CARBON REGULATED SUPPLY CHAIN MANAGEMENT

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

SELCAN CANSIZ

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
INDUSTRIAL ENGINEERING

AUGUST 2010

Approval of the thesis:

CARBON REGULATED SUPPLY CHAIN MANAGEMENT

Submitted by **SELCAN CANSIZ** in partial fulfillment of the requirements for the degree of **Master of Science in Industrial Engineering Department, Middle East Technical University** by,

Prof. Dr. Canan Özgen ----------------------------
Dean, Graduate School of **Natural and Applied Sciences**

Prof. Dr. Nur Evin Özdemirel ----------------------------
Head of Department, **Industrial Engineering**

Ass. Prof. Dr. Pelin Bayındır ----------------------------
Supervısor, **Industrial Engineering Dept., METU**

Ass. Prof. Dr. Tarkan Tan ----------------------------
Co-Supervisor, **Eindhoven University of Technology (TU/e)**

Examining Committee Members:

Assist. Prof. Dr.İsmail Serdar Bakal ----------------------------
Industrial Engineering Dept., METU

Assist. Prof. Dr. Pelin Bayındır ----------------------------
Industrial Engineering Dept., METU

Assist. Prof. Dr. Sinan Gürel ----------------------------
Industrial Engineering Dept., METU

Assist. Prof. Dr.Tarkan Tan ----------------------------
(Industrial Engineering & Innovation Sciences,
Eindhoven University of Technology (TU/e))

Prof. Dr. JAN Fransoo ----------------------------
(Industrial Engineering & Innovation Sciences, TU/e)

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last Name : SELCAN CANSIZ

Signature :

ABSTRACT

CARBON REGULATED SUPPLY CHAIN MANAGEMENT

CANSIZ, Selcan

M.Sc., Department of Industrial Engineering

Supervisor : Asst.Prof. Dr. Z. Pelin Bayındır

Co-Supervisor : Asst.Prof. Dr. Tarkan Tan

August 2010, 120 pages

In this study, carbon dioxide emissions resulting from transportation are assessed, carbon emission reduction opportunities in the current service supply chain design of Cisco Systems, Inc. are explored. Among these opportunities, changing transport mode from a high-carbon transport mode to a low-carbon transport mode is found to be the most promising option and is scrutinized. The effect of transportation mode change on carbon emission and expected total cost are scrutinized by developing a mathematical model that minimizes expected total cost subject to aggregate fill rate constraint. Furthermore, a second model that minimizes the expected total cost under aggregate expected fill rate and carbon emission constraints is developed. In this model transportation mode choice decisions are integrated into inventory decisions. Since it is difficult to make transportation mode selection for each individual item, the items are clustered and transportation mode selection is made for each cluster. Therefore we propose two clustering methods that are k-means clustering and an adopted ABC analysis. In addition, a greedy algorithm based on second model is developed. Since currently there are no regulations on carbon emissions, in order to examine possible regulation scenarios computational studies are carried out. In these studies, efficient solutions are generated and the most preferred solutions that have less carbon emission and lower total cost among all efficient solutions are examined.

Key words: Supply Chain Management, Carbon Emissions, Inventory Management, Transportation Mode Assignment

ÖZ

KARBON DÜZENLEMELİ TEDARİK ZİNİCİRİ YÖNETİMİ

CANSIZ, Selcan

Yüksek Lisans, Endüstri Mühendisligi Bölümü

Tez Yöneticisi : Asst.Prof. Dr. Z. Pelin Bayındır

Ortak Tez Yöneticisi : Asst.Prof. Dr. Tarkan Tan

Ağustos 2010, 120 sayfa

Bu çalışmada, taşıma kaynaklı karbondioksit emisyonları hesaplanmış, Cisco Sistemleri A.Ş'nin mevcut hizmet tedarik zincirinde karbon emisyonunu azaltacak fırsatlar araştırılmıştır. Taşıma modunu, yüksek karbon taşıma modundan düşük karbon taşıma moduna değiştirmek en iyi sonucu verecek seçenek olarak değerlendirilip, gözden geçirilmiştir. Taşıma modu değişikliğinin karbon emisyonuna ve beklenen toplam maliyete etkileri matematiksel bir model geliştirilerek gözden geçirilmiştir. Model, toplam talep karşılama oranı kısıtına bağlı olarak beklenen toplam maliyeti minimize etmeyi amaçlamıştır. Ayrıca beklenen toplam maliyeti, toplam beklenen talep karşılama oranı ve karbon emisyon kısıtlarına göre minimize eden ikinci bir model daha geliştirilmiştir. Bu modelde taşıma modu seçim kararları envanter kararları ile bütünleştirilmiştir. Her bir parça için taşıma modu seçimi zor olduğundan, parçalar kümeleştirilmiş ve taşıma modu seçimi herbir küme için yapılmıştır. Bu nedenle çalışmada, k-ortalamalar kümesi ve adapte edilmiş ABC analizi olmak üzere iki kümeleme metodu önerilmiştir. Ayrıca ikinci modele dayanan bir açgözlü algoritma geliştirilmiştir. Şu anda karbondioksit emisyonlarına dayanan herhangi bir yasal düzenleme olmadığı için olası senaryoları tahlil etmek üzere bilgisayara dayalı çalışmalar yapılmıştır. Bu çalışmalarda, etkili çözümler geliştirilmiş ve en az karbon emisyonu ve düşük maliyet veren çözümler incelenmiştir.

Anahtar kelimeler: Tedarik Zinciri Yönetimi, Karbon Emisyonları, Envanter Yönetimi, Taşıma Modu Ataması

ACKNOWLEDGEMENTS

First of all I would like to express my special thanks to my supervisors, Pelin Bayındır and Tarkan Tan, for their support, guidance and patience through this study. In addition to my supervisors, I would like to thank to the members of my examining committee; Prof. Dr. Jan Fransoo, Ass. Prof. Dr. Sinan Gürel, Ass. Prof. Dr. İsmail Serdar Bakal.

I would like to thank my supervisor Klaas Van De Meent and Satu Van Der Scheer, they were very kind and helpful. Being at Cisco for six months was a nice experience for me.

I would like to thank my friends Merve Demirbaş and Ceren Köksal because they always show that I am not alone.

I would like to thank my family. They have always been with me and believed me sometimes more than I do. To my mum, I am very lucky to have such a mum like you. I only wish that you will never be ill again, you are light of my world. To my dad, you are the strongest person that I have ever seen, thank you for always being my hero. To my sister, best consultant in the world, thank you for being my sister. Finally to Murat Sarıkaya, for being always with me with an incredible passion and support, I cannot succeed lots of things without your support and love.

TABLE OF CONTENTS

LIST OF TABLES

TABLES

TABLE OF FIGURES

FIGURES

CHAPTER 1

INTRODUCTION

“Climate change and greenhouse effect” have become essential issues of this decade with the involvement of different parties including governments, media, industry giants and environmentalists into the discussion.

One of the most abundant greenhouse gases is carbon dioxide as the second most important gas with its contribution (9-26%) to greenhouse effect (Kiehl et al., 1997). “Though the forecasts of future CO_2-emissions from fossil energy use as well as the magnitude of their influence on global warming are much disputed, the impact of CO_2-emissions on global warming itself is widely admitted” (Kessel, 1999).

The consumers have become more conscious about the effects of global warming and carbon emissions and started to demand low carbon products. Companies have started paying more attention to the carbon emissions, since both consumer demand and authorities force companies to reduce their carbon emission levels. Thus, most of the companies have started to create business strategies to succeed reduction in carbon emissions over the entire supply chain.

Cisco Systems, Inc. develops strategies and leading cross-divisional programs to reduce the environmental impact associated with Cisco Systems, Inc. products throughout their lifecycle, including supply chain practices. Recently, Cisco Systems, Inc. has been interested in estimating amount of carbon dioxide emissions caused by transportation and ways to reduce carbon emissions. This study has been carried out at Cisco Systems, Inc. that has been interested in estimating amount of carbon dioxide emissions caused by transportation and ways to reduce carbon emissions.

Company Description- Cisco Systems Inc.

Cisco Systems, Inc. is one of the leader companies in the development of Internet Protocol (IP)-based networking technologies. It is a multinational corporation with more than 66,000 employees and annual revenue of US$39 billion as of 2008 (Source: www.cisco-support.co.uk). Headquartered in San Jose, California, it provides leading products and solutions with its core technologies (routing, switching, software and services) and its advance technologies (storage networking, wireless, security networking, IP telephony, home networking, and optical).

Cisco Systems, Inc. is organized according to three business units: (1) Finished Goods, (2) Professional Services, and (3) Technical Services. The first business unit deals with manufacturing and selling of finished products. The second unit engages in all related activities to optimize the performance of company technologies. The third unit provides services related to the efficient operation of products and networks. Within the Technical Services unit, there are two main departments: (1) the Technical Assistance Centre (TAC), and (2) the Service Supply Chain Delivery (SSCD).

The company has one of the most complex supply chains in the IT industry, with more than 600 suppliers and some 50,000 purchased parts supporting almost 200 product families. There are approximately 10,000 stock keeping units (SKU-s) in the service supply chain.

Cisco Systems, Inc. has one central warehouse located in Helmond, the Netherlands. This warehouse is assigned to the European market and Emerging

Market East (EME). In addition, the company serves its customers through 170 Rapid Fulfilment Depots (RFD's) in Europe and 124 RFD's in Emerging Market. Cisco work with several third party logistic providers (3PL), Kuehne+Nagel operates the central warehouse, while UPS, TNT, and DHL are in charge of the transportation and the operation of the different RFD's in the supply chain.

Our project is carried out for Service Supply Chain Delivery (also known as SSCD or service logistics) unit responsible for replacing parts and providing onsite field service for its customers. One of the most essential technical services is Advance Hardware Replacement.

There are three types of Advance Hardware Replacement Service to maintain customers' business continuity:

- Next Business Day Delivery
- Two-hour Delivery
- Four-hour Delivery

The first service, next business day delivery, is managed by the central warehouse in Helmond, The Netherlands. The required spare parts are shipped to customers from this central warehouse. Two-hour and Four-hour deliveries are managed by Rapid Fulfillment Depots (RFD), which are closely located to the customers because of the time restrictions.

In the system, there are four types of material flows that are examined in the study:

1. *Repair orders:* These orders are divided into two as defective goods and finished goods. The defective goods are the parts that are sent from central warehouse to two repair facilities in Hungary and the finished goods are the parts that are repaired in these repair facilities and sent to central warehouse.

2. *Excess Inventory Pullbacks:* Excess stocks can occur in RFDs because of

service contract changes or product update requests. Cisco needs to pull back the excess spare parts to central warehouse.

3. *Allocation and Returned Material Adjustment (RMA) Outbound Flows:* Allocation orders are replenishment orders for RFDs. These orders are sent from the central warehouse as finished goods. RMA orders are the orders of customers that have Next Business Day Delivery service type. These orders are sent from the central warehouse to customers as finished goods.

4. *Direct Shipments from RFDs:* These are two-hour and four-hour deliveries to customers managed by RFDs.

This study consists of two phases. In the first phase, carbon emission calculation studies are conducted at Cisco Systems, Inc. according to different material flows in the service supply chain, the results of these calculations are presented and the carbon emission reduction opportunities are explored. By considering carbon emission reduction opportunities, we conclude that it is possible to reduce carbon emission by changing transport mode from a high-carbon transport mode (air) to a low-carbon transport mode (road) in allocation order material flow.

The low-carbon transportation modes are slower but cheaper transportation modes than the high-carbon transport modes. There exist trade-offs as low-carbon transportation modes cause increase in lead time and hence large inventory holding costs, while using faster transportation modes lead to higher carbon emissions and higher transportation costs. Therefore in the second phase of the study, in order to scrutinize this trade-off, two mathematical models that minimize the expected total cost for emergency shipment subject to aggregate service level constraint with/without carbon emission constraint are developed.

In the first model, a model to minimize expected total cost subject to aggregate expected fill rate constraint, the aim is to examine the effect of transportation mode change from air to road for allocation orders material flow. The underlying assumption of the first model is that all items are shipped with the same transportation mode. In the second model that minimizes expected total cost subject to aggregate expected fill rate and carbon emission constraints, this assumption is relaxed; since it is difficult to make transportation mode selection for each individual item, the items are clustered and transportation mode choice decision is made for each cluster. Therefore, we propose two clustering methods to make transportation mode assignment not for individual items, but for groups of items with similar characteristics. In addition to classify the items in order to define the mode-selection variables, a greedy algorithm that minimizes expected total cost subject to aggregate expected fill rate and carbon emission constraints is provided. In this greedy algorithm, we not only determine the base stock levels but also make the transportation mode choice decision.

The outline of the thesis is as follows: In Chapter 2, an overview of the related literature on environmentally responsible supply chain management and repairable inventory - spare parts inventory management are scrutinized. In Chapter 3, the scope of the study and the environment of the problem are described; an overview of the current carbon emission calculation methodologies is given and after comparing these methodologies to each other; we scrutinize our carbon emission calculation methodology used in this study. After the carbon emission calculation methodology is examined, we present the carbon emission calculation tool and discuss the data gathered for carbon emission calculations. In Chapter 4, the description of the problem environment analyzed and the underlying assumptions are given. The first model, a model to minimize expected total cost subject to aggregate expected fill rate constraint, and the second model that minimizes expected total cost subject to aggregate expected fill rate and carbon emission constraint are discussed in detail. Then we propose two clustering methods that are k-means clustering and adjusted ABC analyses. In addition to classify the items in order to define the mode-selection variables, a greedy algorithm that minimizes expected total cost subject to aggregate expected fill rate and carbon emission constraints is provided. In Chapter 5, computational studies are conducted. In this chapter, for allocation orders the effects of changing transportation mode from air to road on carbon emissions and expected total cost are examined and the multi-item and single-item approaches are compared in order to understand which approach is suitable for Cisco. Then we present our findings on transportation mode selection model with carbon emission consideration by using k-means clustering algorithm and adjusted ABC analysis. Then after presenting our findings on greedy algorithm, we compare the results obtained from clustering methods and greedy algorithm. Finally in Chapter 6, we discuss our conclusion and present further research direction.

CHAPTER 2

LITERATURE REVIEW

In this chapter, in Section 2.1 we review environmentally responsible supply chain management literature, under this section we also review the literature that are related to carbon emissions examined in supply chain management studies. In Section 2.2, we review the inventory management literature to find the relevant studies that help us

2.1Environmentally Responsible Supply Chain Management

Green Supply Chain Management (GSCM) studies focus on determining the environmental impact of business practices in supply chain management and minimizing this impact. These studies consider carbon emissions mostly qualitatively. According to Srivastara (2007) *GSCM is "integrating environment thinking into supply chain management, including product design, material sourcing and selection, manufacturing processes, delivery of the final product to the consumers, and end-of-life management of the product after its useful life".*

Comprehensive reviews on

- green design,
- issues in green manufacturing and product recovery,
- reverse logistics (RL)
- production planning and control for remanufacturing,
- repairable inventory and
- logistics network design

have been published (Srivastava, 2007).

However in this study, these topics, except repairable inventory, in the Green Supply Chain Management literature are not examined. Since our study is carried out in Service Supply Chain Delivery, repairable inventory-spare parts inventory management literature is also important for us.

Besides carbon emission calculations, one of the goals of this study is to examine the CO_2 trade-offs between carrying inventory and transportation by setting up a mathematical model that takes carbon emissions into account. However, when the literature is overviewed, it can be seen that there is an apparent gap. In the literature, there are only a few numbers of studies that include carbon emissions in analytical models in supply chain management.

Traditional logistics systems do not focus on the environmental concerns and generally focus on cost minimization and profits maximization in the private sector (Daskin, 1995). The environmentally responsible logistics adds another objective to the system as total environmental impact minimization (Wu and Dunn, 1995). In order to achieve this objective, environmental impact from the total system perspective must be evaluated in addition to the traditional trade-offs such as transport versus inventory, inbound versus outbound logistics, transport cost versus transit time, and customer service versus logistics costs as discussed by Copacino and Rosenfield (1987); therefore, environmental costs and benefits should be taken into consideration. However, in the literature how the environmental impacts can be taken into consideration is still missing. The environmental impact of the carbon dioxide emissions is considerable, but the question is that can this impact be converted into numerical values? Although at some point the monetary values can be determined if the firms exceed the prespecified emission limits, the real environmental impact is hard to determine. By considering carbon emission trading scheme (EU ETS), a trading market has been created for carbon allowances and a price for emissions is determined by the market. Over the last few years the price of the carbon has varied between €0 per tonne and €30 per tonne (European Carbon Exchange).

The carbon emission levels can be added to the models in two ways. In the first way the carbon emission levels can be included in constraints and by this way emission levels can be limited to a specified level. The second way can be adding carbon emission levels into the objective function.

