitivity (1), it appeared that the holding cost/penalty cost ratio has high impact on the inventory costs and moderate impact on the service levels. Further, it can be concluded that a low penalty cost rate results in more shipments using ocean transport. In Sensitivity (2), increasing the demand variability has a negative impact on the service levels and increases the inventory costs. Further, the increased demand variability leads to slightly more lanes using air transport. In Sensitivity (3), the leadtime distribution is changed from uniform to Gamma, where in both distributions the same mean leadtime is used. A slight increase in costs and decrease in service levels is observed. However, there is no change in the allocation of transport modes to shipment lanes at zero emission penalty cost. The most important aspect of the sensitivity analyses is whether the final result, the lanes that are recommended for Philips to perform a transport mode shift to ocean, stays the same across several parameter settings. Which lanes are allocated to which transport mode under the different sensitivity analyses is displayed in Appendix D.9. It can be concluded that the results for recommended transport mode shift at zero emission penalty cost are quite stable throughout several scenarios. The assumption with highest impact is the situation where the penalty cost rate is low, corresponding to a z-score of 0.96. Under this assumption, most lanes were allocated to transport mode ocean.

Chapter 6

Improvement directions Philips

This Master Thesis investigates the current environmental impact of Philips' logistics processes for airfreight and the CO_2e reduction potential using transport mode shift. This chapter answers the third and final research sub-question:

3. Which improvements can be made for the logistics planning process to include more sustainable transportation alternatives for the most impactful products/lanes?

Section 6.1 handles the improvement direction of transport mode shift, which can be seen as the improvement with highest focus in this Master Thesis. Then, Section 6.2 provides an overview of the general recommendations for Philips in order to improve the logistics planning process. This includes insights obtained during the Master Thesis project as well as insights from literature.

6.1 Transport mode shift

The topic of transport mode shift has been handled extensively in Chapters 4 and 5. With a transport modality shift, emissions are reduced with switching from a carbon intensive mode of transport to a less carbon intensive mode. The ranking of the different transport modes in order of decreasing carbon intensity is: air, road, rail and water transport (Dekker et al., 2012; Hoen et al., 2014b; van den Akker et al., 2009). When a modal shift occurs to a mode other than road, often a combination of transport modes is required: multi-modal transport in combination with road (Hoen et al., 2014b; Koc, 2010; Smokers, Tavasszy, Chen & Guis, 2014).

Achieving a modal shift is not an easy task, because the alternative freight transport modes have to fulfill shippers' logistical requirements, fit into the supply chain and be feasible in terms of costs (Blauwens, Vandaele, Van de Voorde, Vernimmen & Witlox, 2006). Each transport mode has different characteristics in terms of cost, transit time, accessibility, and also different environmental performance. Time sensitive goods are often supplied by air, while large volumes of commodities like coal are transported by rail, inland barge or pipeline (in case of gas or oils) (Dekker et al., 2012). This Master Thesis research takes into account these factors of costs, transit times, accessibility and product type. For costs the transport cost per mode, holding costs, penalty costs and emission costs are considered. The transit times consider the full distance per mode, including the first and last road leg and the average waiting time at a(n) (air)port. To ensure accessibility, the routes and their distances are investigated on a lane level. Here, it is assumed that a destination always uses the closest (air)port, and the road distances including a detour percentage are determined. With this, some routes might be more efficient in terms of distance to a(n) (air)port, but accessibility is ensured at all routes. Furthermore, Philips' products are not time sensitive in the sense of being perishable and the products are all end-products and thus no bulk items, gasses or oils. For these reasons, all lanes within scope are deemed suitable for transport mode shift. The only aspect that has not been taken into account is the supply chain effect on the production side. Since there is no information available on this aspect, it is assumed that production can always meet up to product deliveries with any transport mode.

A case study is conducted at Philips on a subset of 20 shipment lanes, which together account for 25.6% of all CO_2e emissions. This case study investigated which of the lanes in scope are most suitable for a transport mode shift, considering the costs, emissions and service level. In Chapter 5, it is concluded that 11 lanes can be shifted as win-win situation at zero emission penalty costs. Shifting these 11 lanes to ocean decreases costs with 18.0% while reducing emissions with 53.8%. It is recommended to start implementing transport mode shifts for these 11 lanes, which are the following: 1, 2, 6, 8, 10, 12, 14, 15, 17, 18, and 20. Afterwards, the emission penalty cost is increased and efficient solutions are obtained when an additional lane shifts from air to ocean. The next 2 lanes that shift from air to ocean still have a cost below “Philips’ initial situation” but do incur additional costs as opposed to the “zero emission penalty” situation. Therefore, it is recommended to switch these lanes in a later stage. The other 7 lanes in scope shift at increasing additional costs, due to which these lanes are less suitable for transport mode shift.

When Philips wants to implement a transport mode shift on one of the shipment lanes, there are some additional aspects to take into account. It is recommended to look at the lanes that recently shifted from air to ocean, and see whether the origin or destination port is also suitable for other lanes. For example, Philips’ shipment lane with highest CO_2e emissions (APAC1-NAM1) did a modal shift in 2019. This shipment lane uses ports that are also being used in other shipments which makes it easier to shift those to ocean. It might also be possible for some lanes to not pick the closest port, but the second closest port, when this is a port that Philips already uses for transport. Then, products can be consolidated or changes with 3PLs might be easier to implement. Additionally, it is recommended to Philips to also investigate the lanes that currently fell out of scope of this case study and analyze which lanes use the same product values, shipment weights or locations as the lanes that result in a win-win. Most probably, focusing on these lanes delivers the best trade-off between emission reduction and costs while maintaining service levels. This aspect is discussed further in the implementations of Chapter 7. Finally, it is likely that higher inventory levels are required when a cleaner and slower mode of transport is used (Boere, 2010; Hoen, 2012). If this aspect is not taken into account when planning for a transport mode shift, the increased leadtime variability may lead to stock-outs. These stock-outs lead to reduced service levels and Philips will make use of emergency shipments by air transport in order to still fulfill customer demand. This topic has already been discussed with several supply chain specialists of different segments within Philips and it can be concluded that this emergency shipment situation is a known problem to Philips. Thus, the inventory aspects must be incorporated into supply chain planning when implementing transport mode shifts.

6.2 General recommendations

This section elaborates on the general recommendations to improve logistics planning to include more sustainable choices, for which numerous ‘best practices’ and frameworks have been proposed in literature. The options elaborated below are based on the proposed ‘best practices’ of literature and the findings at Philips throughout this Master Thesis project.

6.2.1 Reconsider emission calculation assumptions

Chapters 2 and 3 describe the CO_2e emission calculation methodology and the application to Philips’ global airfreight shipments. Many of the steps of this methodology are already implemented at Philips (see Chapter 7). However, there are some aspects that Philips did not implement yet. It is recommended that Philips substantiates its decisions for carbon calculations and reconsiders its current assumptions. It should be noted that it cannot easily be stated that one methodology is more correct than the other. However, all assumptions have to be clearly defined and coherent. The most important deviations are described here. The final output of CO_2e emissions of this calculation method are 18.2% higher than the emissions that Philips reported over the same scope. This significant difference can mainly be attributed to the fact that Philips uses EFs of DEFRA with different underlying assumptions. The methodology of this Master Thesis based on NTM EFs is considered to be an improvement as opposed to Philips’ method with DEFRA EFs. This is the case, because the EFs of DEFRA are not clearly defined for use outside of the UK (Downie & Stubbs, 2012). Additionally, the EFs of DEFRA only include tank-to-wheel (TTW) emissions, while the methodology of this Master Thesis reports well-to-wheel (WTW) emissions. WTW reporting is recommended, since it includes the total use of energy including fuel production, distribution and combustion (NTM, 2018b). Finally, Philips currently assumes that all transport activities are performed using full-freighter aircrafts. This assumption has been invalidated by data obtained from a 3PL. However, the impact of this assumption depends on the allocation methodology of emissions over passengers and freight (see Section 8.2).

6.2.2 Collaboration with Third Party Logistics provider (3PL)

Philips performs all its logistics in cooperation with a 3PL. There are contracts with each of these 3PLs that state the costs per transport mode, per route and per shipped chargeable weight. One of these agreements states that Philips always pays for a minimum chargeable weight of 30 kg. After performing the data cleaning steps for the first research question, it is discovered that the total number of shipments with a chargeable weight of 30 kg is 69,473 which equals 25.6% of all shipments in scope. This observation has two implications. Firstly, it can be concluded that Philips logistics planning system is not optimal by sending so many separate shipments of (less than) 30 kg. It should be investigated whether shipments can be consolidated into larger shipments. Secondly, it should be considered to revise the agreements that are made with these 3PLs. When the minimum chargeable weight limit would be decreased from 30 kg to e.g. 20 kg, this saves costs for Philips. Besides, it is expected that this also has a positive effect on the CO_2e calculations, since shipments lighter than 30 kg get less emissions allocated.

Another improvement direction to reduce carbon emissions from logistics in collaboration with 3PLs is to increase the vehicle efficiency. This can e.g. be done by increasing the payload of a vehicle. This leads to more efficient use of transport and to a reduction of the number of trips needed to transport all products (van den Akker et al., 2009). An extension to this option is using transport consolidation, where small shipments are combined with larger ones to achieve efficiencies of scale for transport over longer distances (Dekker et al., 2012). It is also possible to reduce empty kilometers by combining shipments. If the return trip of one shipment can be used to transport a second shipment, then in total less kilometers have to be made and emissions can be reduced significantly (van den Akker et al., 2009). Other options include executing planned route optimization or using alternative fuels instead of diesel, such as biological fuel (Bouman et al., 2017; Oberhofer & Dieplinger, 2014). The use of electric or hybrid vehicles can also be a good option, where emissions depend on the way that electricity is generated (Dekker et al., 2012; Craig et al., 2013).

Since Philips outsources all its logistics activities to 3PLs, Philips has no overview about the load factor that is representative for its shipments. This results in the fact that emission calculation and carbon compensation is performed on assumed load factor numbers. It is likely that there is improvement potential in increasing the load factor for Philips' shipments, which reduces costs and emissions for the 3PL and for Philips. The 3PL reduces costs by providing their services more efficiently and Philips reduces costs by having lower CO_2e emissions to compensate.

6.2.3 Required data and data collection

The final improvement direction to be discussed here lies in obtaining the right data to improve the accuracy of calculations at Philips. This holds for both the first research question as well as for the second research question. Both research questions have been handled generically first, in order to show how the problem could be solved, if the right data is available. Then, two case studies are performed to implement the methodologies in the best possible way with the available data. It is discovered that many useful data aspects could not be obtained, which made the application of calculation methodologies challenging. Table 6.1 states in the first column which data is required for the calculations, and in the second column which data is currently available at Philips. The third column states which data is currently used for application of calculations or which solution is designed to estimate or simulate specific data.

The first nine rows in Table 6.1 are relevant for both the CO_2e calculation as well as the TMSP optimization model. The product type or exact shipment contents are not known within Philips. This means that Philips only knows the high level segments that products are in, but not which products are inside which shipments. Furthermore, Philips also only knows the weight of shipments and not the number of products. The number of products is especially relevant for the TMSP with regard to the inventory and demand calculations. Currently, the inventory and demand simulation are both performed in kilograms of product instead of number of products. For the CO_2e calculations, the volume data of shipments would be especially relevant. Knowing the volumes of shipments, ensures more realistic allocation of CO_2e emissions. This is the case, since not only the maximum load of a vehicle is limited, but also the volumetric space. Currently the chargeable weight input of 3PLs is used, which is the transported volumetric weight that Philips has to pay for. Additionally, the exact origin and destination addresses are required data to calculate the road distances between airports and warehouses. For most shipments, only the origin/destination city is known, due to which road distances could not be calculated in an exact way but had to be obtained using a sampling study.