Martinez and Eliceche (2008) consider carbon dioxide emission in their mathematical models, their main goal is to use the environmental and economic objective functions to select the operating conditions of process plants, the reduction in CO_2 equivalent emissions and its market price is included in the economic objective function. In the study, the environmental objective function is the sum of the emissions of utility plant and imported electricity. The economic objective function includes the operating cost including costs of natural gas, freshwater, cooling water treatment and imported electricity and income generated by greenhouse emission reduction traded in the market. The market price of greenhouse emissions in the international emission trade market is considered in the income calculations. In order to select the operating conditions, the study considers the minimization of greenhouse gas emissions and cost and it is considered as multi-objective Mixed Integer Non Linear Programming (MINLP) problem. In this study, the multi-objective function is converted into a single objective. The objective function is taken as the sum of emissions and economic objectives. Significant reductions in greenhouse emissions and cost are achieved simultaneously.

In the study of Engel et al. (2008), ecological aspects are in four ways: In one group of methods, ecological aspects are expressed in monetary terms by the current or expected price of emission certificates. The second group of methods assigns weights to every objective; the aim of the method is to balance between conflicting objectives. The weighted sum strategy converts the multi-objective problems into a scalar problem. The weights are assigned subjectively. In a third group, ecological aspects are considered by constraints such as limits for maximum emissions. Reduction targets are defined as not given in form of legal regulations for all relevant emissions and it also defines that limit values are solely set by companies subjectively like weight assignments. The last one is a new perception, trying to answer the question of how much should be spent to improve the ecological quality, trade-offs and eco-efficiency frontiers.

Engel et al. (2008) focus on the direct emissions reduction alternatives only. A model is set up to minimize the emissions and total cost. The total emissions are calculated by multiplication of the emissions factors and the amount used of each fuel. Total cost results from an investment by considering depreciations, interest and operating costs. In the solution of the model, subjective weighting, monetization and diverse treatment of ecological and economic aspects are avoided, and visual exploration of the efficient frontier and trade-offs is selected, so decision-maker is allowed to opt on trade-offs between economic and ecological results. This method is also very useful than the other methods because all other methods contain some sort of uncertainty.

Naim et al. (2010) aim to assess the impact of the traditional cost optimization approach to strategic modelling on overall logistics costs and CO2 emissions by taking into account the supply chain structure (number of depots) and different freight vehicle utilization ratios (90%, 75% and 60%). A simulation model is constructed in the study, based on a European case study from the automotive industry, which considers strategic and operational level decisions simultaneously. In the study, the analysis shows that the optimum design based on costs does not necessarily equate to an optimum solution for CO2 emissions, therefore there is a need to address economical and environmental objectives explicitly as part of the logistics design. The methodology for calculating CO2 emissions takes into consideration speed of the vehicle, vehicle type and vehicle utilization. The study based on original locations also indicates that increasing vehicle utilization by 15% could bring economic savings in total logistics costs (7.5%) as well as environmental benefits reflected in reduction of total vehicle kilometres travelled (16.1%) and reductions of transport related CO2 emissions of around 10%. Therefore, due to the increasing environmental concerns, it is important to incorporate environmental objectives as part of logistics design and correctly estimate vehicle utilization ratio factors for emissions calculations, to allow the decision-maker to make an informed and objective decision regarding network design.

2.2 Repairable Inventory - Spare Parts Inventory Management

In the literature, repairable inventory and spare parts inventory management topics are incorporated. As defined in Simpson (1977), there are two inventory types in the repairable inventory system:

- Serviceable inventory
- Repairable (or unrepaired) inventory

Inventory control of spare parts is an essential topic. There exists an important trade-off such that keeping large amount of spare parts in the stock cause high inventory holding cost and low carbon emissions while on the other hand keeping little inventory may result in low customer satisfaction, costly emergency actions that also means high carbon emissions. The spare parts inventory management literature can be categorized according to

- Number of items
- Number of echelons
- Inventory control policy
- Periodic or continuous review
- The type of the analysis done: approximation or exact

In the real life problems, the effective planning and control of inventories in multi-echelon distributions network is difficult. Large amounts of data are required for theoretical models and these theoretical models generally cannot be used in practical business situations. Not having proper coordination and communication between echelons can cause excessive inventories both in the firm and throughout the supply chain.

One of the earliest study is the study of Sherbrooke (1968), Sherbrooke introduced METRIC (Multi-Echelon Technique for Recoverable Item Control) by considering a two echelon spare parts inventory system for repairable items. In this study, all the facilities in the system have ample repair capacity and operate according to a continuous review (S-1, S) policy. He set up a model to minimize the total expected backorders at the depots subject to a constraint on system inventory investment. Marginal allocation combined with a search over the warehouse stocking levels is used to determine the base stock quantities at all facilities. This problem is solved by considering a function of the mean repair times instead of by considering therepair time distributions. Muckstadt (1973) extended METRIC model of Sherbrooke by consideirng a hierarchical parts structure with two indenture levels in a two-echelon situation. His model is known as MOD-METRIC. In Muckstadt (1979), he extended his study to three-echelon situation. Later Slay (1984) developed a model called VARI-METRIC. In his study, he focuses on two-echelon model, however his method is found to be more accurate approximation evaluation method than Sherbrooke's METRIC. For the multi-echelon single-indenture situation Graves (1985) defined exact evaluation. Sherbrooke (1986) extended Slay' s VARI-METRIC for two-echelon two-indenture systems. These all METRIC models are multi-echelon models. Cohen et al. (1989) focuses on single-echelon multi-tem models for period review situations. The study develops a heuristic in which base stock levels for all items are determined to minimize expected cost by considering service level constraint. In the heuristic of Cohen et al., the problem is seperated into single-item sub-problems by Lagrangian relaxation and the optimal value for the Lagrange multiplier is approximated. By using Lagrangian relaxation, a lower bound on the optimal cost is obtained and this lower bound is used for checking the results of heuristics. In this study we also focus on single- echelon multi-item systems.

A continuous review (S - 1, S) inventory policy is used since low-demand; high-cost items comprise the inventory. Feeney et al. (1966) defines continuous review (S - 1, S) inventory policy as placing a reorder immediately for an arbitrary number of units whenever a demand for that number of units is accepted. Accordingly, the total of stock on hand plus on order minus backorders to the spare stock level S is stored. We examine both multi-item approach and single-item approach in our study. As it is mentioned in Wong et al. (2005), in multi-item approach all items in the system are considered when inventory-level decisions are made. In single-item approach, for each individual item inventory levels are set independently.

When the position of the study in literature is examined, we can say that this study is one of the first studies that focus on carbon emissions in supply chain management models. Because there is a large gap in literature: there exist few literatures about including carbon dioxide emissions in models for supply chain design.

CHAPTER 3

DESCRIPTION OF THE PROBLEM ENVIRONMENT AND CARBON EMISSION CALCULATIONS

In this chapter, we start with determining the scope of the study in Section 3.1. In Section 3.2 the environment of the problem is described. In Section 3.3, an overview of the current carbon emission calculation methodologies is given and after comparing these methodologies to each other; we scrutinize our carbon emission calculation methodology used in this study. After the carbon emission calculation methodology is examined, we present the carbon emission calculation tool and discuss the data gathered for carbon emission calculations. In Section 3.4 we provide the results of the carbon emission calculations. In Section 3.5, carbon emission reduction opportunities are discussed.

3.1 Scope of the Study

The study focuses on the carbon dioxide emissions during the transportation activities in Europe that occur

- from the central warehouse to the customers and RFDs in European Market Theatre,
- from the central warehouse to the repair facilities in Hungary,
- from RFDs in European Market Theatre to the central warehouse,
- from RFDs in European Market Theatre to customers in European Market Theatre.

The countries included in European Market Theatre are; Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and United Kingdom. Although they are in the European Theather, Israel, Luxembourg and Iceland are not included in the study, since Israel is not in continental Europe, total annual weight of the shipments belong to Luxembourg are less than 0.4 percent of all shipments and total annual weight of the shipments of Iceland is less than 0.02 percent of all shipments.

The first objective of our study is to estimate the carbon dioxide emissions according to different material flows in the service supply chain. The types of material flows included in the study are *Repair Orders, Excess Inventory Pullbacks, Allocation and Returned Material Adjustment (RMA) Outbound Flows, Direct Shipments from RFDs and Customer Returns.* The carbon dioxide emission amounts caused by transportation are calculated for each type of material flows. In Appendix A, the main material flows of the service supply chain are shown by considering the scope of the study.

3.2 Environment

The details particularly related to transportation activities are essential in carbon emission calculations, therefore in this section material flows that are repair orders flow, excess inventory pullbacks, allocation and returned Material Adjustment (RMA) outbound flows and direct shipments from RFDs are scrutinized carefully in order to calculate the carbon emissions accurately.

<u>*Repair Orders Flow:*</u> There are two repair facilities in Hungary, which are in Budapest and Szombathely. During fiscal year 2009, the transports have been provided by three different carrier companies, which are COMPANY A, COMPANY B, and COMPANY C. The shares of these carrier companies based on total

weights are 47.43, 16.01, and 36.56 percent, respectively. The shipments are done by road and with three types of trucks which are Medium truck, Tractor + semi-trailer and Tractor + city-trailer. The trucks were dedicated to the company except COMPANY B shipments. Dedication is important in the carbon emission calculations because it determines the percentage of carbon emission for which the company is responsible.

COMPANY B provided the transportation just for one month as a trial period with a Tractor + city-trailer. Both in inbound and outbound lanes, parts were shipped to and from Szombathely and Budapest with separate trucks once a week. The trucks were not dedicated to the company and repair parts were consolidated with the cargos of other companies. Therefore, in the carbon emission calculations for COMPANY B shipments, the emissions are allocated considering load factors, capacity of the vehicle and weight of the cargo of the company. Here the capacity of the vehicle and weight of the cargo of the company are known. However, the load factors for COMPANY B shipments are not known. The calculations are done by considering two different load factors, 50% and 75%, for COMPANY B shipments.

Currently, transports to and from Hungary have been provided by COMPANY C since April 2009. In outbound lane, COMPANY C picks up the defective goods twice a week and transports them directly to the repair facilities in Hungary by Light truck or Tractor + semi-trailer. In inbound lane, COMPANY C picks up the finished goods twice a week by Light truck and Tractor + semi-trailer from Budapest and Szombathely and transports them directly to the central warehouse in Helmond.

Unlike COMPANY B, the shipments are made by COMPANY A and COMPANY C with dedicated trucks.

Excess Inventory Pullbacks: The excess inventories sent periodically from RFDs to central warehouse in Helmond are under the responsibilities of the various parties like Cisco, Kuehne & Nagel Transportation Team, Kuehne & Nagel Customer Service Team and the In-Country Depot Vendors; COMPANY D and COMPANY C. The whole lead time of excess inventory pullback procedure is three weeks. In the first week, the excess parts are prepared by the RFDs, and they are transported during the second week, and the third week is the handling time in the central warehouse, which includes unloading, packing operations and management works (Qian, 2009). The shipments are carried out by 18 different local carriers. We know that excess parts are carried by one Tractor + semi-trailer or Tractor + mega-trailer to the central warehouse for all countries. Each local carrier has its own distribution network structure and these structures are not known. However, it is known that the parts, coming from United Kingdom are crossing the English Channel in two ways:

1. The parts are brought to Folkestone in United Kingdom and crossing the English Channel via Eurotunnel by trains.
2. The parts are brought to Harwich in United Kingdom and crossing the English Channel by ferries.

The percentage of the number of shipments crossing the English Channel by trains and ferries is 30 percent and 70 percent, respectively. These percentages are used in the carbon emission calculations.

The excess parts are collected from RFDs, and then combined together for reshipment in one truck at different consolidation points in each country. Since the networks are not known, the consolidation points are not known either. It is not viable to examine each possible consolidation point and calculate the carbon emission for each of them. Thus, in the carbon emission calculations three methods are developed and used.

In the first method, it is assumed that excess inventories are shipped from each RFD to Helmond directly and these parts are shipped with other cargos of other companies.

In the second method, a rough truck routing is considered without any optimization. It is assumed that one truck is travelling all RFDs in one country and bringing the excess parts from the RFDs in that country to the central warehouse in Helmond. If the parts are brought to Helmond by one truck , this truck cannot be a Tractor+ semi-trailer, since for some countries the total weight of the shipments can exceed the weight capacity of the Tractor + semi-trailer, which is 26 tones. Therefore, it is assumed that truck type is Tractor + mega-trailer, which has weight capacity of 33 tones.

In the last method, on the top of the second method when the weight capacity of the truck is exceeded by total quantity carried, extra truck(s) is (are) assumed to be utilized.

Allocation and Returned Material Adjustment (RMA) Outbound Flows: Allocation orders are the replenishment orders for RFDs sent from central warehouse in Helmond as finished goods. RMA orders are the orders of customers that have Next Business Day Delivery service type and sent from central warehouse in Helmond to customers as finished goods. The transport of both allocation orders and RMA orders are provided by COMPANY D.

The transport network of COMPANY D, a sketch of which is given in Figure 1, can be divided into two:

- Shipments of RMA and allocation orders to Europe**,** except Switzerland, Norway and The Netherlands, are first sent to COMPANY D Cologne hub before being sent to associated countries.

- Shipments of RMA and allocation orders to Norway, Switzerland and The Netherlands are first sent to COMPANY D hub in Best. Since Switzerland and Norway are not EU members, extra documentations are needed and these documents are prepared in Best.

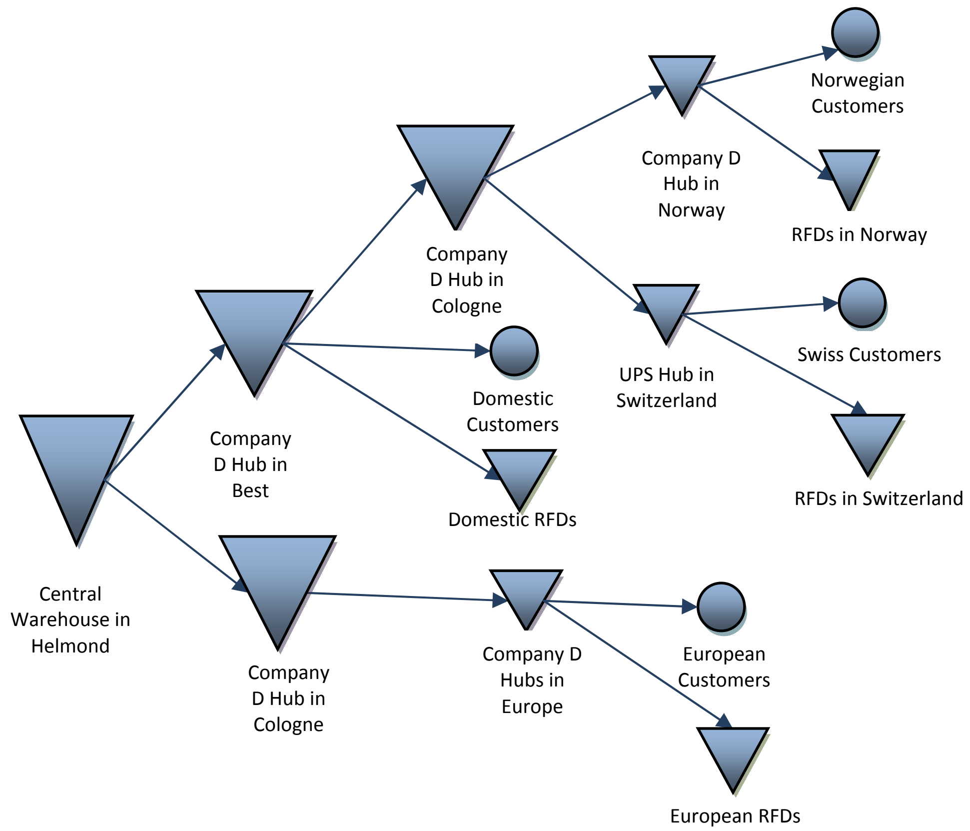


Figure 1 - The Transport Network of COMPANY D

The shipments of European countries except Switzerland, Norway and The Netherlands are picked up once a day with a Tractor + semi-trailer and transported to COMPANY D hub in Cologne.

The shipments of Switzerland, Norway and The Netherlands are picked up once a day with a Medium truck and transported to COMPANY D hub in Best.