Table 6.1: Required data versus available data overview

Required data for calculations	Currently available data	Currently used for calculations
Product type of shipment	High level segment data	Estimated average product based on segment
Number of products per shipment	Only shipment weight	Estimated average weight per product
Product value of shipment	-	Estimated value density per product
Shipment volume data	Volume data is unreliable	Chargeable weight input
Aircraft type (belly/ full freighter)	-	Industry-average aircraft
Load factor of aircraft	-	Industry-average load factor
Origin/destination addresses	Origin/destination city	Origin/destination city
Road distances	-	City-to-city distance based on sampling study
Truck type (size and load factor)	-	Assumed 20-26 t truck with 50% load factor
Actual sending dates of shipments	Year and month of shipping	Assigned a sending day
Actual leadtimes of shipments	Contracted leadtimes per lane	Simulated interval around contracted leadtimes
Inventory policy warehouses	-	Initial inventory based on demand during leadtime
Holding/penalty cost rate	-	Assumption on literature and sensitivity analysis
Demand distribution products	-	Normal demand dist. and sensitivity analysis

Next to the shipment specific data, there is also transport data lacking for CO_2e calculations. Philips outsources all transportation to several 3PLs. Philips currently has no influence over the used vehicles, the vehicle load factor or the vehicle routing. However, when calculating the CO_2e emissions, the vehicle type and load factor can have high impact on the final results. Also vehicle routing, including e.g. stopovers for specific flights has impact on the final result. Currently, industry-average aircraft and truck data is used to calculate the CO_2e impact of logistics. Since Philips makes use of several 3PLs, it is expected that industry-wide averages are representative for a company like Philips. However, actual data would result in a more accurate CO_2e emission calculation.

The last five rows of 6.1 are relevant for the TMSP optimization model. The actual sending dates of shipments and the actual leadtimes are required to know when shipments arrive at a specific warehouse. Furthermore, knowing the exact leadtimes is crucial to calculate realistic inventory levels and holding costs for inventory. Currently, the leadtimes are simulated based on the contracted leadtimes and the leadtime interval of Freightos (2020). This leadtime simulation ensures that there is realistic leadtime variability in the system. The inventory policy in the warehouses, including e.g. the order-up-to level or the order decisions, are required data to calculate the expected inventory on hand and the expected backorders per period. This also depends on the demand distribution for products. It is decided to implement the TMSP model as a simulation model, where demand is simulated using a normal demand distribution based on the mean and standard deviation of demand during the leadtime. Several scenarios for the standard deviation of demand are tested in the sensitivity analysis. The simulation model started with an initial inventory level, and afterwards the inventory was tracked using incoming shipments and outgoing demand. The inventory holding costs and penalty costs are calculated based on the simulated inventory levels and assumed inventory holding and penalty cost rates. A sensitivity analysis is performed on the ratio between these two cost rates to show Philips the effects of the trade-off between high service levels versus low inventory costs.

Obtaining the data aspects as mentioned in Table 6.1 is crucial to improve the calculation accuracy of research sub-questions 1 and 2. It is expected that obtaining high-level data for the first research sub-question would not be very difficult, when collaborating with the 3PLs. This can also be seen from the fact that the aircraft type of recent shipments by 3PL Expeditors could be obtained already during the Master Thesis project. Specific shipment data such as the load factor of each shipment is already more challenging. Furthermore, obtaining the data aspects for the second research sub-question might be more complex since it involves several parties. However, all required data should be available internally within Philips. Improving the calculation accuracy is important when Philips wants to act on results, in order to have reliable expectations for e.g. costs of transport mode shifts.

Chapter 7

Implementations at Philips

This chapter shows the implementations that have been performed during this Master Thesis project at Philips, or that can be performed by Philips after the Master Thesis project. As described in Chapter 3, the carbon calculation methodology is applied to Philips' airfreight logistics data. This calculation has not only been analyzed in R, but is also partially implemented in Philips' official calculations, visualized in a Business Process Model and Notation (BPMN) tool and in a dashboard tool Qlik Sense. The Transport Mode Selection Problem (TMSP) methodology as described in Chapter 4 is implemented as a simulation model in R (see Chapter 5). This chapter shows the implementations and how Philips can use them in the future.

7.1 Implementation carbon calculation in Philips' reporting

The Reporting team within Philips' Group Sustainability is responsible for reporting several types of sustainability aspects of the company. These results are then audited by an external company and published in the annual report. This Master Thesis project contributes to Philips' airfreight logistics CO_2e reporting on several aspects. First, the cleaning of input data of the origin and destination locations with IATA-codes is implemented (see Appendix B.1). This implementation leads to accurate distances for an additional 5% of the shipments compared to Philips' original method. Second, the data cleaning method for weights has also been implemented, as described in Section 3.1.1. This includes cleaning for minimum weight, missing weight values and maximum weights. Third, the distance calculations of Section 2.2 and Section 3.2 have been implemented fully. This consists of the GCD Equation (2.1), the detour distances with Equation (2.2) and the road distance percentage (see Section 3.2.3). The steps described above are implemented in Philips' calculation method, process flow and official CO_2e reporting in the annual report of 2019 (Royal Philips, 2019c).

Some parts of the emission calculation have not been implemented yet in Philips' CO_2e reporting of airfreight logistics. Philips still uses DEFRA emission factors and still assumes that all aircrafts are pure freighters. Since data of Philips' most used 3PL has proven that this last assumption is not valid, it is exptected that these improvements will be implemented later on. However, shifting from DEFRA to NTM, taking into account industry-average aircraft types and reporting WTW instead of TTW leads to CO_2e emissions of 18.2% higher than was currently reported. Therefore, implementing the full method also depends on the target setting and the industry norms for reporting. This has been discussed in formal meetings with the manager of Sustainability Reporting team, and Philips will consider taking the next implementation steps in 2020.

7.2 Implementation of methodology in BPMN

Philips uses BPMN tools in order to visualize processes across the company and to make calculation steps also transparent for the audit. A BPMN tool is built such that everyone can follow the performed calculations and also apply the methodology in the future. For this Master Thesis Project, two tools have been built. The first tool represents the methodology that Philips currently uses and the second tool represents the recommended methodology including the NTM emissions calculation. Figure 7.1 shows an overview of the general BPMN model that Philips currently uses. For each of the sub-process steps of loading data files, general data cleaning, cleaning of chargeable weight and cleaning of distances, a separate model exists with the subsequent steps. Clicking on a step enables a person to see the purpose of a step, the corresponding lines in the R-code and the person who is responsible. This model can even be used to automate the process, e.g. by having fixed email notifications and rerunning the script with monthly updated data.

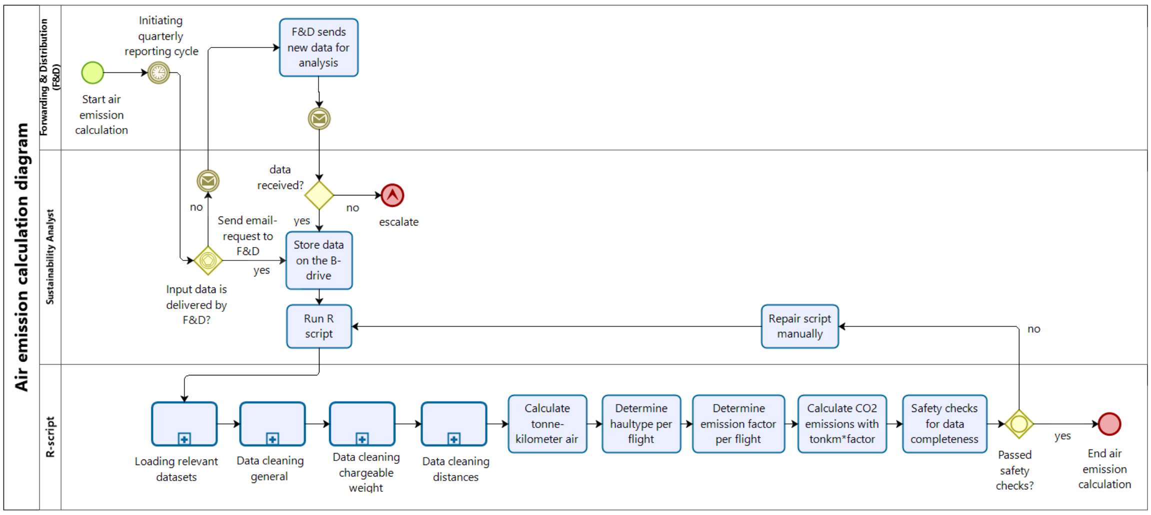

Figure 7.1: BPMN tool overview

7.3 Implementation dashboard tool Qlik Sense

A dashboard tool in Qlik Sense is built such that it can easily be seen on which lanes, segments and periods emissions occur. Qlik Sense is a publicly available business intelligence and visual analytics platform, which allows an individual discovery path through the data (Qlik, 2020). It is an interactive tool in which a person can select e.g. the origin or destination country or the time period and then the selected lanes are shown on a world map. On the world map are also Philips' production sites (orange) and main warehouses (red). When selecting specific lanes, the corresponding CO_2e, costs and number of shipments are shown. Figure 7.2 shows a screenshot of the dashboard tool. Note that this dashboard overview does not give the complete overview of all lanes and cost figures that are used by Philips, in order to ensure confidentiality.

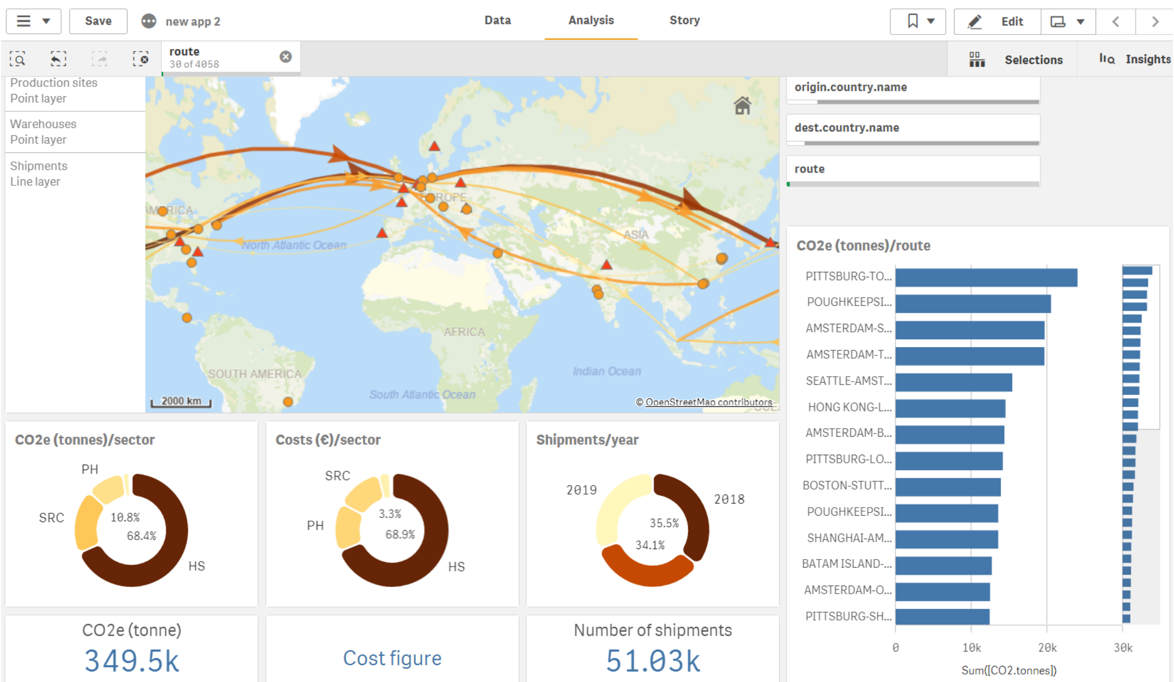

Figure 7.2: Dashboard overview - World map and general figures

The dashboard only uses the shipments, emissions and costs of the lanes that contain both an origin and a destination IATA-code. For the lanes that lack this specific information, only country-to-country details could be calculated. Since country-to-country details are not helpful either for visualization or for transport mode shift calculations, these details are only included in the total emission figures but not in the implemented dashboard. The lanes that are excluded for this reason, account for 2.7% of the total CO_2e emissions within scope.

This dashboard is a useful start for Philips' internal carbon reporting and improvement program. Being able to communicate throughout the company which lanes have the highest emissions impact and by which segment these shipments are transported, enables Philips to get into contact with these specific segments and point out alternatives. The first version of this airfreight dashboard is launched in April 2020 within Philips' Group Sustainability. Philips is currently working on improving the segment mapping, and by narrowing down these segments, it is easier to trace back who sent which shipments. This data can later be added to the dashboard of Figure 7.2, by adding an extra column to the imported data sheet. This will be quite easy for Philips, since this dashboard has been developed in the software tool of Philips preference. Afterwards, the dashboard can be launched to all supply chain segments within Philips.

7.4 Transport Mode Selection Problem (TMSP) tool

The final implementation that has been performed at Philips is the implementation of the Transport Mode Selection Problem (TMSP) simulation model. Due to data limitations, it was not possible to implement the methodology of Chapter 5 right away. Instead, the contingency plan has been applied of building a tool in R, based on both available and simulated data. This tool shows the improvement potential for reducing logistics emissions at Philips on a narrowed scope. There are multiple ways for Philips to use this implementation. Firstly, the results of the current application can be used to apply transport mode shift to (some of) Philips' top 20 lanes. With the help of the tool lanes can be selected and it results in an estimation for the emission decrease (and cost increase) to substantiate decision-making. Secondly, when specific data about the product types, product value, inventory policy, demand distribution or actual leadtimes per mode becomes available, this data can be added to the tool. When more data is available, the accuracy of results increases. The R-code specifies which input is used in which blocks of code, thus data input can be adjusted easily. Thirdly, also when no additional data becomes available, but the results of this chapter are considered to be useful, then the existing simulation model can be applied to a bigger or different scope. In order to do this, the emission calculation (Chapters 2 and 3) can be used to select the lanes with high emission impact for scoping, e.g. lanes 20-40. The methodology of Chapter 5 can be applied to calculate the parameters of these selected lanes (cost, leadtime, demand, inventory). All input parameter estimations have been documented clearly and all steps have been performed in R, which was Philips' preference for coding language. Therefore, future application on wider scope is considered to be feasible for Philips.

Finally, it is also possible to extrapolate current conclusions for the limited scope to a wider scope. This option is a solution that Philips likes to implement on a short-term, while starting the in-depth supply chain investigations and additional data collection. In Chapter 5 it is concluded that shipment lanes with cheaper products shift easier to ocean transportation in than more expensive products. Furthermore, it is concluded that heavier shipments are shipped with cleaner transport modes. Additionally, it can be concluded that for larger distances cleaner modes are selected, because the inventory holding and penalty costs are balanced by lower transport (and emission) costs. Another observation is that there are also transport mode shifts when both air and ocean distances are low. When the ratio between the ocean distance and the air distance is low, this means that the distance difference is not (very) disadvantageous for ocean. These conclusions can be extrapolated to a wider scope by comparing e.g. product categories with value and weight on several shipment lanes. Then it is possible to select lanes with similar characteristics as the lanes that currently shifted to ocean in the TMSP simulation results. This idea is currently being developed and the first proposal is expected to be finished in April 2020.

Chapter 8

Conclusion and discussion

The objective of this Master Thesis is to analyze and visualize the global logistics processes of Philips' airfreight and this research aims to introduce actionable improvements for sustainability. Based on the defined objective, the research question is defined as follows:

What is the current environmental impact of Philips' logistic processes for airfreight and which sustainable improvements can be introduced to drive carbon emission reductions?

First, Section 8.1 briefly summarizes the conclusions of this Master Thesis project, by answering each of the research sub-questions. This is followed by Section 8.2 that presents a discussion on the results, and reflections on the choices made during this Master Thesis.

8.1 Conclusion

To answer the main research question, three sub-questions have been defined. Firstly, Chapters 2 and 3 answer the following research sub-question:

1. How to define a method that can accurately calculate the current environmental impact of Philips' logistic processes for airfreight?

To answer the first research sub-question, Chapter 2 describes a methodology to calculate the carbon dioxide equivalent (CO_2e) emissions of transporting goods, based on Network for Transport Measures (NTM) methodology. This methodology presents a step-by-step overview how to handle distances, weights and emission factors of transportation. Then, this methodology is applied to Philips' airfreight logistics data in Chapter 3. In order to implement the methodology to Philips' data, some adjustments are required. The data is cleaned based on the aspects: origin/destination, weight and cost. The methodology for calculating the chargeable weight of shipments cannot be implemented, because the actual weight and volume data of shipments is incorrect. Therefore, the chargeable weight input of 3PLs is used to calculate emissions. Further, the road distances cannot be calculated, because exact origin/destination address data is missing. For this reason, a sampling study is performed to extrapolate a road distance percentage over all shipments. The CO_2e emissions are calculated for two scenarios, based on the aircraft type: Scenario (1) uses the limited aircraft data available at Philips; and Scenario (2) uses industry-average aircraft data. The second scenario is considered the most representative scenario and results in total WTW CO_2e emissions of 1,192 million kg. Comparing this result to Philips' reported emissions over the same scope, leads to an increase of 18.2%. This increase is, among other things, a result of the emission factor choice, the aircraft type assumption and the reporting scope (WTW). Now the emission impact of every shipment lane is calculated, Chapters 4 and 5 answer the second research sub-question:

2. How to develop a general decision making model that provides a trade-off between emissions, costs and service level indicators?

To answer the second research sub-question, Chapter 4 describes a mathematical model for the Transport Mode Selection Problem (TMSP). This model takes the factors costs, emissions and service levels into account in deciding the best way of applying transport mode shift in a multi-modal multi-item setting. Then, in Chapter 5 this model is applied as a case study to a subset of the 20 most important lanes of Philips' shipments data. Unfortunately, many of the required data inputs cannot be obtained. For this reason, all input parameters are estimated as good as possible with the help of existing data, Philips' analysts and literature. Because the leadtime variability, demand distribution and inventory policy are unknown, it is decided to use simulated data to apply the TMSP optimization model. It is concluded that running the simulation model with zero emission penalty cost, results in a win-win decreasing emissions with 53.8% while reducing costs with 18.0% as opposed to Philips' initial situation. This win-win situation at zero emission cost is found with a proposed transport mode shift for lanes: 1, 2, 6, 8, 10, 12, 14, 15, 17, 18, and 20. As a next step, the emission penalty costs are increased and lanes 19 and 16 can also be shifted against a cost level that is below Philips' initial situation. However, these modal shifts do incur additional costs as opposed to the zero penalty cost situation. Then, the order in which the other lanes can be shifted from air to ocean transport in a cost-efficient way is: 13, 4, 7, 3 and 9, 11, and 5. The total emission reduction potential is calculated to be 96.5% against a cost increase of 31.8%.

To check the robustness of results, three sensitivity analyses are performed. Sensitivity (1) tests different holding cost/penalty cost ratios to show Philips the trade-off between service level and inventory costs. Sensitivity (2) tests the simulation with different demand variability scores. Demand variability is an aspect that Philips cannot control, but it does influence the inventory costs and service level of the system. Sensitivity (3) tests the transportation leadtimes under a Gamma distribution instead of a uniform distribution. The most important aspect of the sensitivity analysis is whether the final result, the lanes that are recommended for Philips to perform a transport mode shift to ocean, stays the same across several parameter settings. It can be concluded that the results for recommended transport mode shift at zero emission penalty cost are quite stable throughout several scenarios. Which lanes are allocated to which transport mode is displayed in Appendix D.9. The assumption with highest impact is the situation where the penalty cost rate is low, corresponding to a z-score of 0.96. Under this assumption, most lanes were allocated to transport mode ocean. Finally, the third research sub-question is answered in Chapter 6:

3. Which improvements can be made for the logistics planning process to include more sustainable transportation alternatives for the most impactful products/lanes?

The improvement direction of transport mode shift has been handled in depth. In Chapter 6, it is described why Philips' lanes within scope are considered suitable for transport mode shift. Afterwards, the aspects are described that should be taken into account when shifting the transport modality from air to ocean. It can e.g. be beneficial to apply transport mode shift to lanes that use a similar route or to start with the lanes where there is relatively low variability in production, leadtime and demand across the supply chain. Next to transport mode shift, also general recommendations are provided that can help to include more sustainable transportation alternatives. First, recommendations are stated to reconsider current emission calculation assumptions within Philips. Second, the collaboration with 3PLs is mentioned, to e.g. decrease the contracted minimum weight of a shipment; apply transport consolidation; use cleaner fuels or vehicles; or increase load factors. Further, improvement directions related to Philips' data collection are described. Obtaining relevant data is crucial to improve the calculation accuracy of research sub-questions 1 and 2. Improved accuracy is important when Philips wants to act upon results in order to have reliable expectations for costs of e.g. a transport mode shift.

8.2 Discussion

8.2.1 Carbon emission calculation method

Applying the carbon emission calculation methodology as a case study to Philips' airfreight logistics, many assumptions have been made to come to the final results. Each of these assumptions has an influence on the accuracy of the final result. Most of the assumptions or estimations are made in the data cleaning phase (Section 3.1). These data cleaning steps are well substantiated and are made in accordance to NTM methodology. E.g. cleaning shipments bigger than the size of an airplane or filling in average weights, is considered the most logical choice to calculate the full impact of Philips' airfreight logistics. The biggest issues come up with the lack of specific shipment data, such as the exact route of a shipment and its final address (Section 3.2), the exact actual weight and volume of a shipment (Section 3.3), and the vehicle type and its load factor (Section 3.4). These data issues result in the fact that the methodology of Chapter 2 cannot be implemented right away. The assumption with the highest impact is the aircraft type, being either a full freighter or a belly freight aircraft. Until now, Philips did not incorporate the use of belly freight aircrafts, whereas the (limited) data obtained during this Master Thesis shows that these aircrafts are used often. According to the EFs of the NTM methodology, the emissions of a belly freighter are much higher than the emissions of a full freighter. This assumption has substantial influence on the final CO_2e number, while the aircraft type is currently fully decided by the outsourced 3PL.