In the carbon dioxide emission calculations, the average load factors of the trucks are taken as 80%, according to information obtained from COMPANY D. COMPANY D did not provide more specific information about their distribution network structures. The types of transport mode used in the network are not exactly known since COMPANY D uses different types of vehicles and planes depending on the size of shipments. It is assumed that international shipments are transported by air with Boeing 757-200SF, since this type of aircraft is the most common one used by COMPANY D (COMPANY D AIRCRAFT FLEET, 2009). Inter-city shipments are made by road with a Tractor + semi-trailer truck and it is also assumed that COMPANY D picks up the shipment from distribution centers with a van by considering the size of the shipments and service times. The transport network of COMPANY D can be seen in Figure 2.

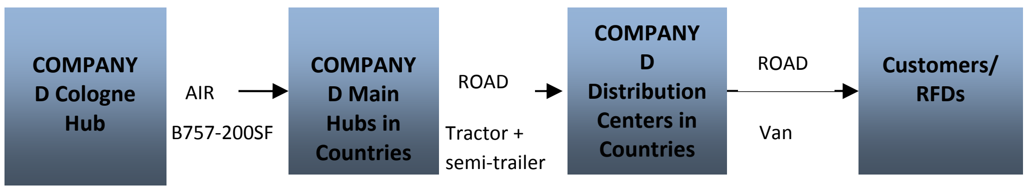


Figure 2 - Transport Network of Company D

The international transport network structures of COMPANY D are known. However these transport networks do not include the networks between main hubs and customers, so there is no information about the inland transport network structures. We assign customers to the nearest main hubs and distribution centers to the nearest main hubs.

After assigning the distribution centers to main hubs, distances are calculated between main hubs and distribution centers. However, since each customer cannot be assigned to one distribution center, the distances between customers and distribution centers are not known. Since the information related to routes is not known, the related literature is reviewed to determine the way of calculating the route lengths.

Daganzo (1999) considers N customers independently scattered in a region according to a spatial customer density (points per unit area) $\delta(\mathrm{a})$ and probability density function $\mathrm{f(a)}$ of the customer has coordinates $\mathrm{a} = (\mathrm{a1}, \mathrm{a2})$, then $\delta(\mathrm{a}) = \mathrm{Nf(a)} = \mathrm{N/A}$, where A is the size of the service region (in square kilometer). Expected tour length, T^* is expressed as

$$\mathrm{T}^* \approx \, \varnothing \, \mathrm{N} \, \mathrm{E}(\delta(\mathrm{a})^{-0.5}) = \varnothing\sqrt{\mathrm{N}}\mathrm{E}(\mathrm{f(a)}^{-0.5}) = \varnothing\sqrt{\mathrm{NA}},$$

where ø is given as an unknown constant. ø = 0.75 is often used for Euclidean metrics (Joseph et al. 2006). Christofides and Eilon (1979) verify the formula experimentally and the value of constant ø determined by solving a large number of problems, of up to 100 customers, randomly generated in the interior of a square, a circle, and an equilateral triangle, in which ø is taken as 0.75. In the study, the effect of the shape of the area is seen to be negligible. We adopt the method by Daganzo (1999) with ø =0.75 to estimate the optimal TSP route for each country.

Direct Shipments from RFDs: The parts transported within two hours and four hours from RFDs to customers, as a requirement of service level, are called premium parts. There are some customers that would like to loosen contract restrictions on delivery times. For these customers, the shipments can be made for a “scheduled time”; the term is stated as a delivery method at Cisco. Since they are also premium orders, they are examined in the carbon emission calculations with premium parts.

The premium parts are transported from RFDs to customers in Europe with COMPANY D and COMPANY C by road.

One of the important pieces of data needed for carbon emission calculations is vehicle types. However, the information related to vehicle types cannot be gathered from COMPANY D and COMPANY C. When the time restriction caused by service level agreements and weights of the parts are taken into account, Pick-up is determined as the most suitable vehicle type to be used in the calculations. Again by taking time restriction into consideration, the vehicles are taken as dedicated pick-ups to company cargo, because the time lost because of other company shipments is not tolerable for Cisco.

Customer Returns: Customer returns are defective goods that are returned from customers according to conditions of different service contracts. These parts are collected from customers by COMPANY B and sent to central warehouse via tractor+ semi-trailers.

In the current service supply chain, the items are shipped mostly by air and road. Other transportation modes, rail and sea, are not used. The lead times for road and air transportations are three days and one day, respectively.

Transportation mode used affects the lead-times and transportation costs. Transportation costs depend on weight of the items and the country, to which the items is shipped. Since Cisco is one of the important customers of carrier companies, it gets discounts from the rates published. Although the other transportation modes are not used in the current service supply chain, in this study in order to explore possible benefits, the other transportation modes are also examined in Chapter 4 and Chapter 5.

3.3 Carbon Emission Calculations

In this study, first we focus on calculating carbon emissions during transportation, which is our first goal. This study is one of the succeeding projects of the Carbon Regulated Supply Chains project (CRSC, 2009) initiated by the European Supply Chain Forum (eSCF), Eindhoven University of Technology (TU/e), at the end of 2007 with the participation of four different eSCF member companies. The objectives of the Carbon Regulated Supply Chains project were (CRSC, 2009)

- To understand the impact of the various regulation alternatives on the design and operation of supply chains
- To assist decision makers in industry by preparing strategies for coping with the upcoming regulations
- To impact policy makers and the public opinion on the effectiveness and problems of new regulations.

Within Carbon Regulated Supply Chains project, four master thesis projects, Van Den Akker (2009), Te Lo (2009), Ozsalih (2009) and Schers (2009) were conducted at four companies. In these master thesis projects, a carbon emissions in transportation calculation methodology was developed, based on Network for Transport and Environment (NTM), Section 3.3.1.2. In this study, carbon emission calculations are based on this methodology. However some of the assumptions like load factors are changed by considering the current supply chain of Cisco Systems, Inc.

In addition to developing carbon emissions in transportation calculation methodology, within Carbon Regulated Supply Chains project, a carbon emission calculation tool, TERRA, (Transport Emission Reporting and Reduction Analysis), was developed in Microsoft Access platform. The detailed information related to TERRA tool is given in Section 3.3.2.

In Section 3.3.1, we review the current carbon emission calculation methodologies and the chosen carbon emission calculation methodology is scrutinized, based upon CRSC (2009). We shortly introduce the carbon emission calculation tool in Section 3.3.2. In Section 3.3.3, we give information about data gathered.

3.3.1 The Carbon Emission Calculation Method

There are different carbon emission calculation methodologies and tools available. We just introduce the main ones shortly. More detailed information about presented methodologies are provided in CRSC Report (2009)

3.3.1.1 Overview of the Available Methodologies for CO2 Emission Calculations

Currently, there are several methodologies available for the calculation of CO_2 emissions. The main ones are

- Assessment and Reliability of Transport Emission Modelling and Inventory Systems(ARTEMIS),
- Ecological Transport Information Tool (EcoTransIT),
- Greenhouse Gas Protocol (GHG) Protocol,
- Network for Transport and Environment (NTM).

Assessment and Reliability of Transport Emission Modelling and Inventory Systems (ARTEMIS)

Artemis Project was initiated by the European Commission in 2000 and has been funded by the European Union (Artemis, 2007). The project develops a model to calculate carbon emissions for all transport modes, which aims to provide reliable emission estimates at the national and international level.

Using a software package with a database containing data per country, carbon dioxide emissions can be calculated for road, rail, water and air transport (CRSC, 2009).

Ecological Transport Information Tool (EcoTransIT)

It is an internet tool developed by the Institut für Energie- und Umweltforschung Heidelberg GmbH to compare the environmental impact of different transport modes. It is initiated and supported by several rail companies from Europe (EcoTransIT 2008).

The internet tool of EcoTransIT has an embedded route planner and calculates the distances between origin and destination (EcoTransIT, 2008).

The Greenhouse Gas (GHG) Protocol

The GHG Protocol was launched in 1998 at the initiative of businesses, non-governmental organizations, governments and other institutes (GHG Protocol, 2005). The mission of the GHG protocol is to develop internationally accepted greenhouse gas accounting and reporting standards and guidelines for businesses, preparing a GHG emissions inventory and promoting the broad adoption of these standards and guidelines. The scope of the GHG Protocol is the world with a focus on the United States of America. The protocol distinguishes three scopes for GHG accounting and reporting purposes:

- Scope 1: Direct GHG emissions - emissions from sources that are owned or controlled by the company.
- Scope 2: Electricity indirect GHG emissions - emissions from the generation of purchased electricity consumed by the company.
- Scope 3: Other indirect GHG emissions- all other emissions that are a consequence of the activities of the company, such as transportation, extraction and production of purchased materials.

The GHG Protocol defines two methods to calculate the carbon emissions during transport, which are fuel-based and distance-based methods. In the *fuel-based method*, fuel consumption is multiplied by the CO_2 emission factor. In the *distance-based method*, emissions are calculated by multiplying the distance with a distance based emission factor. If the information related to fuel consumption is not available, which is the case in most situations, the second calculation method is used, which is the calculation of emissions based on the distance travelled and the type of vehicle used. More detailed information, such as the load factor is not included in the calculation. (GHG, 2005)

Network for Transport and Environment (NTM)

NTM is a Swedish non-profit organization started up in 1993. The aim of the organization is to establish a "common base of values on how to calculate the environmental performance for various modes of transport" (NTM Air Transport, 2008; NTM Rail Transport, 2008; NTM Road Transport 2008; NTM Sea Transport 2008).

The scope of the NTM method is Europe. Moreover, load factors, weight of the shipment, type of transport mode, positioning, empty return trips, number of kilometres, topography and type of road (urban, rural or motorway) are some of the factors that are taken into account in the NTM methodology.

A detailed study is conducted in CRSC project in order to determine the most suitable carbon emission calculation methodology. Based on this study, CRSC (2009), the calculations are done by using the same method used in CRSC project, based on NTM methodology. For the carbon calculation method, in the CRSC project NTM (2008) is chosen as a basis, because NTM:

- has a high level of detail
- offers the possibility to calculate the emissions based on varying levels of detail

- offers the possibility of adding or changing parameters and values
- is aligned with several European studies
- is cooperating with the European Committee for Standardization (CEN) to set a standard for calculating emissions resulting from transport

3.3.1.2 Carbon Emission Calculation Method

The calculation method is mainly based on the NTM method (NTM Air 2008; NTM Rail 2008; NTM Road 2008; NTM Sea 2008).

3.3.1.2.1 Transport Parameters

Transport parameters are the general parameters that are not specific to the transport mode and used in the carbon emission calculations. These parameters are described by considering all transport modes in general as follow

- **Load Factor:** Load factor (capacity utilization) is defined as the percentage of the capacity of the means of transportation used. In the methodologies for road and air transport, load factor is used to calculate the total carbon emission amount and allocate the carbon emission to cargo of company. However, in the rail and water transport, load factor is only used to allocate the total carbon emission to company cargo (Van Den Akker, 2009). When there is no information related to load factors, NTM suggests some average load factor values. For road transportation, NTM proposes two average load factor values for frequent and single shipments, 75% and 50 %, respectively (NTM Road Transport, 2008).

  Assumptions for the load factor values for rail transportation are based on EcoTransIT data (EcoTransIT, 2003). The load factors are proposed as 72%, 58% and 44%, for bulk cargo, average cargo and volume cargo respectively(NTM Road, 2008). The assumptions are based on a study conducted by the Institut für Energie und Umweltforschung Heidelberg GmbH (IFEU).

In NTM, for water transportation the load factor values are proposed as 80% and 50% by considering vessels transport types, which are water direct and water shuttle respectively (NTM Sea Transport, 2008).

For air transportation, the average load factors for aircraft types are not given in the NTM Air (2008). However, load factors are estimated by Van Den Akker (2009), Schers (2009), and Loo (2009) for a case study that includes an airline company and a logistics service provider. In these studies, field data are used to estimate an average load factor. The estimated load factors are 80 % and 85 % for cargo capacity and passenger capacity, respectively .

- **Terrain Factor:** Fuel consumptions change with respect to the topological features. NTM categorizes the countries according to their type of terrain as follows: Denmark, Sweden and The Netherlands as flat countries, Austria and Switzerland as mountainous countries, and all other countries in Europe as hilly countries. The terrain factor is only considered for road and rail transports (NTM Road Transport (2008) and NTM Rail Transport (2008)). For rail transport, the carbon emission calculations are done for hilly countries by considering no terrain factor and then carbon emissions are increased by 20 percent for mountainous countries and decreased by 20 percent for flat countries (NTM Rail Transport, 2008). For road transport, carbon emission calculations are done for flat countries by considering no terrain factor and then carbon emissions are increased by 5 percent for hilly countries and 10 percent for mountainous countries (NTM Road Transport, 2008).

- **Positioning:** The positioning distance is defined as the distance travelled to arrive at the location of the cargo. NTM suggests that the emissions related to the positioning trip before the transport are calculated and added to the emissions from the vehicle during the actual transport for air, road and water transport (NTM Air, 2008; NTM Road, 2008; NTM Water, 2008). For different transport modes, positioning is considered in a different way. According to the case studies that were conducted with different international rail cargo companies in previous master thesis studies, for rail transport, it is found that positioning distance is negligible in comparison to the total distance (Akker 2009; Schers, 2009; Loo, 2009). In addition, Van Den Akker (2009) reports that the positioning distance is in the average 20 percent of the total distance based on real data and this average value is in line with the assumption of NTM. For single road transport, NTM does not provide a reliable assumption. For water transport, because of regular routes operated, it is assumed that positioning distance is zero. In this study, in the total emission calculations, we also consider the positioning distance as 20 per cent of total distance and include carbon dioxide emissions resulting from positioning.

- **Empty Return Trips:** In this study, it is assumed that when the transport is dedicated to the company on its request, the emissions from empty return trips are allocated to the company.

- **Vertical Handling:** Intermodal transport is the transport of cargo using multiple modes of transport without any handling of the product itself (like sorting and repacking) while changing modes. In most cases the cargo is packed in containers or on pallets and the containers or pallets are handled. This handling takes place at a terminal and is called vertical handling (Schers, 2009).

- *Containers:* Vertical handling of containers is done either by a crane or by a reach stacker. A crane can be powered by using electrical energy or a diesel engine. In most cases reach stackers are powered by a diesel engine. Since vertical handling consumes energy, it also causes extra carbon dioxide emissions.

  In the previous master thesis studies average carbon dioxide emissions of a reach stacker, 0.007 tonne per handling, was obtained by contacting two transport terminals and the average carbon dioxide emissions of a crane, 0.002 tonne per handling, was from the IFEU report (Knörr and Reuter, 2005) (Van Den Akker 2009; Schers, 2009; Loo, 2009).

  In this study, vertical handling is assumed to make use of a reach stacker.

In NTM methodology, there are four types of transport methods used in carbon emission calculations.

3.3.1.2.2 Air Transport Method

Although the air transport is fast, it has a significant environmental disadvantage as leading higher carbon emissions compared to other transport modes.

The carbon emission calculations from air transport are based on NTM Air Method (NTM Air Transport, 2008). To be able to calculate the carbon emissions the information pieces needed are *distance of each flight*, *the vehicle used (aircraft model)*, *the load factor*, *the weight of the shipment* or *functional unit chosen.*

Emission calculations are carried out as:

- Calculation of the total emission for the flight
- Allocation of the shipment or functional unit based on the weight and the total weight of all cargo

According to available data, emission calculations are divided into two. The first part is the constant emission and the second part is the variable emission. The first part corresponds to high fuel usage during takeoff and landing. The second part, variable emission, corresponds to constant emissions per kilometre during cruising. The total emission of an aircraft can be calculated as (NTM Air, 2008):

$$\begin{aligned}&\text{Total emissions}\\&= \text{ Constant Emission Factor in kilograms}\\&+ \text{Variable Emission Factor in kilograms per kilometerhandling, was obtained by contacs}\end{aligned}$$

In NTM method, for several aircraft types, different values are given for constant and variable emission factors. In addition to these factors, different load factors are given for cargo aircraft, passenger aircraft and belly freighters. The load factors used for computation of emission data are given as 50, 75, 100 percent (NTM Air, 2008). NTM provides an interpolation formula to calculate constant and variable emission factors for other load factor values different than 50, 75 and 100 (NTM Air, 2008).

The constant and variable emission factors can be calculated for different load factors with the following interpolation formula, a general formula is given for constant and variable emission factors since the interpolation both for variable and constant emission factor is calculated in the same way, it is assumed that there is linearity between emissions for different load factors (Schers, 2009).

$$\mathrm{CVEF}_{\mathrm{x\%}} = \frac{\mathrm{CVEF}_{\mathrm{y\%}} + (\mathrm{CVEF}_{\mathrm{z\%}} - \mathrm{CVEF}_{\mathrm{y\%}})}{(\mathrm{z\%EFc}) \times (\mathrm{x\%} - \mathrm{y\%})}$$

Where

CVEF: Constant Emission Factor or Variable Emission Factor
x: Load factor for which the constant emission factor needs to be calculated
y: Load factor smaller than x for which the constant emission factor is known
z: Load factor larger than x for which the constant emission factor is known

After calculation of the total carbon emission of a flight, this emission should be allocated to the cargo transported. The allocation is based on weight, since the weight is the main factor determining the amount of carbon emissions in the air transport.