Future research is required to investigate the allocation of CO_2e emissions over passengers and freight in a belly freighter aircraft. The allocation of emissions over freight and passengers in a belly freighter differs per methodology, because literature and experts are indecisive which is the preferred allocation methodology. The NTM method allocates emissions corresponding to 100 kilograms of weight to each passenger, and all other emissions to freight. However, it is also arguable that the CO_2e emissions for the weight of seats, galleys, toilets and flight attendants should be allocated to a passenger. A representative of the GLEC framework stated that it is not possible to say one allocation method is more 'correct' than the other, and it is merely a matter of convention. Furthermore, this representative stated that GLEC develops a new standard in the coming 3 years with which it is possible to coalesce on a single belly freight allocation method throughout industry. It is useful for Philips to revise the current assumptions over 3 years to stay informed about the preferred allocation methodology. In the meantime, Philips can obtain reliable data about the type of aircrafts being used with their logistics operations. Next to the recommendation for Philips to obtain more accurate vehicle type data, there are several other data points that can be improved. All data aspects that are currently unavailable or incomplete, are discussed in Chapter 6.

In addition to the assumption of the aircraft type and the emission allocation methodology, there are more aspects to choosing representative EFs. Philips uses EFs of DEFRA with specific underlying assumptions. The methodology of this Master Thesis based on NTM EFs is considered to be an improvement as opposed to Philips' method with DEFRA EFs. This is the case, because the EFs of DEFRA are not clearly defined for use outside of the UK (Downie & Stubbs, 2012). Additionally, the EFs of DEFRA only include tank-to-wheel (TTW) emissions, while the methodology of this Master Thesis reports well-to-wheel (WTW) emissions. WTW reporting is recommended, since it includes the total use of energy including fuel production, distribution and combustion (NTM, 2018b). Reporting the full WTW CO_2e impact is relevant for Philips in their ambition to become fully carbon neutral in its operations. The most important goal of this discussion is to create awareness at Philips that its current assumptions of TTW reporting and EFs might not be representative. It is recommended that Philips substantiates the decisions for carbon calculations and reconsiders the current assumptions. This has been discussed in formal meetings with the manager of Sustainability Reporting team, and Philips will consider taking the next implementation steps in 2020.

8.2.2 TMSP optimization model

The application of the Transport Mode Selection Problem (TMSP) optimization model as a case study to Philips' top 20 lanes, also requires several estimations and assumptions. Most of the assumptions on input parameters of the model (Section 5.2) are considered to be valid and realistic. This includes the product values; the shipment distances; the contracted leadtimes; the holding and penalty cost rate; the transportation costs; and the general transport parameters. However, the model would be more precise when the exact product type, weight, volume and value are known. When the product type and dimensions are known, logistics planning could be more efficient. For example, then one would know how many products fit inside one container and shipping quantity can be optimized accordingly. Besides, when the product value is known, all equations and parameters can be expressed in units of product instead of units of weight. That would increase the reliability of the penalty cost and the holding cost calculation for items in transit or items in stock.

A discussion point for the distances and routes can be seen in the somewhat simplistic assumption that there is only one route available for each transport mode. Each route uses the (air)ports that are closest to the origin and destination respectively. However, in real life it can also be more convenient to drive a bit further and consolidate shipments of different destinations at one (air)port. Or, a shipment can go by air transport to the nearest coast and then switch to ocean transport. This might be a good solution for destinations that are e.g. in the middle of the United States. Further, it is assumed that air and ocean are the only possible modes for Philips. This could be extended to e.g. a multi-modal option with rail transport. There are many possibilities per transport lane and figuring out which is the most efficient one requires detailed data on a lane level. Since no actual product level data can be obtained, this falls out of scope for this Master Thesis. Another shortcoming of the case study in this Master Thesis, is that it only considers 20 lanes within scope, corresponding to about a quarter of Philips' total CO_2e emissions. It would have been more useful to Philips when all lanes were considered for a transport mode shift. Note that this scoping decision is made due to lacking data. In cooperation with Philips, the possibility for extending the results over other lanes is investigated. Here, the conclusions for e.g. certain product segments are reviewed and suitability for transport mode shift on all lanes with these characteristics is considered.

The simulation parameters (Section 5.3), including leadtime variability, demand simulation and starting inventory, are more up for discussion. Since there is no data at all about the actual leadtimes, it is hard to justify any assumption on the leadtime variability. The uniform distribution that is currently used forms a reasonable starting point of what this variability could be. A sensitivity analysis is performed for leadtimes, changing the uniform distribution to a Gamma distribution. Only minor changes in the costs and service level are observed. For the demand simulation it is defensible that the total shipped weight equals the total demand over the years within scope. However, it is unknown whether a demand of the normal distribution with a stable mean over the years is representative. A sensitivity analysis is performed changing demand variability scores to show the effect on service level and inventory costs. Further, the inventory model of the system does not respond as it would be desirable in reality. Every transported shipment is based on historical shipments and there cannot be any additional shipments when demand or leadtime variability is high in certain periods. This is done in order to provide the transport mode selection trade-off for Philips with the use of their actual historical emissions. However, this results in a simulation model where it is not possible to order additional products when the warehouse is out of stock. Due to this choice, the service levels in some of the warehouses can be below an acceptable level for real-life situations.

Since the TMSP model is applied with simulated data, the outcome of the model is not the same at every simulation run and every emission penalty cost value (λ). It can be the case that at a specific λ value, in one run the inventory costs are much higher than in another run, due to the stochastic arrival of shipments and demands. For this reason, it can only be stated approximately which transport mode for shipment lanes is applied at which emission penalty cost. The final discussion point about the TMSP results are the costs. The win-win situation only holds for the costs as included in the model, being: transportation costs, holding costs for items in transportation, holding costs for items in warehouse inventory, penalty costs for not fulfilling customer demand, and emission penalty cost. It is very likely that in reality there are other cost factors included in applying a transport mode shift. These additional costs could occur for, among others: changing of production schedules, warehouse capacity expansion, increase of handling costs at ports, etc. Therefore, it is expected that the actual costs of a transport mode shift could be higher than the costs presented in this Master Thesis. This requires further investigation as soon as more data is available.

Several improvement possibilities and/or future directions for the TMSP model are identified. In the current model, the service level is only taken into account indirectly by charging higher costs for not fulfilling demand from stock. It is also possible to set a service level constraint and then solve the model using two Lagrangian multipliers (λ_k), where each λ_k can be interpreted as a penalty for violating the k-th constraint. Another useful addition to the model can be to implement the option for a transport mode mix. Then, the model would not necessarily pick one transport mode per shipment, but could indicate which percentage is performed by one mode or the other. Additionally, it can be interesting in the future to also include the transport mode rail to Philips' case study, or to use other multi-modal transport combinations. Furthermore, future research can be performed on how this model with single echelon perspective can be extended to a supply chain perspective. Currently, it is assumed that production always meets the amounts that should be transported. However, this assumption might not hold in reality, leading to logistics planning issues.

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Appendix A

Appendix to Chapter 2

A.1 Literature review emission factors

This appendix provides a short overview of the literature review that has been performed on the emission factor (EF) per transport mode for the relevant emission calculation methodologies. These methodologies are: the GHG Protocol (Greenhouse Gas Protocol, 2015), the NTM framework (NTM, 2018b) and the GLEC framework (Greene & Lewis, 2019). Additionally, the EFs of DEFRA are included in this literature review (UK Department for Environment Food and Rural Affairs, 2019). This is the EF source that Philips currently uses. All these EFs present the average kilograms of CO_2e emissions that are emitted with the transportation of one tonne-kilometer under certain assumptions. The full literature study describing all underlying assumptions can be found clicking HERE.

Figure A.1 provides an overview of five different EFs for air transport. The EFs for air transport are considered for different haul-types that are based on certain distance intervals. This system is designed, because of the fact that flying and landing of the airplane costs a lot of energy. Thus, taking this fixed amount of emissions over a shorter distance leads to a higher amount of CO_2e per tonne-kilometer. In this figure all airplanes are assumed to be full freight flights. When calculating aircraft emissions care needs to be taken in choosing the right aircraft or type of aircrafts, since environmental performance varies both with aircraft/engine configuration and the type of aircraft.

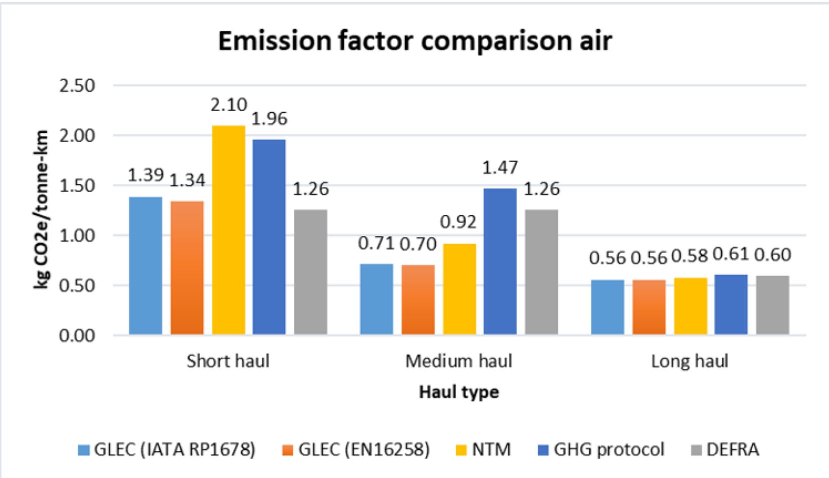

Figure A.1: Emission factor comparison for air freight

Figure A.2 provides an overview of the emission factors for three road vehicle types within Europe. Note that it is quite difficult to compare different vehicle types across several methods, since not every method reports the same type or load of vehicles. Further, it can be concluded that the average EFs for the US are slightly higher than the EFs for the EU. This can be attributed e.g. to a lower energy efficiency of the vehicles being used. Since not all methods provide EFs globally, it is decided to only visualize Europe in this figure. However, the NTM method provides also clear averages for the EU, US, Asia, South America and global averages. Overall, it can be concluded that a smaller vehicle uses to result in higher CO_2e emissions per transported tonne-kilometer of freight.

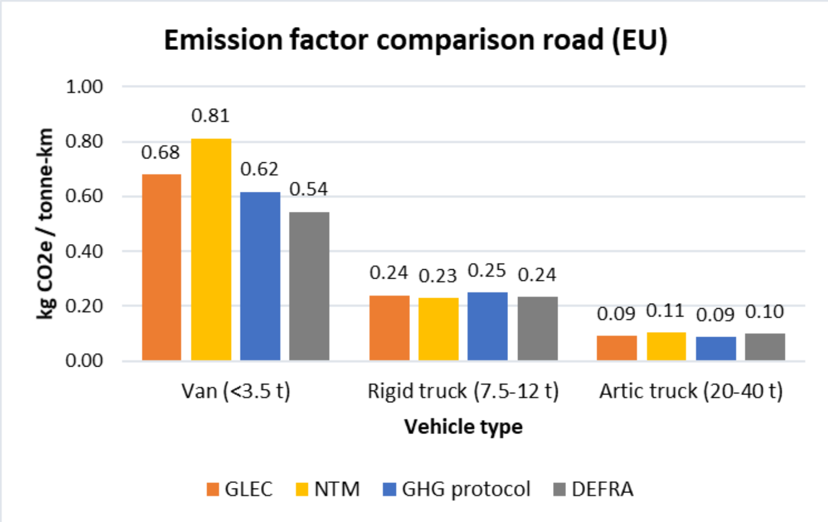

Figure A.2: Emission factor comparison for road freight

Figure A.3 provides an overview of the emission factors for diesel trains within Europe. It can be observed that the NTM method presents a lower EF for rail transport than the other methods. No clear statement could be found why this is the case, since the compared methods are all on the same scope and on the same type of rail transport. However, the most logical explanation is that NTM assumes a higher average load factor than DEFRA. The underlying assumptions of DEFRA are not specified, but it is known that NTM and GLEC assume an average load factor of 60%.

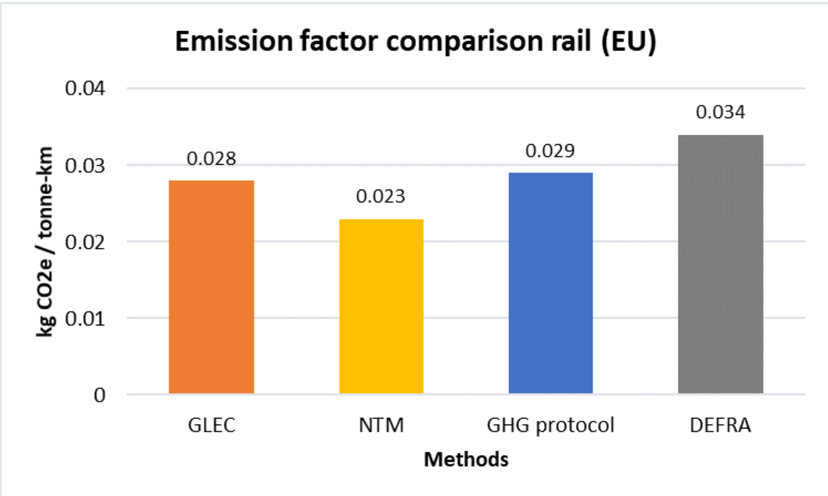

Figure A.3: Emission factor comparison for rail freight

Finally Figure A.4 provides an overview of the emission factors for ocean, consisting of bulk carrier and container ship. This is an average global figure of EFs. For ocean transport, the EFs are dependent on the size, load and the speed of the ship. Further, also the type of water is relevant, since inland waterways have higher EFs than the ocean. Generally it holds that the lower the speed of the ocean transport, the lower the emissions per tonne-km. This Master Thesis project assumes that ocean freight is transported using container ships.

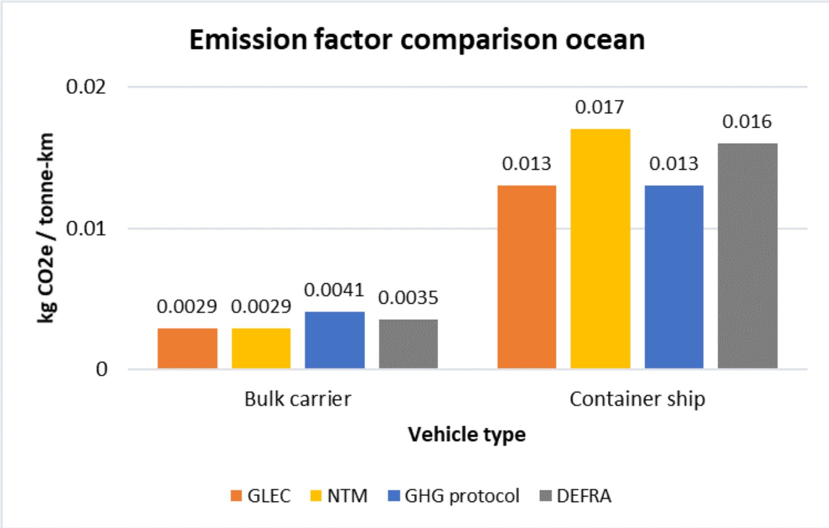

Figure A.4: Emission factor comparison for ocean freight

A.2 Flight detour distance

Figure A.5 shows the detour distance of the ten lanes that are used most often by Philips. Here, the yellow line is calculated with NTMCalc 4.0 online tool (NTM, 2019). The blue dotted line is calculated using Equation (2.2). The percentage of absolute difference between the Equation and the online NTMCalc 4.0 tool on these ten lanes, equals 0.009%. It can thus be concluded that the Equation fits the NTMCalc 4.0 tool very well. The big advantage of the Equation as opposed to the online tool is that the Equation can be automated easily and calculated for thousands of flights at the same time.

Further, it can be seen that shorter flights have relatively higher detour distances. This makes sense, since for shorter flights, the detour at e.g. take-off or landing is a bigger portion of the total flight. It can be concluded that the total flight distance including detour for these lanes is on average 2.83% higher than the Great Circle Distance (GCD).

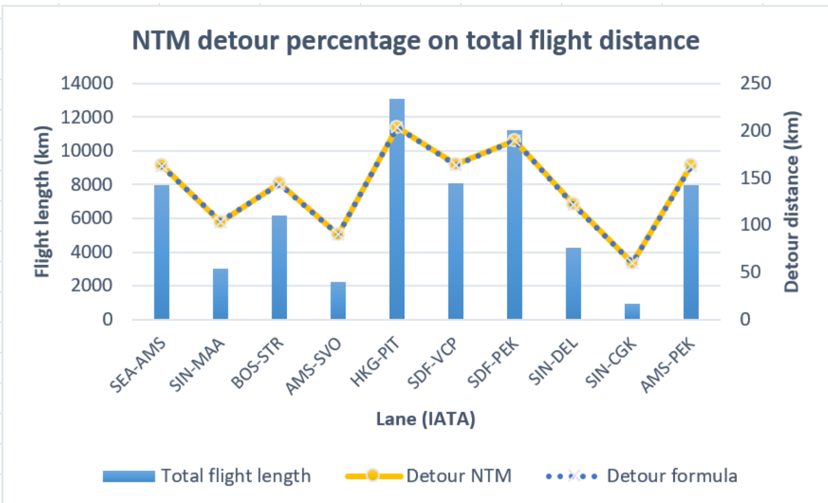

Figure A.5: Detour percentage top-10 lanes

Appendix B

Appendix to Chapter 3

B.1 IATA-code input rectification

This appendix provides an overview of the IATA-code mistakes that are found in the input data. Since the IATA-codes in the input data are entered manually, it can occur that an employee enters a combination of letters that is not an IATA-code but e.g. a city code. Table B.1 shows in the most left column the 'wrong' inputs that are used as an IATA-code. Then, the corresponding city and country are specified. The next column provides official IATA-code(s) as are known in this specific city (Codes, 2019). Finally, the most right column provides the final IATA-code as being rectified for the calculations. For determining this code the following methodology is used: (1) If only one available IATA then pick this; (2) If more than one available IATA then pick the one that is most often used by Philips; (3) If more than one available IATA and none of them are used by Philips, pick the largest airport.

Table B.1: Airfreight IATA-code input mistakes

Input IATA	City	Country	Official IATA code(s)	Output IATA
ZSN	Manitoba	Canada	XSI	XSI
SPL	Amsterdam	Netherlands	AMS	AMS
BJS	Beijing	China	PEK / NAY	PEK
BUH	Bucharest	Romania	OTP / BBU	OTP
TYO	Tokyo	Japan	NRT / HND / OKO	NRT
MIL	Milan	Italy	MXP / LIN / BGY / PMF	MXP
MMA	Malmö	Sweden	MMX	MMX
LON	London	England	LHR / LGW / LTN / STN / LCY / SEN	LHR
KUB	Kunshan (Shanghai)	China	PVG	PVG
OSA	Osaka	Japan	KIX / ITM / UKB	KIX
REK	Reykjavík	Iceland	KEF / RKV	KEF
SEL	Seoul	South Korea	ICN / GMP / SSN	ICN
BAK	Baku	Azerbaijan	GYD / ZXT	GYD
BUE	Buenos Aires	Argentina	EZE / AEP	EZE
DTT	Detroit	United States	DTW / DET / YIP	DTW
BHZ	Belo Horizonte	Brazil	CNF / PLU	CNF
JKT	Jakarta	Indonesia	CGK / HLP	CGK
PAR	Paris	France	CDG / ORY / LBG / BVA / POX / XCR	CDG
STO	Stockholm	Sweden	ARN / BMA / NYO / VST	ARN
ZIX	Zhuhai	China	ZUH	ZUH

B.2 Data cleaning visualization transport costs

This appendix shows some figures supporting the data preparation statement of having no clear relation between the cost of a shipment, and its weight or distance. This explanation supports the data preparation section as explained in Subsection 3.1.1. A relation between the variables cost and weight or between cost and distance would help to determine which cost values are outliers.

First, it was tried to find a relationship between the costs and the shipment weights, using boxplots. Figure B.1 shows the the costs for several weight categories. The first weight category is from 0-5,000 kg, and every following category is with an interval of 5,000 kg more. The last box contains the shipments of 70,000 kg and more, which are just 5 shipments in the total data. From this plot it is concluded that there is no clear relation between the costs of a shipment and the shipped weight. Most of the boxplots are overlapping with other categories. Especially for the first category, no clear boxplot can be seen, since there are many outliers in terms of costs. For higher weight categories, the price seems quite stable (no outliers). Note, however, that most of the shipments have a weight between zero and 10,000 kg.

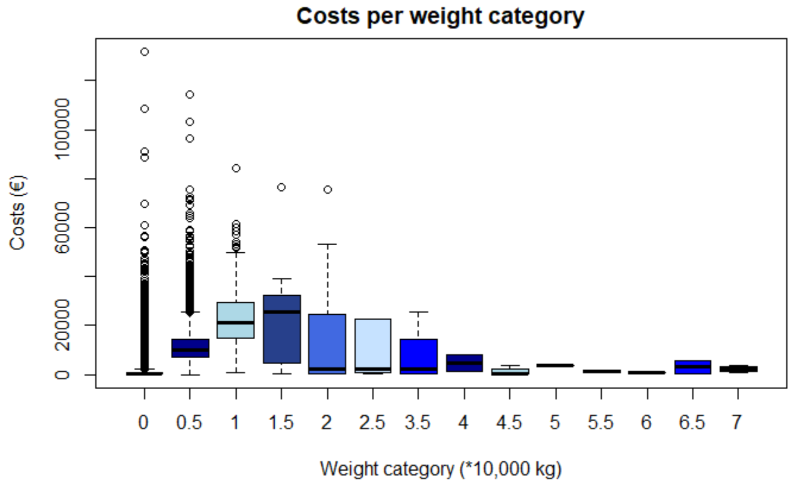

Figure B.1: Costs per weight category

After plotting the normal variables of weight and cost to another, the next option was to log-transform the variables and to check whether there is a linear relation between the two. Figure B.2 shows the plot of the log-transformed variables cost and chargeable weight. The Figure shows some trend for a portion of the data-points. Unfortunately, no clear linear function can be identified, due to the wide spreaded data points and many data points along the axes. Therefore, using the chargeable weight of a shipment to clean the data input of costs cannot be substantiated.