In addition to calculations, it is assumed that all planes are operating on JetA-1 fuel, since JetA-1 is the most common fuel type used in the air transport (NTM Air Transport, 2008).

3.3.1.2.3 Road Transport Method

The advantages of road transportation are flexibility, ability to reach remote locations and the security of goods since there is always a driver who can control the load. There are some limitations related to road transportation such as loading capacity limited by regulations, maximum size of the vehicles and dependence upon drivers. In addition to these, congestion problems are drawbacks in some areas (NTM Road Transport, 2008).

There are two specific parameters which are road type and vehicle type. NTM Methodology considers three types of roads: motorways, urban roads and rural roads (NTM Road, 2008), there are ten different vehicles, from a small pick-up to a 60 ton Truck + semi-trailer. Types of the vehicles can be seen in detail in Appendix B.

NTM emission calculation is based on the vehicle fuel consumption. NTM presents some default fuel consumption values for empty and fully loaded vehicles, so it is suggested that these values should be used in calculations for normal European traffic system for respective vehicle types and roads when there is no specific data.

To calculate the fuel consumption of the specific vehicle by considering the load factor, the following formula is used:

$$\mathrm{FC_{LF}} = \mathrm{FC_{EMPTY}} + (\mathrm{FC_{FULL}} - \mathrm{FC_{EMPTY}}) \times \mathrm{LF}$$

Where

LF	Load Factor
FC_{LF}	Fuel Consumption at the Specific Load Factor, in liters per kilometer
FC_{EMPTY}	Fuel Consumption of the Empty Vehicle, in liters per kilometer
FC_{FULL}	Fuel Consumption of the Fully Loaded Vehicle, in liters per kilometer

As it is mentioned, the total carbon emission is based on the vehicle fuel consumption. The total carbon emission is formulated as:

$$\mathrm{TE} = \mathrm{FC_{LF}} \times \mathrm{D} = \mathrm{EF_{CO_2}}$$

Where

LF	Load Factor
TE	Total Emission, in kilograms
$FC_{Load\ Factor}$	Fuel Consumption at the Specific Load Factor, in liters per kilometer
EF_{C02}	Emission Factor for Fuel, in kilograms carbon dioxide per liter fuel
D	Distance, in kilometers

For the fuel consumption calculation above, the weight of the cargo must be used since the larger dynamic mass and higher rolling resistance connected with the weight of the cargo is the cause of the increase in fuel consumption (NTM Road Transport, 2007).

If the company cargo is only the cargo transported by the vehicle, the emissions should be allocated to the cargo. Allocation is either based on weight or on volume (volumetric weight); therefore, physical weight and volumetric weight should be compared and the allocations should be based on the highest value(NTM Road Transport, 2007).

Furthermore, there are some assumptions used in the carbon emission calculations that are given as follows (Van Den Akker, 2009):

- the increase in fuel consumption is approximated by a linear function,
- the fuel consumption values based on ARTEMIS(Artemis, 2007) are averages for Europe and the differences between countries or specific traffic conditions are not taken into consideration,
- the fuel consumption resulting from idling of the truck is not taken into account in the carbon dioxide emissions calculation, and
- speed and driver behavior factors are not considered in this method.

3.3.1.2.4 Rail Transport Method

The advantages of the railway transport are weight and volume capacities, energy efficiency and low emission levels for the electric trains. The disadvantages are that they are not flexible, they cannot reach the further customers easily and there can be congestions throughout the railway system (NTM Rail Transport, 2008).

Locomotives are classified into two as electric locomotives and diesel locomotives. Rail transport has several specific transport parameters such as type of cargo, size of the train, traction type, and electricity generation (Schers, 2009).

Emission calculations can be done for both diesel and electrical trains. The calculations are scrutinized in studies of Van Den Akker (2009), Schers (2009), and Loo (2009). Since these calculations are not used in this study, the details are not given.

3.3.1.2.5 Water Transport Method

As well as the energy efficiency, the capacity in weight and volume are the advantages of water transportation. The disadvantages are reaching beyond the port due to handling times in ports (NTM Sea Transport, 2008).

The carbon dioxide emission is calculated as the multiplication of fuel consumption, distance and carbon content of the fuel. After calculating the carbon emission, this emission is allocated to the cargos of different companies that are transported by the vessel. Allocation is done in different ways for different vessel types (Schers, 2009)

The calculations are scrutinized in studies of Van Den Akker (2009), Schers (2009), and Loo (2009). Since these calculations are not used in this study, the details are not given.

3.3.2 TERRA Calculation Tool

The carbon dioxide emissions are calculated by using Terra Microsoft Access Tool developed by Van Den Akker, I.J.G., Te Loo, R. and Schers, R., master students at Technology University of Eindhoven. NTM method explained in Section 3.3.1.2 is implemented in Terra tool. The carbon emission calculations can be done per lane or per batch of lanes. In this study, carbon emission calculations are done per batch of lanes. The calculations per batch of lanes are done by importing transport data into tool. The data, as required by the method, are stored in different tables and a Visual Basic Code links these tables with each other and performs the calculations. After performing the calculations, the carbon emission calculation result can be exported to Excel.

Before carbon emission calculations are carried out, the Visual Basic Code in the Access was checked and a number of test runs were performed with artificially generated data sets.

3.3.3 Data Gathering

The important data that should be gathered for the carbon emission calculations are *type of the transport* (i.e air, road, water, and rail), *type of the transport mode* (the type of the vehicles), *weight of the parts*, *weight of the total cargo in the vehicle, load factor*, *positioning distance*, *empty return*. In the calculations, gathering the real data plays an important role. When gathering the real data is not possible; assumptions are made.

The data collection is carried out in two parts, which are internal data collection and external data collection. Internal data collection involves the shipments that have been transported from the central warehouse in Helmond during fiscal year 2009. In this study, approximately 84000 orders are examined. The data that are retrieved from internal system are origins and destinations of shipments, type and quantity of products, dates, logistics service providers and weights of shipments. The external data collection involves the places of the hubs and transportation modes of carriers. Distance data could not be obtained from the available internal and external data. Since they are very important for the carbon emission calculations, distances between origins and destinations of shipments are calculated. To calculate distances one Google Spreadsheet is prepared which can calculate 50 distances at once with the help of formulas used in the Google Spreadsheet which are given in Appendix C.

3. 4 The Results of Carbon Emission Calculations

In this section, a summary of the carbon emissions is provided according to four material flows that are explained in Section 3.2. Total carbon emissions for different material flows can be seen in Table 1.

Table 1 - Total Annual Carbon Emissions for Material Flows in the Service Supply Chain

Material Flows	Total Annual Carbon Emission ($mT\ CO_2$)
Repair Orders (Load Factor=50%)	245.80
Repair Orders (Load Factor=75%)	243.41
Excess Inventory Pullbacks (Load Factor=50%)	57.41
Excess Inventory Pullbacks (Load Factor=75%)	43.11
Allocation Orders	99.07
RMA Orders	284.28
Premium orders with 4 hour service type	78.061
Premium orders 2 hour service type	8.207
Premium orders scheduled time service type	73.429

In Figure 3, the contributions of each type of material flow in total carbon emission are shown. Note that based on NTM methodology load factor is assumed to be 75% for shipments of repair orders made by COMPANY B and excess inventory pullbacks.

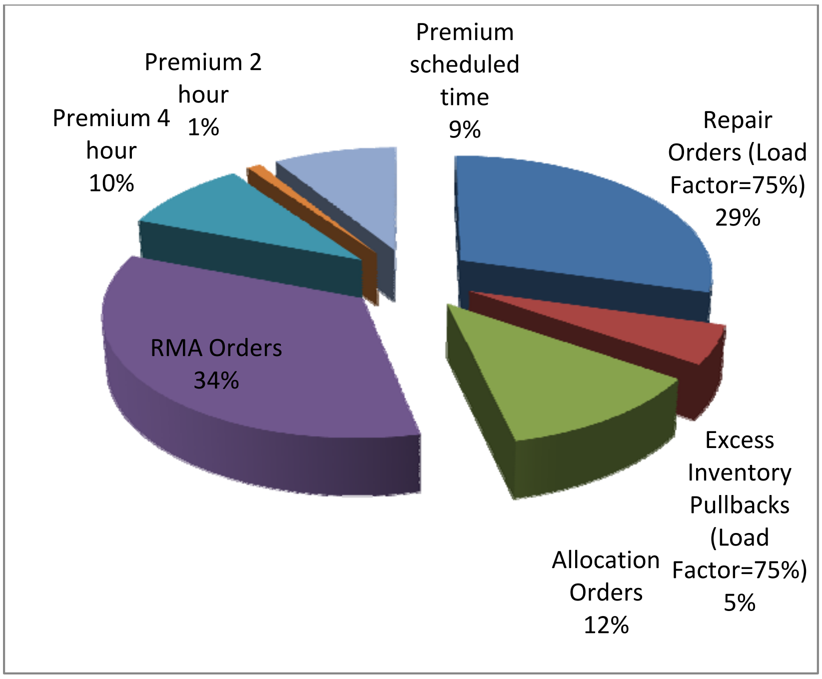


Figure 3 - The Percentages of the Carbon Emissions by Considering Material Flows

Some shipments of RMA and allocation orders are made by air. Total carbon emissions of the shipments made by air comprise 42.4 percent of total carbon emission. As it is seen in Table 1 and Figure 3, since the RMA orders are transported mostly by air, the highest carbon emission (34% of total emission) belongs to the RMA order shipments. Although the shipments of the allocation orders are also mostly made by air, emissions of these orders are not so high because of the small share of these orders based on total weight (6.17% of total weight).

The second highest carbon emission amount belongs to repair order shipments (29% of total emission). The shares of these shipments based on total weights are very high (35% of total weight) and most of the shipments are done by dedicated trucks. Although excess inventory pullbacks have higher total weight (37% of total weight) than repair orders, total carbon emission of excess inventory pullbacks is lower. The reason of this is that shipments are done by trucks shared with other companies and number of shipments in a year is low. The total weight of excess inventory pullbacks is also higher than the total weight of the premium orders (3.4% of total weight). However the carbon emissions of the premium orders are higher than the carbon emissions of excess inventory pullbacks, because the premium orders are transported by dedicated vehicles and the vehicles used are smaller than the vehicles used in the excess inventory pullback shipments (If the same parts are shipped with bigger vehicles with other cargos, the ratio of the weight of cargo to used capacity of vehicle becomes very small. Therefore the carbon emission allocated to the company would be smaller).

The lowest carbon emission belongs to the shipments of premium orders with 2 hour service type and this can be explained by their low shares based on total weight (0.44% of total weight) and short distances.

In addition to examining the carbon emission results according to materials flows, carbon emissions for each material flow are examined according to countries.

- For Repair Orders: The percentages of the total carbon emissions that result from inbound shipments and outbound shipments are 56 percent and 44 percent, respectively.
- For Excess Inventory Pullbacks material flow: 73 percent of the total carbon emissions are caused by the transports from the United Kingdom, Spain, Italy, Germany and France.
- For RMA orders: The sum of carbon emissions that result from transport to Italy, the United Kingdom, Spain and France constitute 79 percent of the total carbon emission caused by shipments of RMA orders.
- For allocation orders: The sum of carbon emissions that result from transport to Italy, the United Kingdom, Spain and France constitute 67.6 percent of the total carbon emission of allocation orders.

- For the parts with 4 hour service and scheduled time type orders: 82 percent of the total emissions are caused by the transport to the customers in the United Kingdom, Germany, Spain, France and Italy.
- For the parts with 2 hour service type orders: The percentage of the sum of carbon emissions of the United Kingdom, Germany, Spain, France and Italy is 97.2 percent of total carbon emissions

From the results of the carbon emission calculations, it is seen that Hungary, the United Kingdom, Spain, Italy and France have the highest share of the carbon emissions. Unlike excess inventory pullbacks and premium orders, for RMA and allocation orders Germany does not have a high share of carbon emissions, since the shipments are made mostly by road.

3.5 Carbon Emission Reduction Opportunities

There are different ways to reduce the carbon dioxide emissions resulting from transport. In this section, we discuss possible carbon emission reduction opportunities at Cisco.

3.5.1 Load Factor Increase

One way of reducing the carbon emissions is increasing the load factors. Although the load factors are controlled by carrier companies, if there is collaboration with carriers, the load factors can be improved. Our analysis reveals that increasing the load factor from 50% to 75% improves the CO_2 emission by 0.28% and 1.69% for the COMPANY B shipments and the excess pullbacks flow, respectively. These improvements are very small because of this reason it can be said that increase in the load factor for these shipments are not significant.

3.5.2 Revising Shipments of Dedicated Vehicles

The result of the carbon emission calculations proves that the dedicated trucks cause high carbon emissions, since the dedicated truck means that there are no other companies to share the responsibility of the carbon emissions, the utilizations of the capacities and empty returns are under the responsibility of the company. If the trucks are dedicated to the company, consolidating shipments by relaxing lead times may help to reduce the carbon emissions. This also leads low shipment frequencies, which helps to decrease transportation costs but causes high inventory, which means higher inventory holding costs.

3.5.3 Consolidation Opportunities

Consolidation opportunities have been examined for the repair order shipments and two scenarios have been developed. In the first scenario, the cargos of the trucks, which come from Szombathely and Budapest separately, are consolidated into one truck, Tractor+ MEGA Trailer; this would bring 0.7 percent reduction in the CO_2 emission. Under this proposal, there is no expected delay in the shipments, since the shipments are usually carried out on the same day. Cost reduction possibility cannot be examined with available data, since the rates for the Tractor+ MEGA Trailer is not known. Therefore, it can be said that this consolidation can be helpful to decrease the carbon emissions and decrease the transportation costs.

In the second scenario, two different outbound shipments carried out in a week are combined together. This consolidation brings 2.13 percent reduction in the CO_2 emission. Although this scenario brings higher reduction than the first one, it is important to mention that in order to consolidate these two shipments, the first shipment of the week should wait for four days. If the lead times are relaxed, the consolidation of the shipments can help to reduce both the carbon emissions and transportation costs with low shipment frequencies. The costs that can result from delays in the shipments and inventories should be taken into consideration. However with the available data the complete analyses cannot be carried out.

3.5.4 Changing Transportation Mode

In this study, it has been seen that changing transportation mode from air to road for allocation order flow brings 10.25 percent carbon emission reduction on the average. This is a significant carbon emission reduction opportunity compared to other reduction possibilities, so a more detailed study that takes associated costs into account should be made. In the next chapters, Chapter 4 and 5, CO_2 trade-offs between carrying inventory and transportation are examined in detail.

CHAPTER 4

THE MATHEMATICAL MODELS AND SOLUTION APPROACHES

This study consists of two phases. In the first phase, carbon emission calculation studies are conducted at Cisco Systems, Inc. according to different material flows in service supply chain, the result of these calculations are presented and the carbon emission reduction opportunities are explored, Chapter 3.

Based on the results of the carbon emission calculations, Section 3.4, we conclude that it is possible to reduce carbon emission by changing transport mode from a high-carbon transport mode that is air to a low-carbon transport mode that is road in allocation order material flow.

The low-carbon transportation modes are slower but cheaper transportation modes than the high-carbon transport modes. There exist trade-offs as low-carbon transportation modes lead to increase in lead time and hence decrease in service level or large inventory holding costs, while using faster transportation modes lead to higher carbon emissions and higher transportation costs. Therefore in the second phase of the study, in order to scrutinize this trade-off, two mathematical models that minimize the expected total cost that consists of inventory holding cost, transportation cost and additional cost for emergency shipment subject to aggregate service level constraint with/without carbon emission constraint are developed.

In Section 4.1, the description of the problem environment analyzed and the underlying assumptions are given. In the first model, a model to minimize expected total cost subject to aggregate expected fill rate constraint, the aim is to examine the effect of transportation mode change from air to road for allocation orders material flow. The underlying assumption of the first model is that all items are shipped with the same transportation mode. In the second model that minimizes expected total cost subject to aggregate expected fill rate and carbon emission constraints, this assumption is relaxed; transportation mode selection for each individual item is made. In Section 4.2, and Section 4.3, the first and the second models are discussed in detail, respectively. In the second model that minimizes expected total cost subject to aggregate expected fill rate and carbon emission constraints, since it is difficult to make transportation mode selection for each individual item, the items are clustered and transportation mode choice decision is made for each cluster. Therefore in Section 4.3, we propose two clustering methods to make transportation mode assignment not for individual items, but for groups of items with similar characteristics. In addition to classify the items in order to define the mode-selection variables, in Section 4.4, a greedy algorithm that minimizes expected total cost subject to aggregate expected fill rate and carbon emission constraints is provided. In this greedy algorithm, we do not only determine the base stock levels but also make the transportation mode choice decision.