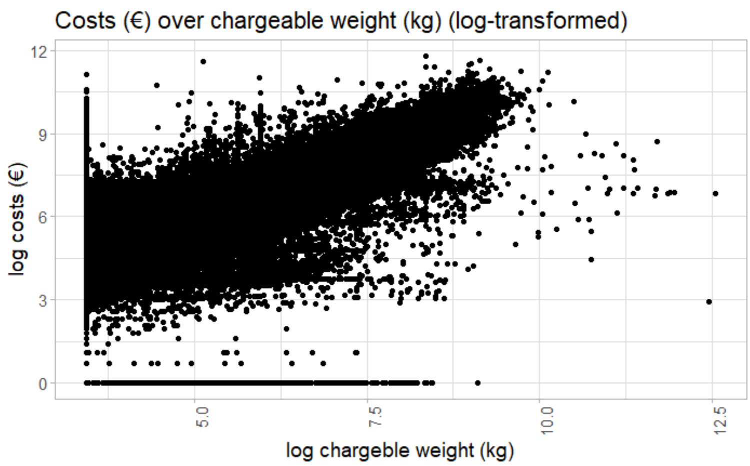

Figure B.2: Log-transformed costs over chargeable weight

Next to the possible relation between costs and shipped weight, the relation between costs and distance is tested. Figure B.3 shows a boxplot of the costs for several distance categories. The first cost category is from 0-3,000 km and every following category is with an interval of 3,000 km bigger. From this plot it is concluded that there is no clear relation between the costs of a shipment and the shipped distance. The average cost for every boxplot is in the same range and all boxplots overlap another. There are so many outliers that for most of the distance intervals, no real boxplot can be seen.

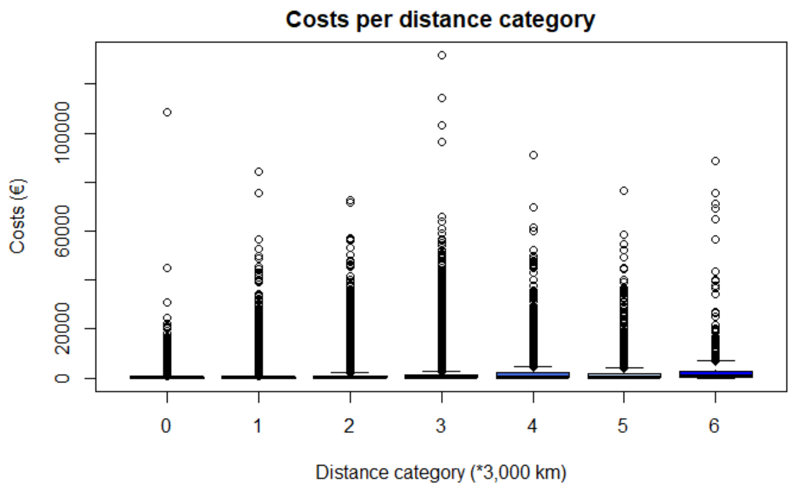

Figure B.3: Costs per distance category

Finally, also the log-transformation for costs and distance has been tested, in order to seek for a linear relationship between the two. Unfortunately, the relation was even more spread out than the one of Figure B.2, and resulted in one big cloud, as can be seen in Figure B.4. Therefore, using the flight distance of a shipment to clean the data input of costs cannot be substantiated.

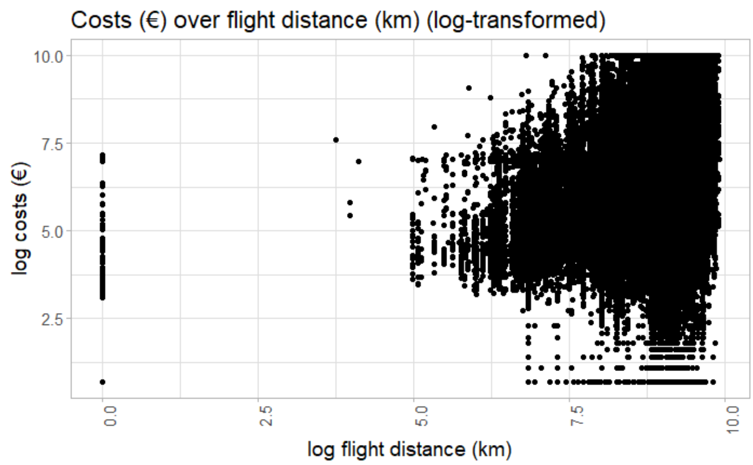

Figure B.4: Log-transformed costs over flight distance

B.3 Data cleaning overview

Table B.2 provides an overview of the data cleaning changes applied for chargeable weight and cost input values. The first column shows the reason for data cleaning, as explained in Chapter 3. The second and third column show the absolute and relative change respectively. It can be concluded that none of the cleaning steps has a major impact on the total data set. Note that there are no cases observed where the input for chargeable weight was below 30 kg.

Table B.2: Data cleaning overview

Data cleaning reason	Absolute change	Relative change
Chargeable weight below 30 kg	-	-
Chargeable weight above max. load	- 1,483,311 kg	- 0.939%
Chargeable weight NA value	+ 366,459 kg	+ 0.232%
Cost value negative	- 25 shipments	-
Cost value NA	+ 11,995,833 €	+ 0.037%
Cost outlier values	- 7,189,912 €	- 0.022%

As explained in Chapter 3, Philips likes to have realistic cost results but prefers to stay as close as possible to the original values. For the outlying cost values, a winsorizing of 99.5% is applied. This means that the top 0.25% and the bottom 0.25% of the data is winsorized and that only the most extreme cases have been cleaned. Table B.3 provides an overview of the data before and after winsorizing.

Table B.3: Winsorizing shipment cost data (€)

	Min.	1st Quartile	Median	Mean	3rd Quartile	Max.
Original data	0	119	346	1,205	1,059	132,007
Winsorized data	1	119	346	1,180	1,059	21,773

B.4 Missing coordinates input data

After sorting out the IATA-codes that Philips uses, and checking the correctness of the corresponding coordinates, there are 12 IATA-codes for which no coordinates were found. Note, however, that these IATA-codes are not used very often, just 0.43% of the total amount of flights. Table B.4 provides an overview for which IATA-codes the coordinates were missing. The coordinates have been filled in by using Google GeoHack and are used in the calculation method of distances. After this step the complete data input file of airport contains 9,052 airports with coordinates.

Table B.4: Missing coordinates rectification

IATA	Country	Longitude	Latitude
EOS	United States	-94.392	36.811
GDY	United States	-82.125	37.233
GUM	Guam	144.797	13.484
JMN	United States	-93.995	44.169
MLH	France	7.529	47.590
MOR	United States	-83.376	36.179
MOW	Russia	55.756	37.617
SAO	Brazil	-23.507	-46.634
TOV	Tortola	-64.600	18.450
UXM	United States	-158.145	61.044
YTN	Canada	-62.620	45.610
ZBD	China	118.623	28.739

B.5 Distance differences between methods

This appendix provides an overview of the lanes for which the highest percentage of difference in distances are found between Philips' method and the calculation method as described in Section 2.2. In total there are 2,989 lanes with same origin and destination IATA in both distance methods. The top 10 of highest percentage differences is displayed in Table B.5. A negative distance difference represents that the calculated distance is lower than the original distance of Philips and vice versa. The top 3 lanes with the highest percentage difference is due to the very short total distances. The remaining airports in this table are checked based on coordinates and no mistakes could be identified. Thus, it is unknown why these distance differences exist. The lanes in Table B.5 together make up for only 0.11% of the flights. Therefore, the impact of these distance differences is considered to be low.

Table B.5: Origin-Destination (IATA) lanes with highest percentage distance difference

Lane (IATA)	Distance Philips	Calculated distance	km difference	% difference
HKG-SZX	26.8	38.3	11.5	42.8
SZX-HKG	26.8	38.3	11.5	42.8
DXB-MCT	370.6	348.9	-21.7	-5.9
BUD-NBO	5,406.4	5,692.5	286.1	5.3
STR-NBO	5,897.7	6,173.7	276.0	4.7
AMS-NBO	6,408.4	6,684.9	276.5	4.3
SDF-GDL	2,507.1	2,592.1	85.1	3.4
TLV-IST	1,134.1	1,167.0	32.9	2.9
GDL-SEA	3,357.5	3,451.9	94.4	2.8
PIT-GDL	3,035.2	3,118.0	82.8	2.7

B.6 Sensitivity analysis road assumption

In Subsection 3.2.3, the methodology for calculating road distances has been discussed. It appeared that some of the shipments have a city-name that is equal to the city corresponding the IATA-code. This results in the problem that the within-city distance can not be calculated. It is assumed that on average, this road distance equals 25 kilometers. Table B.6 provides an overview of the impact of this assumption. With assuming 25 kilometers average, the resulting total road-percentage was 1.38% of the GCD respectively. However, varying the assumed distance between 10 and 40 kilometers, the road distance percentages range between a minimum of 1.25% and a maximum of 1.52% respectively.

Table B.6: Sensitivity analysis of within-city distance assumption

Road distance (km)	Distance first leg (km)	Distance last leg (km)	% first leg of GCD	% last leg of GCD
10	55.99	47.13	0.68%	0.57%
15	57.39	49.37	0.70%	0.60%
20	58.80	51.60	0.71%	0.63%
25	**60.20**	**53.84**	**0.73%**	**0.65%**
30	61.61	56.08	0.75%	0.68%
35	63.01	58.31	0.77%	0.71%
40	64.42	60.55	0.78%	0.74%

Appendix C

Appendix to Chapter 4

C.1 Lagrangian function

This appendix clarifies the calculation steps that are performed in order to find the Lagrangian function and the decentralized Lagrangian. According to (Joachim Arts, 2018), a Lagrangian function is set up as follows:

$$L(\mathbf{x}, \lambda) = f(\mathbf{x}) + \sum_{j \in J} \lambda_j (g_j(\mathbf{x}) - \epsilon),$$

Where $f(\mathbf{x})$ is the cost function of Problem (P), $g(\mathbf{x})$ is the emission function of Problem (P) and ϵ is the emission constraint of Problem (P). Then the Lagrangian function of Equation (4.11) is obtained:

$$L(\mathbf{x}, \lambda) = \sum_{j \in J} \left(\sum_{i \in I} x_{i,j} C_{i,j} \right) - \lambda \left(\sum_{j \in J} \left(\sum_{i \in I} x_{i,j} E_{i,j} \right) - \epsilon \right).$$

First, the sums over j are combined to one sum and the ϵ is moved out of the brackets:

$$L(\mathbf{x}, \lambda) = \sum_{j \in J} \left(\sum_{i \in I} x_{i,j} C_{i,j} - \lambda \left(\sum_{i \in I} x_{i,j} E_{i,j} \right) \right) + \lambda \epsilon,$$

Now it is easily observed that the costs and emission function are separable in j. The implicit constraint $((x) \in (X))$, is also separable in j and thus Lagrangian is also. Hence the Lagrangian can be written as:

$$L(\mathrm{x}, \lambda) = \sum_{j \in J} L_j \left(\mathrm{x}_j, \lambda \right) + \lambda \epsilon,$$

Where the left part is defined as:

$$L_j \left(\mathbf{x}_j, \lambda \right) = \sum_{i \in I} x_{i,j} C_{i,j} - \lambda \sum_{i \in I} x_{i,j} E_{i,j}$$

which is the *decentralized Lagrangian* for product j. Note that the Lagrangians are only connected by a single multiplier λ of the emission constraint.