4.1 Problem Environment

Like most of the service part inventory systems, the items that are stocked for Cisco are slow-moving and expensive. When the annual demands of all items at one depot are examined it is observed that the annual demands of 90 per cent of the items are less than 3 and mean of the demands of items is 1.57. The unit prices of 90 per cent of the items are higher than 400 Euro and the mean of the unit prices is 15855€. The system analysis reveals that inventory related cost items are inventory holding cost, transportation cost and additional cost for emergency shipment (that is made when a shortage occurs). It is observed that all these cost items are linear in number of units carried in inventory or transported. There is no fixed component of the replenishment related costs. Therefore, there is no need for batch ordering. Hence we consider $(S-1, S)$ continuous review inventory control policy.

The transportation costs depend on modes of transportation, weights of the items and country to which the item is shipped. The transportation cost ranges from 9€ to 293€. A holding cost is incurred for each unit on stock for each period. Since the items are expensive items, inventory holding costs are comparably higher than the other cost components.

The orders that cannot be delivered on time are backordered. If the depot is out of stock, the demand for that part is fulfilled through an emergency shipment from the central warehouse. The emergency shipments are made mostly by air transport and bring extra costs, however there are no certain costs determined for emergency shipments. When the need arises for emergency shipment, Cisco calls the 3PL company and this company sets the price for emergency shipments by considering the vehicle and aircraft availabilities at that moment. Since the emergency shipment costs are not definite, in the calculations, the emergency shipment costs are taken as multiples of air transport costs.

It is assumed that the central warehouse has ample stock, so the system is modelled as a single echelon system. In the single echelon system, each depot is responsible for its own stocking policies, independent of each other and of the central warehouse. This enables us to study each depot's problem individually.

The replenishment lead time is assumed to be deterministic. In the current system, the items are shipped mostly by air and the lead time is one day. Since customer satisfaction is very important for Cisco, the lead time cannot be increased for material flows; except allocation order material flow which is replenishment orders for RFDs.

In the second phase, by considering the carbon emission improvement opportunities, see Chapter 3, and possible increase in lead time, allocation order material flow is scrutinized. Allocation order material flow of one depot that consists of n different items (SKUs) is taken into consideration. There is no enough data accumulated to perform a formal goodness of fit test to find out underlying demand distribution. The demand for each item at each depot is assumed follow a Poisson distribution, which is a common assumption in almost all service parts models in the literature (Axsater, 1993).

Assumptions:

The following assumptions are made in the model formulations as follows:

- Demands occur one at a time and follow independent Poisson distributions. There are no batch orders.
- A one-for-one replenishment policy is applied for all SKUs at the depot.
- Unfilled demand is backordered. There are no lost sales.
- Replenishment lead times are fixed and known. There is no randomness in replenishment lead times. The replenishment lead times depend on transportation modes.
- The orders are placed electronically. The fixed costs are insignificant.
- Emergency shipment costs, to ship items that should be shipped as express cargos are multiples of air transport costs.
- Annual unit inventory holding cost of an item is one fourth of the unit value of the item, i.e., annual inventory carrying charge is 25%.

System Approach versus Item Approach:

In this study, the "system approach" is compared to the "item approach". In the item approach, a pre-determined and identical service level is assigned to each individual part; inventory control policy parameters for each individual item are set independently (Wong et al., 2005). In the system approach, the inventory decisions are made by considering all items and an aggregate service level is met by considering all items together (Kranenburg, 2006). The previous works of Mitchell (1988), Sherbrooke (2004), Thoneman et al. (2002), and Rustenburg et al. (2003) also compare system approach and item approach and show that the system approach gives significant savings in inventory cost compared to the item approach. In this study, a similar comparison is made by considering not only costs but also carbon emissions. Since Cisco considers fill rate, the fraction of demand satisfied from stock, as the service level measure, in this study fill rate is taken as service level measure.

4.2 A Model to Minimize Expected Total Cost Subject to Aggregate Expected Fill Rate Constraint

In this model, we use system approach; the objective is to minimize the expected total annual cost while meeting the aggregate expected fill rate constraint. The first model does not include carbon emissions as a constraint or a part of objective function. The purpose of this model is to examine the effects of a mode change from air to road on carbon emissions and expected total cost (the recommendation that we make Cisco for allocation orders, Chapter 3).

In Table 2 the notation used is given.

Table 2 - Notation Used

Symbol	*Unit*	*Description*
I		Set of items, indexed by $i = 1, 2, 3\ldots, \lvert I\rvert$
t_i	€ / unit	Unit regular shipment cost for item i
es_i	€ / unit	Emergency shipment cost for item i, multiple of air transport cost
p_i	€ / unit	Unit additional cost for emergency shipment, when a shortage occurs, difference between emergency shipment cost and regular shipment cost, $es_i - t_i$
h_i	€ / unit / year	Unit annual inventory holding cost for item i
m_i	Units/ year	Expected annual demand for item i
m	Units/ year	Expected total demand $m = \sum_{i \in I} m_i$
l		Replenishment lead-time
θ_i		Expected lead time demand for item i, $m_i \times l$
β		Target aggregate expected fill rate
X_i	Units	Random variable representing demand during replenishment lead time for item i
S_i	Units	Base stock level for item i

Let $f(x_i)$ is probability mass function of X_i. Since, customer demands follow independent Poisson random variables; the demand during lead time has also Poisson distribution with mean θ_i , demand during lead time $(m_i \times l)$ (Zipkin, 2000).

$$f(x_i) = \frac{e^{-\theta_i} {\theta_i}^{x_i}}{x_i!} \quad x_i = 0,1,2, ...$$

Let $G(x_i)$ is cumulative mass function (cmf) of demand during replenishment lead time

$$G(x_i) = \sum_{k=0}^{x_i} f(k)$$

According to base stock policy, the depot keeps its inventory position for an item i constant at the base stock level, S_i. According to Hopp and Spearman (2008), at any point in time, if we let X_i represent demand during lead time, then at a point where the number of outstanding orders is $X_i = x_i$, which is the orders that have yet to be fulfilled, the backorder level is $x_i - S_i$ if $x_i \geq S_i$ and on-hand inventory is $S_i - x_i$ if $x_i < S_i$. In addition, expected backorder level and expected on-hand inventory for each item are computed, respectively, by taking the average over possible values of x_i:

$$\text{Expected backorder level} = \textstyle\sum_{x=S_i+1}^{\infty}(x_i - S_i)f(x_i) \qquad (4.1)$$

$$\text{Expected on} - \text{hand inventory} = \textstyle\sum_{x=0}^{S_i}(S_i - x_i)\, f(x_i) \qquad (4.2)$$

Based on equation (4.1) and (4.2), the proposed mathematical model can be stated as follows:

$$\text{Minimize } \textstyle\sum_{i \in I}\left[\sum_{x=S_i+1}^{\infty} p_i\,(x_i - S_i)f(x_i) + \sum_{x=0}^{S_i} h_i(S_i - x_i)\, f(x_i) + t_i m_i\right] \qquad (4.3)$$

subject to

$$\beta - \textstyle\sum_{i \in I} \frac{m_i}{m}\left(1 - \frac{\sum_{x=S_i+1}^{\infty}(x_i - S_i)f(x_i)}{\theta_i}\right) \leq 0 \qquad (4.4)$$

$$S_i \geq 0 \text{ and integer } i \in I \qquad (4.5)$$

The objective function (4.3) minimizes the expected total cost, composed of the three cost components: The term $\sum_{i \in I} t_i m_i$ shows the expected total transportation cost and the term $\sum_{x=S_i+1}^{\infty} p_i\,(x_i - S_i)f(x_i)$ shows the expected total additional costs for emergency shipments. The number of the items that need to be shipped as emergency shipments is equal to expected backorder level at the depot. The term $\sum_{x=0}^{S_i} h_i(S_i - x_i)\, f(x_i)$ is the expected total inventory holding cost. Constraint (4.4) represents expected aggregate fill-rate constraint. The fill rate for each item is fraction of demand satisfied from stock. Under Poisson demand assumption, item fill rate, the probability of satisfying demand from stock for item i is $1 - \frac{\sum_{x=S_i+1}^{\infty}(x_i - S_i)f(x_i)}{\theta_i}$. The aggregate fill rate is a weighted sum of fill rates for individual items, with the fractions m_i/m as weights (Kranenburg, 2004) Finally, constraints (4.5) are the integrality and non-negativity restrictions on the base stock levels.

The model includes a non-linear objective function due to the expected backorder level and expected inventory level terms, a non-linear constraint due to backorder level term, and integer decision variables. Therefore the problem is a nonlinear integer programming problem.

Both the objective function and the constraint are convex in decision variables as shown in Appendix D. Karush–Kuhn–Tucker (KKT) conditions can be used to characterize the optimal solution. In our case, since our decision variable is discrete, KKT conditions are given via difference equations.

KKT conditions for our problem can be stated as follows:

1.

$$\sum_{i\in I} h_i\left[\sum_{x=0}^{S_i} f(x_i)\right] - \sum_{i\in I} p_i\left[\sum_{x=S_i+1}^{\infty} f(x_i)\right] - \boldsymbol{\lambda}\left[\sum_{i\in I}\frac{m_i}{m\theta_i}\left[\sum_{x=S_i+1}^{\infty} f(x_i)\right]\right]=0 \tag{4.6}$$

where λ is Lagrange multiplier.

2.

$$\lambda\left[\beta - \sum_{i\epsilon I}\frac{m_i}{m}\left(1 - \frac{\sum_{x=S_i+1}^{\infty}(x_i - S_i)f(x_i)}{\theta_i}\right)\right] = 0 \tag{4.7}$$

3.

$$\lambda \geq 0, S_i \geq 0 \text{ for } i \in I \tag{4.8}$$

For 2nd condition, equation (4.7), there are two situations, $\lambda = 0$ or $\lambda > 0$. If $\lambda = 0$, then this corresponds to the case where the aggregate expected fill rate constraint is non-binding. In this case, the optimal S values can be found by solving the unconstrained problem. When the unconstrained problem is considered, due to the convexity of the objective function, (4.3), the optimal stock level is the smallest nonnegative integer, S_i, for which

$$G(S_i) \geq \frac{p_i}{h_i + p_i} \qquad i \in I$$

If $\lambda > 0$, then $\beta = \sum_{i \in I} \frac{m_i}{m}\left(1 - \frac{\sum_{x=S_i+1}^{\infty}(x - S_i) f(x_i)}{\theta_i}\right)$ from equation (4.7). The optimal S_i values corresponding to a given λ value can be obtained from equation (4.6). The optimal S_i for a given value of λ is the smallest nonnegative integer value for which

$$G(S_i) \geq \frac{\frac{\lambda m_i}{m\theta_i} + p_i}{h_i + p_i + \frac{\lambda m_i}{m\theta_i}} \quad i \in I$$

Based on these, we employ the following algorithm to solve the problem numerically.

Algorithm 1- for solving the problem:

Step 1: Set λ=0

Step 2: Solve the unconstrained problem for each item i, find the smallest non-negative integer value of S_i satisfies that

$$G(S_i) \geq \frac{p_i}{h_i + p_i} \; i \in I$$

Step 3: If S_i values found in Step 2 satisfy the aggregate expected fill rate constraint $\beta - \sum_{i\in I}\frac{m_i}{m}\left(1 - \frac{\sum_{x=S_i+1}^{\infty}(x_i - S_i)f(x_i)}{\theta_i}\right) \leq 0$ and non-negativity constraints, the solution is optimal, stop, otherwise go to Step 4.

Step 4: Increase λ by $\text{stepsize}_{\lambda}$ (The details on updating λ are given in Appendix E)

Step 5: For each item i, find the smallest non-negative integer values of S_i s satisfies

$$G(S_i) \geq \frac{\frac{\lambda m_i}{m\theta_i} + p_i}{h_i + p_i + \frac{\lambda m_i}{m\theta_i}} \quad i \in I$$

Step 6: If the S_i values satisfy the aggregate expected fill rate $\beta - \sum_{i\in I}\frac{m_i}{m}\left(1 - \frac{\sum_{x=S_i+1}^{\infty}(x_i - S_i)f(x_i)}{\theta_i}\right) \leq 0$ and non-negativity constraints, the solution is optimal, stop, otherwise go to Step 4.

Single-Item Approach:

In the single-item approach, instead of meeting an aggregate service level by considering all items together, the identical fill rate is assigned to all items. In this approach, $G(S_i; \theta_i)$ represent the fraction of demands that are filled from stock, fill rate. Since in this situation demand during replenishment lead time is discrete, expected fill rate of item i under Poisson demand is represented as $G(S_i - 1; \theta_i)$, Zipkin (2000), Hopp and Spearmann (2008). $G(S_i - 1; \theta_i) \geq \beta$ calculates the base stock level for each item to satisfy the specified service level (β). In the single-item approach, our objective function does not change and additional cost for emergency shipment, inventory holding cost and transportation cost are calculated by using formulas $\sum_{x=S_i+1}^{\infty} p_i\,(x_i - S_i)f(x_i)$, $\sum_{x=0}^{S_i} h_i(S_i - x_i)\,f(x_i)$, $\sum_{i\in I} t_i m_i$ as in (4.3), respectively.

4.3 A Model to Minimize Expected Total Cost Subject to Aggregate Expected Fill Rate and Carbon Emission Constraints

In the second model, in addition to the aggregate expected fill rate, a new constraint that limits the carbon emissions to a specified level is considered. Since the carbon emission cost is very insignificant compared to other cost components, the carbon emissions are not considered in the objective function. The study of Hoen et al. (2010) also shows that the emission cost is only a small part of the total cost and they conclude that introducing an emission cost for freight transport, e.g. via a market mechanism such as cap-and-trade, will not result in large emission reductions, since significant changes in transport modes are not likely to take place for plausible carbon prices.

In this model, the transportation mode choice decisions are integrated into inventory decisions. The first decision is assignment of transportation modes to items and second decision is determining base stock levels. These two decisions will affect not only the total cost but also the carbon emissions.

In Table 3 the notation used is given.

Table 3 - Notation Used

Symbol	***Unit***	***Description***
I		Set of items, indexed by $i = 1, 2, 3 \ldots \|I\|$
J		Set of transportation modes, indexed by $j = 1, 2, 3, 4$
h_i	€ / unit/year	Unit annual inventory holding cost for item i
t_{ij}	€ / unit	Unit regular shipment cost for item i by using transportation mode j

Table 3 (Cont'd) - Notation Used

Symbol	*Unit*	*Description*
es_i	€ / unit	Emergency shipment cost for item i, multiple of air transport cost
p_{ij}	€ / unit	Unit additional cost for emergency shipment, when a shortage occurs, difference between emergency shipment cost and regular shipment cost for item i by using transportation mode j
m_i	Units/ year	Demand for item i
m	Units/ year	Total demand that is equal to $\sum_{i \in I} m_i$
l_j		Replenishment lead time when the transport mode j is used
θ_{ij}	Units	Expected demand during lead time l_j of item i while using transportation mode j, $m_i \times l_j$
β		Target aggregate expected fill rate
e_j	mT $C0_2$	Carbon emission amount resulting from shipping an item that weighs one tonne by transportation mode j, from central warehouse to depot
e_a	mT $C0_2$	Additional carbon emission amount resulting from shipping item that weighs one tonne as an emergency shipment from central warehouse to depot. The additional carbon emission is the difference between carbon emission result from selected transportation mode and air transport
EM_{max}	mT $C0_2$	Maximum allowable annual carbon emission amount resulting from transportation
w_i	Tonnes	Weight of item i
M		Very large number
S_{ij}	Units	Base stock level for item i when the item i is shipped by transportation mode j
X_{ij}	Units	Demand during replenishment lead time when the item i is shipped by transportation mode j

The second proposed mathematical model can be stated as follows:

$$\text{Minimize } \sum_{i\in I}\sum_{j=1}^{4}\left[\sum_{x=S_{ij}+1}^{\infty} p_{ij}y_{ij}\left(x_{ij}-S_{ij}\right)f\left(x_{ij}\right)+\sum_{x=0}^{S_{ij}} h_i\left(S_{ij}-x_{ij}\right)\ f\left(x_{ij}\right)+t_{ij}y_{ij}m_i\right] \tag{4.9}$$

$$\text{Subject to} \qquad \beta - \sum_{i\in I}\frac{m_i}{m}\left(1-\frac{\sum_{j=1}^{4}\sum_{x=S_{ij}+1}^{\infty}\left(x-S_{ij}\right)f\left(x_{ij}\right)}{\sum_{j=1}^{4}\theta_{ij}y_{ij}}\right)\le 0 \tag{4.10}$$

$$\sum_{i\in I}\sum_{j=1}^{4}\left[e_j y_{ij} w_i m_i + e_a w_i \sum_{x=S_{ij}+1}^{\infty}\left(x_{ij}-S_{ij}\right)f\left(x_{ij}\right)\right]-EM_{max}\le 0 \tag{4.11}$$

$$\sum_{j=1}^{4} y_{ij}=1 \qquad i\in I \tag{4.12}$$

$$S_{ij}\le My_{ij} \qquad i\in I, j\in J \tag{4.13}$$

$$S_{ij}\ge 0 \text{ and integer } \quad i\in I, j\in J \tag{4.14}$$

$$y_{ij}\in\{0,1\} \qquad i\in I, j\in J \tag{4.15}$$

Objective function (4.9) minimizes the expected total cost, explained in Section 4.1. Constraint (4.10) ensures that target aggregate expected fill rate is satisfied. Constraint (4.11) is the emission constraint which ensures that total carbon emissions caused by transportation in one year cannot exceed a maximum allowable carbon emission amount. The total carbon emission is calculated by considering regular shipments and emergency shipments. The carbon emission caused by regular shipments, $\sum_{i\in I}\sum_{j=1}^{4} e_j y_{ij} w_i m_i$, is calculated by considering unit carbon emission amount of mode j, e_j, weights of items, w_i, and yearly demand for item i, m_i . If the demand is not satisfied immediately from stock, emergency shipments are done by air transport. Because of this reason, total additional carbon emission resulting from emergency shipments, $\sum_{i\in I}\sum_{j=1}^{4}\left[e_a w_i \sum_{x=S_{ij}+1}^{\infty}\left(x-S_{ij}\right)f\left(x_{ij}\right)\right]$ is calculated by considering expected number of backorders $\sum_{i\in I}\sum_{j=1}^{4}\left[\sum_{x=S_{ij}+1}^{\infty}\left(x-S_{ij}\right)f\left(x_{ij}\right)\right]$, unit carbon emission amount results from additional shipment which is the difference between unit carbon emission of air and unit carbon emission of assigned transportation mode j, e_a and weight of the item i, w_i.