C.2 Everett result

This appendix clarifies the Everett result (Everett, 1963) that is being used to decompose problem (P) into problem (Q). First the Everett result theorem is explained. The Everett result can be especially useful when the Lagrangian dual function cannot be obtained analytically; e.g. because the solution space is limited to integer solutions. Then there might be a gap between the optimal solution and the maximum value of the Lagrangian dual function.

Everett result (Joachim Arts, 2018; Everett, 1963): If, for a given $\lambda \geq 0, \mathbf{x}(\lambda)$ minimizes $L(\mathbf{x}, \lambda)$ over $\mathbf{x} \in \chi$, then $\mathbf{x}(\lambda)$ is optimal for all $b_j \in (0, \infty), j = 1, \cdots, m$, that satisfy

$$b_j \geq g_j(\mathbf{x}(\lambda)) \text{ and } \lambda_j \left[g_j(\mathbf{x}(\lambda)) - b_j\right] = 0, \quad j = 1, \ldots, m \quad (1)$$

For a given value of λ there is a solution $\mathrm{x}^*(\lambda) = (\mathrm{x}_1^*(\lambda), \ldots, \mathrm{x}_m^*(\lambda))$ that minimizes the Lagrangian. Then $\mathbf{x}^*(\lambda)$ is optimal for Problem (P) for all $\epsilon \in (0, \infty)$ that satisfy

$$\epsilon_j \geq \sum_{j \in J} \sum_{i \in I} x_{i,j} E_{i,j}(\mathbf{x}(\lambda))$$

$$\lambda_j (\sum_{j \in J} \sum_{i \in I} x_{i,j} E_{i,j}(\mathbf{x}(\lambda)) - \epsilon_j) = 0$$

Thus, if $\epsilon = E\left(\mathrm{x}^*(\lambda)\right),$ then, by the Everett result (Everett, 1963)) $, \mathrm{x}^*(\lambda)$ is the optimal solution to the mathematical Problem (P) and the constraint will be met with equality. Then, it follows from Theorem 1 of this (Everett, 1963) that these solutions are efficient solutions for the unconstrained multi-criteria Problem (Q):

$$\min_{\mathrm{x} \in \mathrm{X}} C(\mathrm{x})$$

$$\min_{x \in X} E(\mathrm{x})$$

Appendix D

Appendix to Chapter 5

D.1 World regions

Figure D.1 provides an overview of the regions worldwide as used in this Master Thesis. In this figure, every world region is colour coded as follows: red = APAC; green = EUR; blue = LATAM; orange = MEA; and yellow = NAM. These regions are also used in the confidential coding of shipments and in multiple linear regression model as described in Appendix D.5.

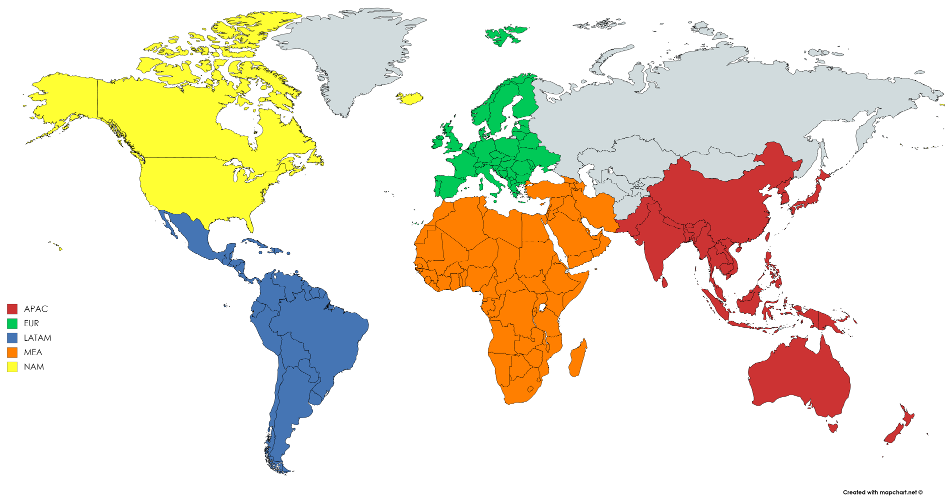

Figure D.1: World regions

D.2 Value density per segment

Table D.1 provides an overview of the value density numbers per segment. As explained in Chapter 5, the average product value and product weight are estimated with the help of multiple professionals and data sources. Then, these value density numbers are multiplied with the weight of a shipment to obtain the estimated shipment value. Note that the segment names have been replaced with letters for confidentiality reasons.

Table D.1: Average product value and weight per segment

Segment	Avg. product value (€)	Avg. product weight (kg)	Value density (€/kg)
A	15	4.0	3.8
B	690,000	5,200	133
C	60,000	250	240
D	520	5.0	104
E	20	1.2	16.7
F	5,000	600	8.3

D.3 Overview distances per transport mode

Table D.2 provides an overview of the calculated distances per transport mode. The first three columns show the lane number and its origin and destination. The fourth and fifth column show the air distance and the corresponding distance of the road legs for air transport. The sixth and seventh column show the ocean distance and the corresponding distance of the road legs for ocean transport. The road distances of both transport modes include the additional 20% for detours and pre-positioning.

Table D.2: Distance per transport mode

Lane	Origin	Destination	Air (km)	Road-air (km)	Ocean (km)	Road-ocean (km)
1	NAM1	APAC2	10,773	179	17,935	628
2	NAM2	EUR1	5,931	98	6,265	265
3	EUR1	APAC3	9,084	151	19,492	125
4	EUR1	APAC2	9,505	158	20,728	125
5	NAM3	EUR1	8,011	133	16,381	125
6	APAC1	EUR2	9,820	163	17,977	60
7	EUR1	APAC4	7,998	133	20,468	301
8	NAM1	EUR2	6,121	102	6,458	628
9	NAM3	EUR3	6,146	102	5,963	692
10	NAM2	APAC3	11,975	199	19,598	200
11	APAC3	EUR1	9,085	151	19,492	125
12	APAC4	NAM4	15,626	259	19,024	944
13	EUR1	APAC5	9,427	156	20,341	125
14	NAM1	APAC3	11,945	198	19,550	628
15	EUR1	NAM5	6,942	115	6,712	1,193
16	EUR1	APAC1	9,460	157	18,053	125
17	NAM5	APAC6	15,747	261	19,198	1,128
18	NAM5	EUR1	6,942	115	6,712	1,193
19	EUR1	APAC6	10,712	178	15,349	125
20	APAC1	NAM3	10,639	177	10,630	60

D.4 Overview leadtimes per region

This appendix provides some insights on the average contracted leadtime per region. This data is used in the multiple regression model of D.5. The transport times per region are defined based on the contracts that Philips has with its 3PLs. Table D.3 shows an overview of the contracted transport time in days for the transport mode air. On top of this, an average 2.3 additional days are used per shipment for handling and waiting.

Table D.3: Airport-to-airport transport times per region (in days)

Region from/to	APAC	EMEA	LATAM	NAM
APAC	4	5	7	5
EMEA	5	5	5	5
LATAM	6	5	3	5
NAM	5	5	5	5

Table D.4 shows an overview of the contracted transport time in days for the transport mode ocean between specific regions. On top of this, an average 3.2 additional days are used per shipment for handling and waiting.

Table D.4: Port-to-port transport times per region (in days)

Region from/to	APAC	EUR	LATAM	MEA	NAM
APAC	10	30	34	21	21
EUR	36	15	26	25	17
LATAM	39	28	18	39	13
MEA	31	18	42	29	26
NAM	29	21	37	26	-

D.5 Multiple linear regression model leadtimes

Figure D.2 shows the multiple linear regression model that has been applied in order to predict the missing values for contracted ocean leadtime. The interpretation is complex, since multiple variables are used in order to predict the ocean leadtime. It can be concluded that the prediction power of this model is $R^2 = 0.62$.

```
Call:
lm(formula = ocean.leadtime ~ ocean.dist.km + origin.region +
    dest.region, data = Philips_transport)

Residuals:
    Min      1Q  Median      3Q     Max
-7.0503 -4.7613  0.5467  2.1734 20.9906

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                 3.657e+01  2.199e-01  166.36   <2e-16 ***
ocean.dist.km              -1.318e-04  6.755e-06  -19.52   <2e-16 ***
origin.regionemea           3.572e+00  1.331e-01   26.84   <2e-16 ***
origin.regionnorth_america -8.959e+00  1.034e-01  -86.67   <2e-16 ***
dest.regionemea            -1.802e+00  1.056e-01  -17.07   <2e-16 ***
dest.regionnorth_america   -1.896e+01  1.497e-01 -126.67   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4.823 on 37048 degrees of freedom
  (2625 observations deleted due to missingness)
Multiple R-squared:  0.6239,    Adjusted R-squared:  0.6239
F-statistic: 1.229e+04 on 5 and 37048 DF,  p-value: < 2.2e-16
```

Figure D.2: Multiple linear regression model ocean leadtime

Table D.5 provides an overview of the application of the leadtimes for ocean. The first row shows the overview after applying only the contracted country-to-country ocean leadtimes. Here, it can be seen that there are 2,625 NA values (equals 6.6%) in the ocean leadtimes. The second row shows the predicted values of the multiple linear regression model on the NA values. The bottom row shows the summary of the complete ocean leadtime data.

Table D.5: Ocean leadtime overview (days)

	Min.	1st Qu.	Median	Mean.	3rd Qu.	Max.	NA's
Country-to-country leadtimes	15.2	24.2	27.3	28.7	32.2	49.2	2,625
Predicted leadtimes	15.1	16.2	37.8	30.7	37.8	37.8	-
Complete overview	15.1	24.2	27.2	28.9	32.2	49.2	-

Table D.6 provides an overview of the application of the leadtimes for air. The first row shows the overview after applying only the country-to-country air leadtimes. Here, it can be seen that there are 12,112 NA values (equals 30.5%) in the air leadtimes. The second row shows the region-to-region air leadtimes that have been applied to the NA values. The bottom row shows the summary of the complete air leadtime data.

Table D.6: Air leadtime overview (days)

	Min.	1st Qu.	Median	Mean.	3rd Qu.	Max.	NA's
Country-to-country leadtimes	5.0	5.0	7.0	6.5	8.0	10.0	12,112
Region-to-region leadtimes	5.0	5.0	7.0	6.3	7.3	10.0	-
Complete overview	5.0	5.0	7.0	6.4	7.6	10.0	-

The expected leadtime for the road legs is determined by taking the road distance of a specific transport mode and shipment lane and dividing this with an average speed of 400 km/day. An overview of the road distances per transport mode is shown in Table D.7.