Unit carbon emission calculations are done by considering the same factors explained in the carbon emission calculations such as distances, type of vehicles, load factors, etc in Section 3.3.

Constraints (4.12) ensure that only one transportation mode is assigned to each item. Constraints (4.13) ensure that if one transportation mode is assigned to each item, then base stock levels are determined by considering assigned transportation modes. Constraints (4.14) are the non-negativity and integrality restrictions on the base stock levels. Finally, constraints (4.15) are the binary restrictions on transportation mode selection variables.

The second model has also a non-linear objective function, non-linear constraints and integer decision variables.

Since mode selection decision variables make the problem very difficult to solve, we focus on the solution by taking the mode selection variables, y_{ij}, as given. Although the transportation modes other than air and road are not used in the current system, we assume that there are four transportation mode alternatives, air, road, rail and water, for each item. In total there are 4^n possible mode selection combinations that we need to examine, where n is the number of items. Instead of examining all of these alternatives, in Section 4.3 we propose two clustering methods that are k-means algorithm and classification with an adopted ABC analysis in order to partition the data into clusters. After partitioning the data, we assign the transportation modes to the clusters. By this way, we can reduce the number of the alternatives that are examined from 4^n to 4^k where k is the number of clusters.

The convexities of objective function (4.9) and constraints (4.10) and (4.11) in the decision variables S_{ij} for given values of y_{ij} values are proved in Appendix F.
KKT conditions for our problem can be stated as follows:

1.
$$\sum_{i \in I} \sum_{j=1}^{4} \left(h_i \left[\sum_{x=0}^{S_{ij}} f(x_{ij}) \right] - p_{ij} y_{ij} \left[\sum_{x=S_{ij}+1}^{\infty} f(x_{ij}) \right] - \lambda \left[\frac{m_i}{m \sum_{j=1}^{4} \theta_{ij} y_{ij}} \left[\sum_{x=S_{ij}+1}^{\infty} f(x_{ij}) \right] \right] - \varepsilon \left[e_a w_i \left[\sum_{x=S_{ij}+1}^{\infty} f(x_{ij}) \right] \right] \right) = 0 \quad (4.16)$$

2.
$$\lambda \left[\beta - \sum_{i \epsilon I} \frac{m_i}{m} \left(1 - \frac{\sum_{j=1}^{4} \sum_{x=S_{ij}+1}^{\infty} (x - S_{ij}) f(x_{ij})}{\sum_{j=1}^{4} \theta_{ij} y_{ij}} \right) \right] = 0 \quad (4.17)$$

3.
$$\varepsilon \left[\sum_{j=1}^{4} \sum_{i \epsilon I} \left[e_j y_{ij} w_i m_i + e_a w_i \sum_{x=S_{ij}+1}^{\infty} (x - S_{ij}) f(x_{ij}) \right] - EM_{max} \right] = 0 \quad (4.18)$$

4. $\lambda \geq 0$ (4.19)

5. $\varepsilon \geq 0$ (4.20)

where λ and ε are Langrange multipliers.

If $\lambda > 0$ and $\varepsilon > 0$, then $\beta = \sum_{i \epsilon I} \frac{m_i}{m} \left(1 - \frac{\sum_{j=1}^{4} \sum_{x=S_{ij}}^{\infty} (x - S_{ij}) f(x_{ij})}{\sum_{j=1}^{4} \theta_{ij} y_{ij}} \right)$ from equation (4.17) and $\sum_{j=1}^{4} \sum_{i \epsilon I} \left[e_j y_{ij} w_i m_i + e_a w_i \sum_{x=S_{ij}}^{\infty} (x - S_{ij}) f(x_{ij}) \right] = EM_{max}$ from equation (4.18). The optimal S_{ij} values corresponding to given λ and ε values can be obtained from equation (4.16). The optimal S_{ij} for given values of λ and ε is the smallest nonnegative integer, S_{ij}, for which

$$G\,(S_{ij}) \geq \frac{\frac{\lambda m_i}{m\sum_{j\in J}\theta_{ij}y_{ij}}+p_{ij}y_{ij}+\varepsilon e_a w_i}{h_i+p_{ij}y_{ij}+\frac{\lambda m_i}{\sum_{j\in J} m\theta_{ij}y_{ij}}+\varepsilon e_a w_i} \qquad i\epsilon I, j\epsilon J$$

The Poisson inverse cumulative mass function (cmf) gives the smallest non-negative integer value, S_{ij} such that the Poisson cmf that is evaluated at S_{ij} equals or exceeds $\frac{\frac{\lambda m_i}{m\theta_{ij}y_{ij}}+p_{ij}y_{ij}+\varepsilon e_a w_i}{h_i+p_{ij}y_{ij}+\frac{\lambda m_i}{m\theta_{ij}y_{ij}}+\varepsilon e_a w_i}$, using mean parameter θ_{ij}, the reason of not guaranteeing the equality is the discreteness of the Poisson distribution.

We employ the following algorithm to solve the problem numerically. In this algorithm, since currently there is no carbon emission regulation, our aim is to obtain carbon emission amounts correspond to different ε values in order to examine different carbon emission restriction scenarios.

Algorithm 2- for solving the problem:

Step 1: Set $\varepsilon = 0$

Step 2: Set $\lambda = 0$

Step 3: For each item i and assigned transportation mode j, find the smallest non-negative integer S_{ij} values that satisfy

$$G(S_{ij}) \geq \frac{\frac{\lambda m_i}{m\sum_{j\in J}\theta_{ij}y_{ij}} + p_{ij}y_{ij} + \varepsilon e_a w_i}{h_i + p_{ij}y_{ij} + \frac{\lambda m_i}{\sum_{j\in J} m\theta_{ij}y_{ij}} + \varepsilon e_a w_i} \qquad i\epsilon I, j\epsilon J$$

Step 4: If S_{ij} values found in Step 3 satisfy aggregate expected fill rate constraint, $\beta - \sum_{i\epsilon I}\frac{m_i}{m}\left(1-\frac{\sum_{j=1}^{4}\sum_{x=S_{ij}+1}^{\infty}(x-S_{ij})f(x_{ij})}{\sum_{j=1}^{4}\theta_{ij}y_{ij}}\right) \leq 0$ and non-negativity constraints, the solution is optimal, go to Step 6. Otherwise go to Step 5.

Step 5: Increase λ by stepsize_λ and go to Step 3

Step 6: Increase ε by $\text{stepsize}_\varepsilon$ and go to Step 2, if ε hits the predetermined upper limit stop.

A short pseudo code of algorithm 2 is given in Appendix G.

4.3.1 Possible Ways to Determine Mode Selection Variables

Since there are 4^n possible mode selection combinations, where n is the number of items, considering all alternatives and carrying out a complete enumeration procedure are not viable, especially if the number of items is high. Therefore we need to find possible ways to reduce search space. One of these ways to define the mode-selection variable is clustering the items and then assigning the transportation modes to clusters. Clustering has been extensively used to partition data into groups so that degree of association is high among members of the same group and low among members of different groups. (Jung et al., 2002). In Section 4.3.1.1, K-means clustering, a well-known algorithm to partition the data based on attributes into k number of group is examined. In addition to K-means clustering, the other way to define the mode-selection variable is classification of the items with an adopted ABC analysis, Section 4.3.1.2. Since carbon emissions are not considered in the traditional ABC analysis, we adjust traditional ABC analysis by considering carbon emissions. In this method, the aim is to classify the items with similar characteristics.

In this study, both in k-means clustering algorithm and in our ABC classification in order to make right transportation mode choice decisions in terms of cost and carbon emission, we consider unit prices, annual demands and weights of the items, which is an important factor in carbon emission. These three attributes are equally important.

4.3.1.1 K-Means Clustering

K means clustering algorithm is used to partitioning data into k groups, and has been shown to be effective in providing good clustering results for many practical applications (Fahim et al., 2006). K-means clustering algorithm partitions a given data set, X ={x_1,..., x_N}, into k disjoint subsets (clusters) C_1, C_2, ..., C_k such that a clustering criterion is optimized (Likas et al. 2003). Most widely used clustering criterion is the sum of Euclidean distances between each data point x_i and a centroid m_n, that is the cluster centre of the subset C_n which contains x_i. This criterion is called clustering error and depends on the cluster centres m_1... m_k and can be expressed as (Likas et al. 2003)

$$E(m_1, \ldots, m_k) = \sum_{i=1}^{N} \sum_{n=1}^{k} I(x_i \in C_n) \|x_i - m_n\|^2$$

where $I(X) = 1$ if X is true and 0 otherwise.

In our problem, the data points are items and our aim is to partition these data points, items, into k clusters based on attributes the unit prices, annual demands and weights of the items as explained in Section 4.3.1 by assuming each attribute contributes to the clustering process equally.

In this study, we use Matlab's built-in k-means clustering function. Matlab selects k observations from the data set randomly in order to form initial cluster centroid positions. However different initial seeds may produce different results. Matlab guarantees a solution that is a local minimum, a partition of the data where moving any single point to a different cluster increases the total sum of distances.

Since there are four transportation modes, there are also 4^k ways to assign the transportation modes to k clusters of items. Because of high number of alternative assignments, large number of clusters cannot be examined, in our study we examine the number of clusters from 4 to 6, see Chapter 5.

It is important to mention that K-means clustering algorithm has some weaknesses such as being sensitive to initial cluster centroid positions, seeds. In addition, in k means clustering, it is assumed that each attribute, which are annual demand, unit price and weight for this case, has the same weight and it is not known that which attribute contributes more to the clustering process. As a result, it is hard to interpret the common characteristics of the item clusters generated by k-means algorithm.

4.3.1.2 Clustering with ABC Analyses

ABC analysis, which is a well-known classification technique in inventory management, sorts the SKUs into three categories that are A, B and C (Chen et al., 2006). In conventional ABC analysis, the classification is based on annual dollar usage. Items in class A are relatively few in number but constitute a relatively large amount of annual dollar usage, while class C items are relatively large in number but constitute a relatively small amount of annual dollar usage and items between these two classes constitute class B (Ramanathan, 2006). However in our case, conventional ABC analysis is not sufficient, because it does not consider the factors affecting carbon emissions. Therefore we extend the conventional ABC analysis such that the items are sorted based on both annual dollar and total annual ton usages. Since total annual ton usage, the multiplication of weight of item and annual demand, is one of the important factors in the carbon emission calculations, we take it into consideration in our ABC analysis. In order to define the groups of items for which a common transportation mode assignment is made, two ABC analyses are conducted. The first one is traditional ABC analysis and in this analysis items are sorted based on the total annual dollar usage. In the second ABC analysis items are sorted based on total annual tonne usage. The number of items in class A are relatively few but these items form a relatively large amount of total annual ton usage, whereas the number of items in class C is relatively large but these items form a relatively small amount of total annual ton usage. Items between these two classes comprise class B. Then by considering the results of these two ABC analyses, the items are classified by considering their contributions to both annual dollar usage and total annual ton usage. There are nine categories that are given in Table 4.

Table 4 - Categories of Items and Properties of These Categories

Categories	**Properties**
AA	Contribution to annual dollar usage: High Contribution to total annual ton usages: High
AB	Contribution to annual dollar usage: High Contribution to total annual ton usages: Medium
AC	Contribution to annual dollar usage: High Contribution to total annual ton usages: Low
BA	Contribution to annual dollar usage: Medium Contribution to total annual ton usages: High
BB	Contribution to annual dollar usage: Medium Contribution to total annual ton usages: Medium
BC	Contribution to annual dollar usage: Medium Contribution to total annual ton usages: Low
CA	Contribution to annual dollar usage: Low Contribution to total annual ton usages: High
CB	Contribution to annual dollar usage: Low Contribution to total annual ton usages: Medium
CC	Contribution to annual dollar usage: Low Contribution to total annual ton usages: Low

After determining the categories, decision on the suitable transportation modes that can be assigned to categories is made. The possible transportation modes for each category are given in Table 5.

Table 5 - Possible Transportation Modes for Categories

Categories	Possible Transportation Modes
AA	Air, Road
AB	Air, Road
AC	Air
BA	Road, Rail, Water
BB	Road, Rail, Water
BC	Road, Rail, Water
CA	Water
CB	Water, Rail
CC	Water, Road, Rail

While assigning the transportation modes to categories, the properties of the categories and transportation modes are taken into consideration. In traditional ABC analysis, items in class A have to be controlled tightly and monitored closely (Ramanathan, 2006). By using the same logic, items in the class AA have to be controlled tightly and monitored closely, since the items in this class have the largest contribution to both total annual dollar and ton usage. However, when the items in class CC is examined, there is no need to monitor the items in this class closely, because they do not contribute to both total annual usage and total ton usage very much.

Some of the facts that are considered as follows,

- Air transportation is generally used for light, expensive and high-demand items. Therefore items in class AC is very appropriate to be transported by air.
- Water transportation mode is very suitable to transport heavy, not expensive and low-demand items. Thus items in class CA can be transported by water.

These are general facts that can be considered, however for other categories, different possible transportation modes are taken into consideration. Since currently there are no carbon regulations, the prices of the items play more significant role in transportation mode choice decisions.

4.4 Greedy Algorithm

In Kranenburg (2006), the author defines heuristics as approximation algorithms in order to find a feasible solution for optimization problem.

Greedy methods are iterative and also known as marginal analysis. The reason to call marginal analysis is explained in Sherbrooke (2004) as at each step in the algorithm only to look at one number for each item is needed to determine the next item that should be bought and the marginal or incremental value provides all the information necessary on each item. This technique has been widely used for many years; one of the earliest references is Karush (1957). The author presents a multi-item method for a single location problem with lost sales. His greedy method distributes a given budget over the items such that the aggregate fill rate is maximized. Some of the recent studies that use greedy algorithm in their studies are Rustenburg et al. (2000), Wong et al. (2005), Kranenburg (2006). In these studies, greedy methods are used to stepwise increase base stock levels until a certain stopping criterion is satisfied. Rustenburg et al. (2000) studies the availability of a single-indenture system consisting of a number of different components, which, when failed, are replaced by spare items stocked at a single-location. Authors use a greedy approach to determine the target inventory positions under which the total expected number of backorders is minimized, subject to a limited budget available for the total number of spare parts to be purchased. In Wong et al. (2005), the authors analyse a multi-item, continuous review model of a multi-location inventory system of repairable spare parts, in which lateral and emergency shipments occur in case of stock-outs. In their greedy heuristic, base stock levels start as zero values for all SKU-s in all local warehouses, in each iteration the base stock level is increased for an item and local warehouse, if this increase has the largest ratio of decrease in waiting time to cost increase. Kranenburg (2006) studies spare parts inventory control problem under system availability constraints, where he focuses on the incorporation of five features that he identifies as challenges: commonality, service differentiation, lateral transhipment, two-echelon structure, two transportation modes. The basic idea of the greedy heuristic in the study of Kranenburg (2006) is adding one unit of SKU $i \in I$ at a warehouse $n \in N$ iteratively such that the largest decrease in distance to the set of feasible solutions per extra unit of additional cost and the procedure is terminated when a feasible solution is obtained. A similar study is conducted by Wong et al. (2007); the difference of the study of Wong et al. (2007) is that the authors also investigate the improvement potential when a local search is added.