Table D.7: Road leadtime overview (days)

	Min.	1st Qu.	Median	Mean.	3rd Qu.	Max.
Road leadtimes with air	0.25	0.29	0.33	0.35	0.39	0.65
Road leadtimes with ocean	0.15	0.31	0.31	0.89	1.57	2.98

D.6 Multiple linear regression model ocean transport costs

Figure D.3 provides an overview of the multiple linear regression model that has been applied in order to estimate the missing transport cost values for ocean. Both the dependent and independent variables have been log-transformed. This is done in order to prevent negative cost predictions. Log-transforming only the transportation costs and not the independent variables decreased the predictive value of the model.

```
Call:
lm(formula = log(ocean.total.spend) ~ log(chargeable.weight.kg) +
    log(ocean.dist.km), data = Philips_transport)

Residuals:
     Min       1Q   Median       3Q      Max
-0.58324 -0.23786 -0.04263  0.24742  0.68557

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)               1.0449710  0.0271326   38.51   <2e-16 ***
log(chargeable.weight.kg)  1.0220535  0.0008935 1143.94   <2e-16 ***
log(ocean.dist.km)        -0.3577971  0.0027434 -130.42   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2618 on 37065 degrees of freedom
Multiple R-squared:  0.9738,    Adjusted R-squared:  0.9738
F-statistic: 6.878e+05 on 2 and 37065 DF,  p-value: < 2.2e-16
```

Figure D.3: Multiple linear regression model ocean transport cost

Table D.8 provides an overview of the application of the transport costs for ocean. The first row shows the overview after applying only the country-to-country ocean transport costs (€/shipment). Here, it can be seen that there are 2,611 NA values in the ocean transport costs. The second row shows the predicted values of the multiple linear regression model on the NA values. The bottom row shows the summary of the complete ocean transportation cost data.

Table D.8: Ocean transport cost (€/shipment) overview

	Min.	1st Qu.	Median	Mean.	3rd Qu.	Max.	NA's
Country-to-country costs	1.85	10.58	34.61	111.14	110.77	3,134.02	2,611
Predicted costs	2.76	12.15	89.33	118.38	187.61	966.00	-
Complete overview	1.85	10.70	35.59	111.62	124.33	3,134.02	-

D.7 TMSP simulation demand characteristics

Table D.9 provides an overview of the demand characteristics of the lanes within scope. It is assumed that the total amount of shipments within scope (January 2017 until October 2019) reflect the total demand during scope. The demand is calculated by summing the total shipments per lane and dividing by the total number of days. Here, it is assumed that each year consists of 365 days on which shipment and demand can occur. The second and third column of Table D.9 show the origin and destination respectively. From the fourth column can be seen from which segment the shipments are. The fifth and sixth column show the transported mean weight per day and its standard deviation.

Table D.9: Overview of simulation demand characteristics of the 20 lanes in scope

Lane	Origin	Destination	Segment	μ (kg/day)	σ (kg/day)
1	NAM1	APAC2	A	2,596.4	878.3
2	NAM2	EUR1	A	4,028.3	1,681.1
3	EUR1	APAC3	B	2,520.5	577.7
4	EUR1	APAC2	B	2,405.2	722.7
5	NAM3	EUR1	C	2,236.0	247.7
6	APAC1	EUR2	A	1,720.9	665.5
7	EUR1	APAC4	B	2,089.8	495.7
8	NAM1	EUR2	A	2,691.4	707.4
9	NAM3	EUR3	D	2,632.9	210.5
10	NAM2	APAC3	A	1,317.6	452.2
11	APAC3	EUR1	C	1,735.6	430.61
12	APAC4	NAM4	E	945.7	786.9
13	EUR1	APAC5	B	1,539.4	630.1
14	NAM1	APAC3	A	1,209.1	599.1
15	EUR1	NAM5	B	1,855.1	369.3
16	EUR1	APAC1	B	1,286.2	275.0
17	NAM5	APAC6	F	772.1	169.0
18	NAM5	EUR1	F	1,668.6	90.93
19	EUR1	APAC6	B	962.0	122.3
20	APAC1	NAM3	A	924.0	284.6

D.8 TSMP simulation service level boxplot

Figure D.4 shows the TMSP simulation service level boxplots for each of the shipment lanes within scope. Recall that all service level results are obtained using simulation, which can result in a different service level for each simulation run. This figure shows the service level ranges for each of the shipments. Each shipment is denoted using the shipment lane number, as also denoted in e.g. Table 5.1, and the allocated transport mode. Here, A stands for air transport and O stands for ocean transport. When the boxplot and the whiskers of a specific lane are narrow, this means that the service level range is small and vice versa. A small service level range means that the service level is more stable across several simulation runs. It can be concluded that for most lanes, the service level boxplot covers a range of 10 to 15%. For some lanes the variation in service levels is bigger. This is especially the case for lanes 12, 13 and 14. The most logical explanation for the high service level variation of these lanes is the relatively high standard deviation of demand (see Table D.9).

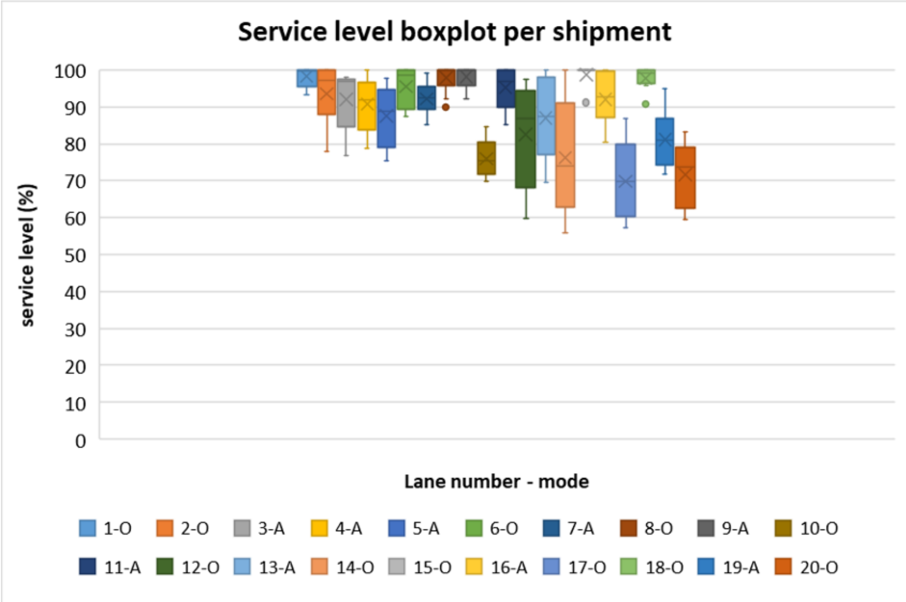

Figure D.4: Service level boxplot per shipment

D.9 TMSP sensitivity analyses mode allocation

This appendix shows for the TMSP sensitivity analyses which shipments are allocated to which transport modes and the corresponding CO_2e emissions in kilotonnes (kt). Each shipment is displayed using the shipment lane number, as also denoted in e.g. Table 5.1. Figure D.5 shows an overview of the transport mode allocation per lane at different z-scores, for Sensitivity 1. These z-scores represent different holding cost/penalty cost ratios, where the penalty cost rate is 5, 10, 50, and 100 times higher than the holding cost rate respectively. Note that the z-score of 1.33 represents the original TMSP simulation model. It can be concluded that a low penalty cost rate leads to increased use of the transport mode ocean, which results in reduced CO_2e emissions. Furthermore, it can be concluded that only one lane changed from ocean to air at z-score 1.33 to 2.06 and no changes occurred between z-score 2.06 and 2.33.

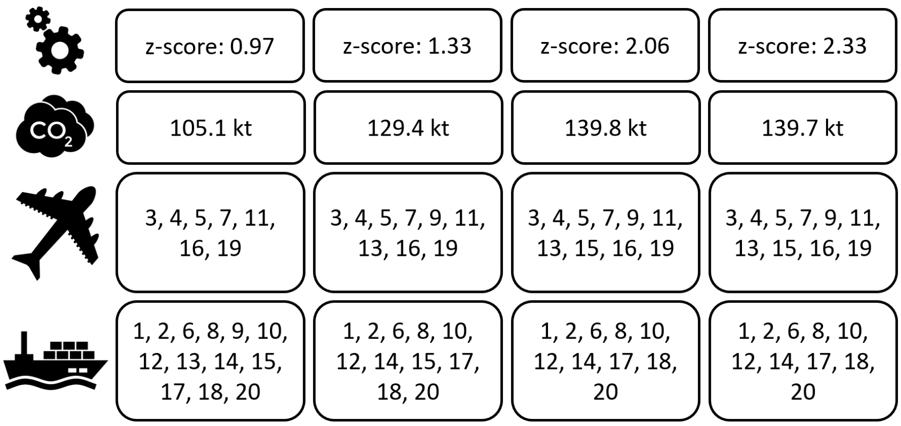

Figure D.5: Sensitivity 1 - Transport allocation per lane at different z-scores

Figure D.6 shows an overview of the transport mode allocation per lane at different demand variability scores, for Sensitivity 2. These demand variability scores represent a multiplication factor with the standard deviation of demand, as in Table D.9. The demand variability score of 1.0 represents the original TMSP simulation model and corresponding demand. It can be concluded that there is only a slight change in the solution from factor 1.0 to 2.0, then one lane changed from ocean to air transport. This corresponds to a slight increase in CO_2e emissions. No other changes can be observed, which means that the solution is quite robust for changes in the demand variability.

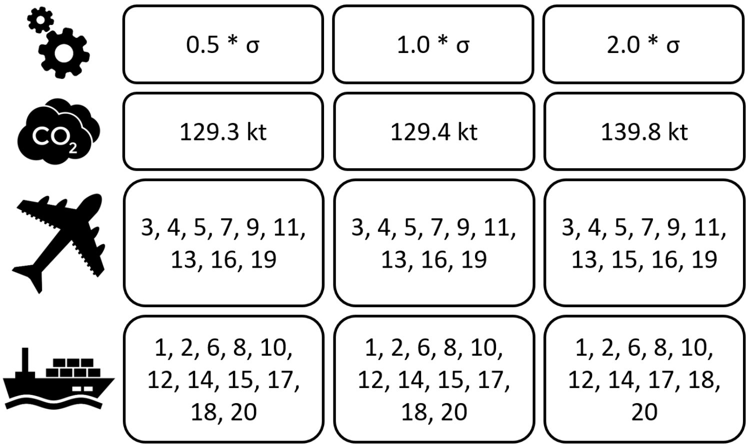

Figure D.6: Sensitivity 2 - Transport allocation per lane at different demand variability scores

Figure D.7 shows an overview of the transport mode allocation per lane using different leadtime distributions in the TMSP simulation. It can be concluded that there are no changes in transport mode allocation between the uniform and the Gamma distributed leadtimes. Therefore, also no changes occur in the CO_2e emissions. It can be concluded that the mode selection at zero emission penalty cost is robust for this analyzed change in leadtime distribution.

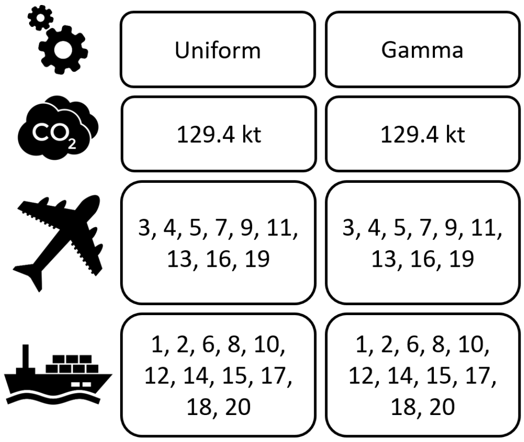

Figure D.7: Sensitivity 3 - Transport allocation per lane at different leadtime distributions