Similar to the greedy procedures described in the studies of Rustenburg et al. (2000), Wong et al. (2006), Kranenburg (2006), our greedy algorithm also builds up inventory for all items i □ I, however in this study it is not possible to check the accuracy of the algorithm; since an approximate evaluation method is used, optimal values are not found. In our greedy algorithm, the carbon emissions are taken into consideration by focusing on a single depot and our service measure is aggregate expected fill rate. Our greedy algorithm is based on our second model that minimizes expected total cost subject to aggregate expected fill rate and carbon emission constraints. Since there are no regulations on carbon emissions, instead of examining a certain maximum allowable amount of carbon emission, we examine different possible maximum allowable carbon emissions.

The algorithm is started by setting all base stock levels for items that transported by different modes equal to zero, $S_{ij} = 0$ i □ I, j □ J where S_{ij} represents the base stock level of item i transported by mode j. In each iteration, one unit of stock is added for the item i that is transported by mode j in order to approach the set of feasible solutions. Let A be a matrix that has size $|I| \times |J|$; this matrix consists of zero values at each cell, A_{ij} $i \in I, j \in J$, except one cell that has value of one in the ith row and jth column $A_{ij} = 1$, which signifies that one unit of stock for item i transported by mode j and zero stocks for all other items transported by other modes. In each iteration, for each item, the total cost, aggregate expected fill rate and emission differences are calculated, respectively, as follows:

$$\Delta TC = TC(\mathbf{S} + \mathbf{A}) - TC(\mathbf{S})$$
$$\Delta F = F(\mathbf{S} + \mathbf{A}) - F(\mathbf{S})$$
$$\Delta E = E(\mathbf{S}) - E(\mathbf{S} + \mathbf{A})$$

Where ΔTC, ΔF and ΔE are total cost, fill rate and emission differences, respectively. ΔTC, ΔE, ΔF are $|I| \times |J|$ matrices. Emission difference is taken as the amount of decrease in carbon emission when the base stock level is increased for one unit, which is improvement in carbon emissions. While determining the item for which the base stock level is increased, two ratios are considered. Although it is not expected for Cisco, because of very high inventory holding costs compared to emergency shipment costs, for a general case if a decrease in total cost for an item is observed when the base stock level is increased by one unit then the base stock level of this item is increased by one unit directly. One of the ratios considered in the algorithm, r_1, is the ratio of increase in aggregate expected fill rate to total cost increase and the second one, r_2, is the ratio of decrease in carbon emission to total cost increase. In each iteration, r_1 and r_2 are calculated for each combination of item $i \in I$ and transportation mode $j \in J$ as

$$r_1(i,j) = \Delta F(i,j) / \Delta TC(i,j) \quad i \in I \;\; j \in J$$

$$r_2(i,j) = \Delta E(i,j) / \Delta TC(i,j) \quad i \in I \;\; j \in J$$

An increase of a base stock level always leads to an increase in inventory holding cost and a decrease in expected emergency shipment cost. Since in the current situation the inventory holding costs are significantly higher than emergency shipment costs, an increase of a base stock level always leads to increase in expected total cost. In addition, decrease in the number of emergency shipments causes decrease in carbon emissions. As a result, the second ratio is positive. At the same time, with an increase in base stock level, aggregate expected fill rate always increases; hence the aggregate expected fill rate differences and therefore first ratio is always positive.

A weighted ratio for each combination of item $i \in I$ and transportation mode $j \in J$ is calculated as;

$$r_3\,(i,j) = w_1\; r_1(i,j) + (1 - w_1)\, r_2(i,j)$$

At each iteration, the base stock level of the item i transported by transportation mode j with the highest, r_3, ratio is increased by one unit.

It is not possible to determine the weight, w_1, certainly by a decision maker at company. Accordingly, with this algorithm, we consider different choices of weights for r_1 and r_2. Different weights correspond to different carbon emissions and giving different weights give the chance to examine different carbon emission restriction scenarios and weights that should be assigned to ratios under these scenarios. Since currently there is no carbon emission regulation, decision maker at company tends to give high weights, generally 1, to r_1. However possible future regulations can force the company to give higher weights to r_2, which is ratio of change in carbon emission to change in total cost.

It is assumed that in the beginning of algorithm all items are transported by air, because it is known that if the base stock level of an item is zero, when a demand occurs the item has to be shipped by air as an emergency shipment. The transportation mode assignment is done, as the base stock level is increased by one for the first time.

Formal description of the greedy heuristic is as follows:

Step 1 : Set $S_{ij} = 0$ $i \epsilon I, j \epsilon J$, $w_1 = 0$

Step 2 : For each item $i \epsilon I$ and transportation mode $j \epsilon J$, calculate ΔTC, $\Delta F, \Delta E$

Step 3 : Calculate r_1, r_2 and r_3

Step 4 : Determine i^* and j^* such that $r_3(i^*, j^*) = \max_{i \epsilon I, j \epsilon J} r_3(i, j)$

Step 5 : Set $S(i^*, j^*) = S(i^*, j^*) + 1$ and assign item i to transportation mode j

Step 6 : Check whether aggregate expected fill rate constraint is satisfied, if the aggregate expected fill rate constraint, is not satisfied, go to step 2, otherwise increase w_1 by stepsize_{w_1}. Since currently there are no regulations on carbon emissions resulting from transportation, we examine different choices of weight, w_1. In our algorithm, the weight w_1 is increased by different step sizes, that are 0.005, 0.02, 0.05 and it is observed that by considering the computational times and representativeness of the results, step size can be determined as 0.02.

CHAPTER 5

COMPUTATIONAL STUDY

In this chapter, we present the computational study carried out to gain managerial insights on the tradeoffs involved in replenishment decisions.

In Section 5.1, the computational study environment is analyzed. In Section 5.2, for allocation orders the effects of changing transportation mode from air to road on carbon emissions and expected total cost are examined and the multi-item and single-item approaches are compared in order to understand which approach is suitable for Cisco. In Section 5.3, we present our findings on transportation mode selection model with carbon emission consideration. Since it is difficult to make transportation mode choice decisions for each item, the items are clustered and transportation mode choice decision is made for each cluster, therefore we propose two clustering methods that are k-means algorithm, Section 4.3.1.1, and classification with an adopted ABC analysis, Section 4.3.1.2, in order to partition the data into clusters and in this section we observe the results obtained from these clustering methods. Then in the same section, Section 5.3, we present our findings on greedy algorithm. Since currently there are no regulations on maximum allowable carbon emissions resulting from transportation, by carrying out computational studies our aims are to generate efficient solutions that are not dominated by other solutions with less carbon emissions and lower expected total cost, and then assist the decision maker at Cisco in selecting the most preferred solutions that have less carbon emission and lower total cost among all efficient solutions. Although for the current situation where no regulation on carbon emissions exists, the efficient solution that has minimum expected total cost can be most interesting point, with legal regulations different carbon emissions become more interesting for the company. At this point according to efficient solutions, expected total cost can be estimated under different carbon emission regulation scenarios. In these computational studies, each expected carbon emission value can be considered as a different carbon emission regulation scenario.

5.1 Environment

In the computational study, the real data obtained from Cisco are used. Among possible carbon emission reduction opportunities, Section 3.5, changing transportation mode from high-carbon transportation mode to low-carbon transportation mode for allocation material flow is found to be the most promising carbon reduction opportunity to reduce carbon emission. Therefore in the computational study, we focus on allocation order material flow.

Since the system is modelled as a single echelon system, by considering the number of the items in the depot, one of the largest RFD in Milan, Italy (MXP), is selected. Currently in this RFD there are 532-items stocked.

For allocation orders material flow, there are two transportation modes used; air and road. The items are transported from central warehouse to Cologne hub by road, from Cologne hub to Milan airport by air and from Milan airport to MXP by road. In the current situation, since all items are mostly transported by air regardless of the order type, the lead time for all shipments is one day. However, for allocation orders, replenishment orders for RFDs, the lead times are not as rigid as customer orders. Therefore there is a possibility to ship the allocation orders by road. If the shipments are made only by road, from Cologne Hub to distribution centres in countries, items are transported by road instead of air, so lead time increases from one to three days.

In the current system, rail and water transportation modes are not used, for more detailed examinations; we assume that these transportation modes can also be used. By considering the distances, the lead times of these transportation modes are determined as 5 and 7.5 days for rail transport and water transport, respectively.

The unit carbon emissions are calculated in exactly the same way as given in Chapter 3, by considering the same parameters and assumptions. For road transport, we assume that a Tractor + Semi-trailer is used, because this is a common vehicle type used for long distances (Hoen et al., 2010). Load factor assumptions are made based on the NTM methodology. The load factor for road transport is assumed to be 70%. For rail transport we use electrical trains and load factor is assumed to be 50%. For water transport, we assume that inland waterways are used for transport and that a general cargo vessel is used (Hoen et al., 2010). For inland waterways, a load factor of 50% is assumed. For each transportation mode from stations or ports to depots, and vice versa, we assume that items are transported with a vehicle that has average properties. The unit emissions (mT CO_2) for all transportation modes can be seen in Table 6.

Table 6 - Unit Carbon Emissions

Transportation Mode	**Unit Emission (mT CO_2)**
Road	0.1249
Air	0.9814
Rail	0.0892
Water	0.0595

In this study, we examine the sensitivity of the model to the change in aggregate fill rates and emergency shipment costs. In addition to the current target aggregate fill rate of 98%, we consider different aggregate fill rates such as 95% and 99%. Since the emergency shipment costs are not definite, different emergency shipment costs are examined.

The computational studies have been executed on an Intel(R) Core(TM) 2Duo CPU processor of 2 GHz, 4GB RAM. The Nonlinear Integer Programming (NLIP) models in Section 4.1 and Section 4.2 are solved by implementing two clustering methods, Section 4.3.1, and greedy algorithm, Section 4.4, have been implemented using MATLAB Version 7.5 (R2007b), which is a high-level language for technical computing, since our NLIP models cannot be solved with commercial solvers such as LINGO and GAMS. MATLAB is easy to use and has useful mathematical functions that can be used without writing special codes such as *k-means*.

5.2 The Effects of a Mode Change From Air to Road on Carbon Emissions and Expected Total Cost

The notations used in this section are the notations described in Chapter 4. Emergency shipment cost for item i is represented by $\mathrm{es_i}$ and $\mathrm{t_{i4}}$ represents the transport cost for the item i shipped with air transport. Since currently there are no determined costs for emergency shipments, by considering that the emergency shipments are made by air transport, we set emergency shipment costs as equal to $\mathrm{t_{i4}}$, $\mathrm{t_{i4}} * 5$, $\mathrm{t_{i4}} * 10$, and $\mathrm{t_{i4}} * 15$. However, our calculations show that since the emergency shipment costs are significantly lower than inventory holding costs, which are on the average 754 times higher than air transportation costs, increase in emergency shipment cost does not force the model to keep more inventories at the depot and makes no significant changes in carbon emissions, expected inventory levels, backorder levels and related costs. Therefore since the model is insensitive to the change in emergency shipment costs, we assume that emergency shipment cost is equal to air transportation cost.

In Table 7, comparison between multi-item and single-item approaches can be seen. In the single item approach, inventory levels for each individual item are set independently by assigning identical fill rates of 95 %, 98 % and 99% respectively, to all items.

Table 7 - Comparison between Multi-Item and Single-Item Approaches

		Aggregate Fill Rate	Expected Backorder Level	Expected Inventory Level	Expected Transportation Cost	Expected Inventory Holding Cost	Expected Emergency Shipment Cost	Expected Carbon Emission	Expected Total Cost
Air Transport	**Multi-Item Approach**	0.95	0.11	515.8	14,652	1,276,947	2.70	4.6914	1,291,602
		0.98	0.04	552.8	14,652	1,655,228	0.87	4.6905	1,669,881
		0.99	0.02	562.7	14,652	1,863,476	0.40	4.6903	1,878,129
	Single-Item Approach	1.00	0.01	530.7	14,652	2,101,380	0.15	4.6902	2,116,033
		1.00	0.01	536.7	14,652	2,136,234	0.10	4.6902	2,150,887
		1.00	0.00	559.7	14,652	2,285,111	0.06	4.6902	2,299,763
Road Transport	**Multi-Item Approach**	0.95	0.34	543.5	9,650	1,305,824	8.12	0.6005	1,315,482
		0.98	0.12	593.3	9,650	1,749,655	2.38	0.5979	1,759,307
		0.99	0.06	616.2	9,650	1,931,930	1.25	0.5974	1,941,581
	Single-Item Approach	0.99	0.05	535.2	9,650	2,140,074	0.82	0.5971	2,149,725
		1.00	0.02	582.2	9,650	2,515,742	0.44	0.5970	2,525,392
		1.00	0.01	655.1	9,650	2,872,073	0.28	0.5970	2,881,723

As it is seen in Table 7, the results of single-item and multi-item approaches are relatively different from each other. The multi-item approach gives significant savings in inventory cost in comparison to the single-item approach, therefore we can say that our results are consistent with the results of previous studies, Mitchell (1988), Sherbrooke (2004), Thoneman et al. (2002), and Rustenburg et al. (2003). As it is stated in Thonemann (2002), system approach ensures that a demand-weighted average fill rate is achieved at low inventory investment by assigning low fill rates to items with high costs and high fill rates to items with low costs, whereas in item approach identical fill rates are assigned to all items, which leads to high inventory investment.

According to Table 7, the multi-item approach leads to a slight increase in carbon emissions in comparison to the single-item approach, due to the increase in the number of emergency shipments. The increase in the carbon emissions is not significant, because the increase in the number of emergency shipment is reflected in the carbon emission as a function of weights of the items and unit carbon emission of air transport.

It is also seen in Table 7 that changing transportation mode change from air to road leads to a significant decrease in carbon emissions. Although this transportation mode change causes increase in the number of emergency shipments, the difference between carbon emissions of regular shipments made by air and road transports dominates the increase in carbon emissions resulting from emergency shipments. In addition, when the lead time is increased from one day to three days, expected inventory levels, expected total inventory holding cost and as a result expected total costs increase.

5.3 Transportation Mode Selection with Carbon Emission Consideration

In order to reduce feasible space obtained for complete enumeration, we propose two clustering methods to make transportation mode assignment not for individual items, but for groups of items with similar characteristics in Section 4.3.1. In the first method, we used k-means clustering algorithm, Section 4.3.1.1, and in the second method we make use of classification with an adopted ABC analysis, Section 4.3.1.2. In addition to these methods, we construct a greedy algorithm, Section 4.4, to consider transportation mode assignment decisions with replenishment decisions.

In our second model, by using clustering methods (for different ε values, Section 4.3), and greedy algorithm, we obtain many solution points, however not all of these solutions are efficient solutions, the solutions that cannot be improved without increasing expected carbon emissions or expected total cost and not dominated by a solution point with less carbon emissions and lower expected total cost. Our aims are to get the trade-off curves, efficient frontiers and show the efficient solution points for each clustering method and greedy algorithm. Because if the decision maker decides to put an upper limit to carbon emissions or a possible future regulation restricts the carbon emissions to a certain level, then by considering efficient solution points, decision maker can get an insight about the carbon emissions, corresponding total costs and transportation modes.

5.3.1 K-Means Clustering

Increasing the number of clusters always reduce the error in the resulting clustering. If each data point is considered as one cluster which means that the number of the clusters is equal to the number of data points, then the error becomes zero. However in computational studies, we set the number of clusters to 4, 5 and 6, by considering the computational times range from 56 minutes for 256 (4^4) problem instances when the number of clusters is 4, to 21.59 hours for 4096 (4^6) problem instances when the number of clusters is 6.

In this method, the first aim is to determine mode-selection variables. Therefore the data are divided into k clusters by using Matlab function *kmeans*. Complete enumerations of all possible transportation mode - cluster assignments are examined.

In Figure 4, the efficient solutions of different numbers of clusters are shown when expected aggregate fill rate is 98%.

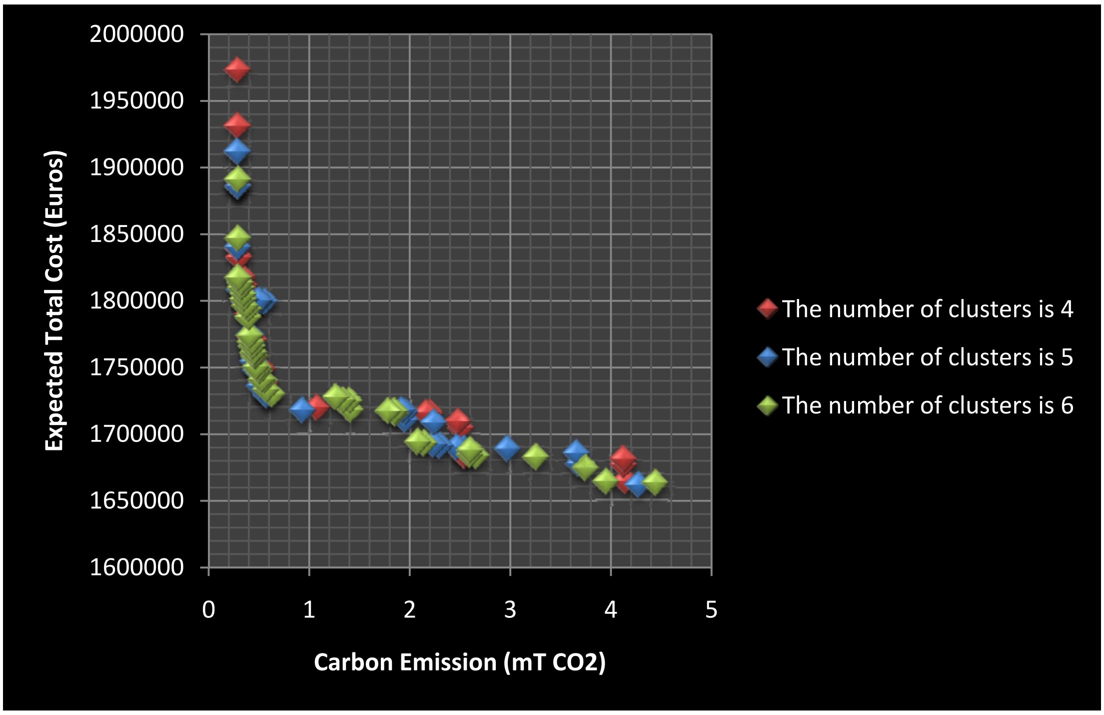


Figure 4 - The Efficient Solutions for Different Number of Clusters when Aggregate Expected Fill Rate is 98%

According to Figure 4, we observe that the solution points of k-means algorithm with 6 clusters mostly dominate the other solution points. These solution points verify that increasing the number of clusters reduces the error in clustering and gives better solutions in terms of expected carbon emissions and expected total cost.

In Figure 4, the solution points below 1 mT CO_2 show that there are no significant differences between the solutions of k-means algorithm with the number of clusters 4, 5 and 6, the solutions are very close to each other. In addition, below 1 mT CO_2, small decreases in carbon emissions cause significant cost increases, this means that the cost of reducing carbon emissions in this range significantly higher than cost of reducing carbon emissions in other ranges, since transportation modes of solution points below 1 mT CO_2 are mostly slower transportation modes that lead to low carbon emissions and therefore keeping more inventories due to increase in lead times. The region below 1 mT CO_2 is not preferable because of high costs. However above 1 mT CO_2, high-carbon transport modes start to be used more in the mode-cluster assignments. In Figure 4, we observe the trade-off as low-carbon transportation modes lead to increase in lead time and therefore large inventory holding costs, while using faster transportation modes lead to higher carbon emissions and higher transportation costs, however since the transportation costs are significantly smaller than inventory holding costs in the current system, increase in transportation costs has very small effect on expected total cost compared to the effect of decrease in inventory holding cost.

Since there are no restrictions on carbon emissions, the companies tend to prefer the solution point with the lowest expected total cost (4.44 mT CO_2, 1662461.3Euro). However, our aim is to present all efficient solutions in order to examine expected total costs and transportation mode assignments under different possible carbon emission regulation scenarios.

When the solution point that has lowest total expected cost is scrutinized, it is observed that for this solution point transportation modes used are water, rail and air. The water transport is assigned to the cluster that has highest unit cost and this cluster is also the smallest cluster and rail transport mode is assigned to second smallest cluster that has the second most expensive items. System approach ensures that demand-weighted average fill rate is achieved at low inventory investment by assigning low fill rates to items with high costs, the base stock levels of these items are generally zero and if slower and cheaper transport modes that generate low carbon emissions are assigned to these items, this assignment causes no change in total inventory holding cost but increase in total emergency shipment cost, since the emergency shipment costs are lower than inventory holding costs, these points lead to lower carbon emissions with lower costs than a solution in which these expensive items are assigned to higher-carbon transport mode. Therefore current system of Cisco is not an efficient solution, because current situation is dominated by this solution point obtained from our second model by using k-means algorithm. However it should be noted that this assignment can only give the smallest carbon emission in this system where the inventory holding costs are significantly higher than emergency shipment costs.

Since customer satisfaction is very important for the company, currently target aggregate fill rate is determined by company as 98 per cent. We also consider other possible aggregate fill rates that are 95 per cent and 99 per cent (except for the data with 6 clusters, because of high computational times, for data with 6 clusters only fill rate of 98% is examined). The efficient solutions for different number of clusters corresponding to these target aggregate fill rates are shown in Figure 5.

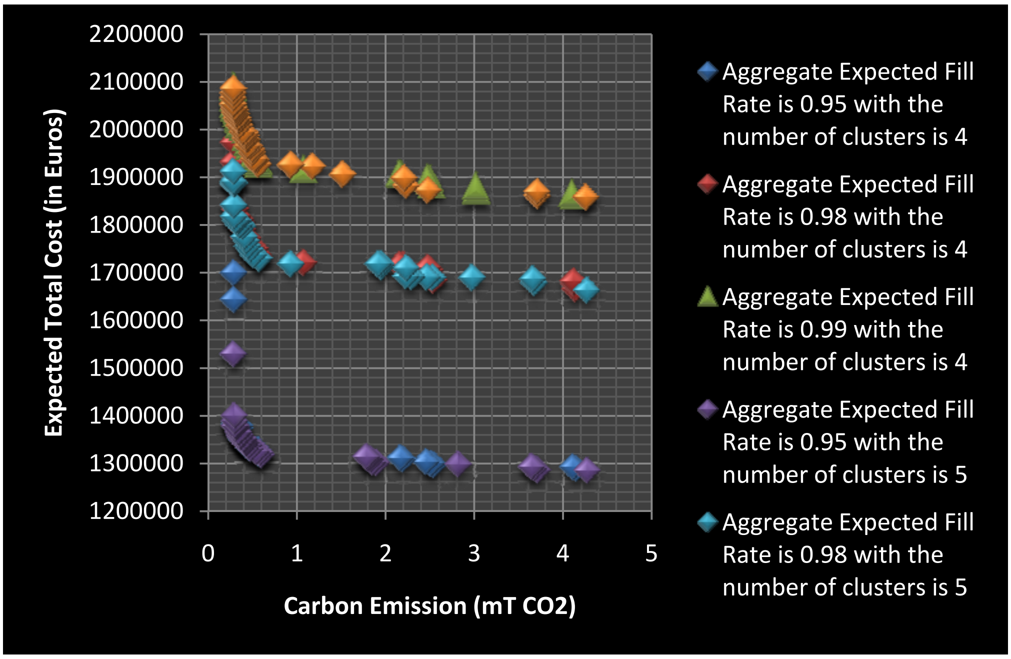


Figure 5 - Efficient Solutions of Data Set Partitioned into 4, 5 According To Different Aggregate Expected Fill Rates

In Figure 5, the trade-off between service levels and costs can be observed. In addition, we observe that for all aggregate fill rate levels, efficient solutions of k-means algorithm when the number of clusters is 5 mostly gives better solutions than the number of clusters 4.

According to Figure 5, the preferable points are determined by considering minimum expected total costs and it is observed that these all three points belong to the data set partitioned into 5 clusters. When the aggregate expected fill rate is set to 95%, the preferable solution point is (4.26 mT CO_2, 1282957 Euro) s. When we scrutinize this point, we see that two transportation modes, air and water are used. When the aggregate expected fill rate is 98 % the preferable point is (4.27 mT CO_2, 1661107 Euro). The transportation modes are rail, water and air. If aggregate expected fill rate is a higher value such as 99%, the efficient solution point that has the lowest cost is (4.26 mT CO_2, 1855969 Euro). The transportation modes used for this efficient solution point are air and water. From these results, we conclude that at the preferable efficient solution points most of the items are transported by air and the items, in the cluster that has most expensive items, are transported by using slowest transportation mode.

In Table 8, the preferred solution points are compared according to different aggregate fill rates. It is observed that at the approximately same expected carbon emission level, as the aggregate expected fill rates increases expected inventory levels increase and expected backorder levels decrease.

Table 8 - Comparison of Preferable Solution Points with respect to Aggregate Expected Fill Rate, Expected Carbon Emission, Expected Inventory Level, Expected Backorder Level and Related Costs

Aggregate Expected Fill Rate	Total Expected Inventory Holding Cost	Total Expected Emergency Shipment Cost	Expected Total Cost	Expected Backorder Level	Expected Inventory Level	Expected Carbon Emission
0.99	1842730	2.75	1856688	0.13	562.02	4,26
0.98	1647042	5.13	1661108	0.25	551.41	4,27
0.95	1268987.70	14.79	1282957	0.55	515.44	4,26

Although determining the number of clusters is a common problem in data clustering, it is known that increasing the number of clusters improve the accuracy of clustering. It is observed that the solution points of data set partitioned into high number of clusters, 6, are mostly not dominated by the points of data sets partitioned into small number of clusters, 4 and 5. These solutions show that increasing the number of clusters gives better results in terms of expected carbon emissions and expected total cost. However since the computational times increase significantly, while the number of clusters is increasing, it is not viable to increase the number of clusters more. Average computational times for k-means clustering are given in the Table 9.

Table 9 - Computational Times According to Different Number of Clusters

	Cluster No	Computational Times(Seconds)
K- Means Clustering	4	4597
	5	7900
	6	57520

In order to shorten the computational times by interpreting the clusters, some of the cluster-transportation mode assignments can be eliminated. However since the clusters cannot be interpreted logically, we develop a different method by considering clustering based on ABC analyses, explained in the Section 5.3.2

5.3.2 Clustering with ABC Analyses

The efficient solution points of the clustering based on ABC analyses considering aggregate expected fill rate of 98 per cent are given in Figure 6. As it is seen in Figure 6, since all transportation mode options are not considered, only a certain carbon emission levels can be observed (between 0.4 mT CO_2 and 0.8 mT CO_2 and between 2.5 mT CO_2 and 2.6 mT CO_2).

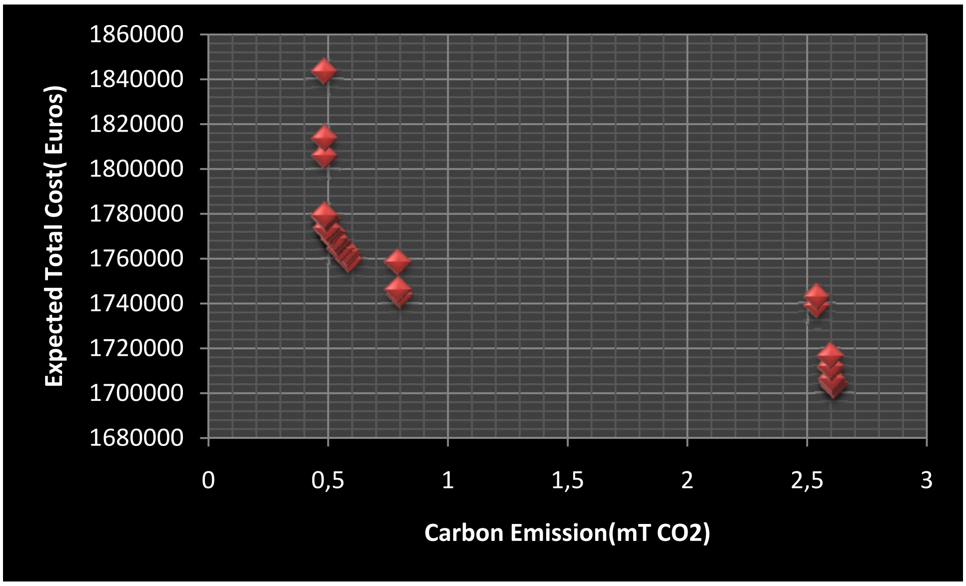


Figure 6 - Efficient Solutions under Clustering with ABC Analyses when Aggregate Fill Rate is 98 per cent

When transportation modes are examined for the efficient solution point with minimum expected total cost, it is observed that the possible highest-carbon transportation modes are assigned to classes, Table 10.

Table 10 - Transportation Modes for Chosen Solution Point

		Aggregate Fill Rate
		0.98
Clusters	**AA**	Air
	AB	Air
	AC	Air
	BA	Road
	BB	Road
	BC	Road
	CA	Water
	CB	Rail
	CC	Road

In Figure 7, the efficient solutions of k-means clustering and clustering with ABC analyses are compared and it is seen that efficient solution points obtained from ABC analyses are dominated by other data sets partitioned into 4, 5 and 6 clusters.

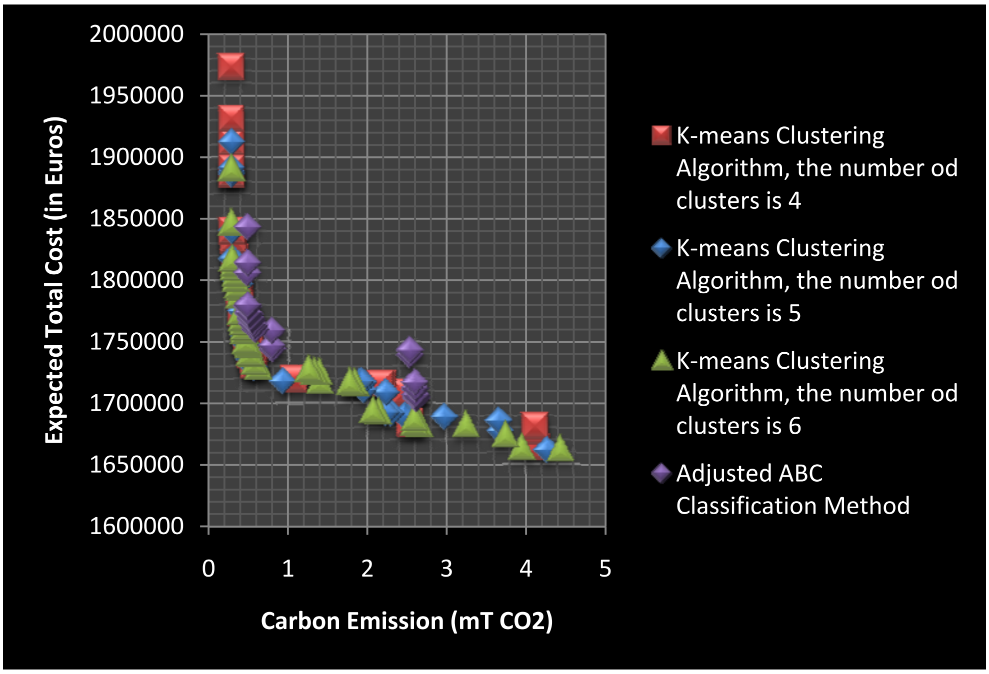


Figure 7 - Comparison between Efficient Solutions Obtained From k-means Clustering and our Adjusted ABC Analyses

From Figure 7, it is seen that assigning the transportation modes to clusters by considering common facts in transportation, for instance transporting heavy and invaluable items by water, is not valid for Cisco data. Because the items in Cisco inventory system defined as invaluable in CA class are so valuable that assuming these items as invaluable lead to incorrect results. Therefore even the items in class CA should be transported by air or road. The items are so expensive that slower transportation modes are not suitable and the system cannot tolerate increases in lead times due to high inventory holding costs. In a similar way, since the items classified as heavy items are not as heavy as it is defined, classifying these items as heavy items and assigning water transport to these items lead to inefficient results. Therefore we assign the transportation modes to Cisco items by considering special characteristics of these items. Considering this special situation for Cisco data, cluster- transportation mode assignments are redone as in Table 11.

Table 11 - Possible Transportation Modes for Categories

Categories	Possible Transportation Modes
AA	Air, Road
AB	Air, Road
AC	Air, Road
BA	Air, Road
BB	Air, Road
BC	Air, Road
CA	Air, Road
CB	Air, Road
CC	Air, Road

Based on new assignments, the efficient solutions are given in Figure 8.

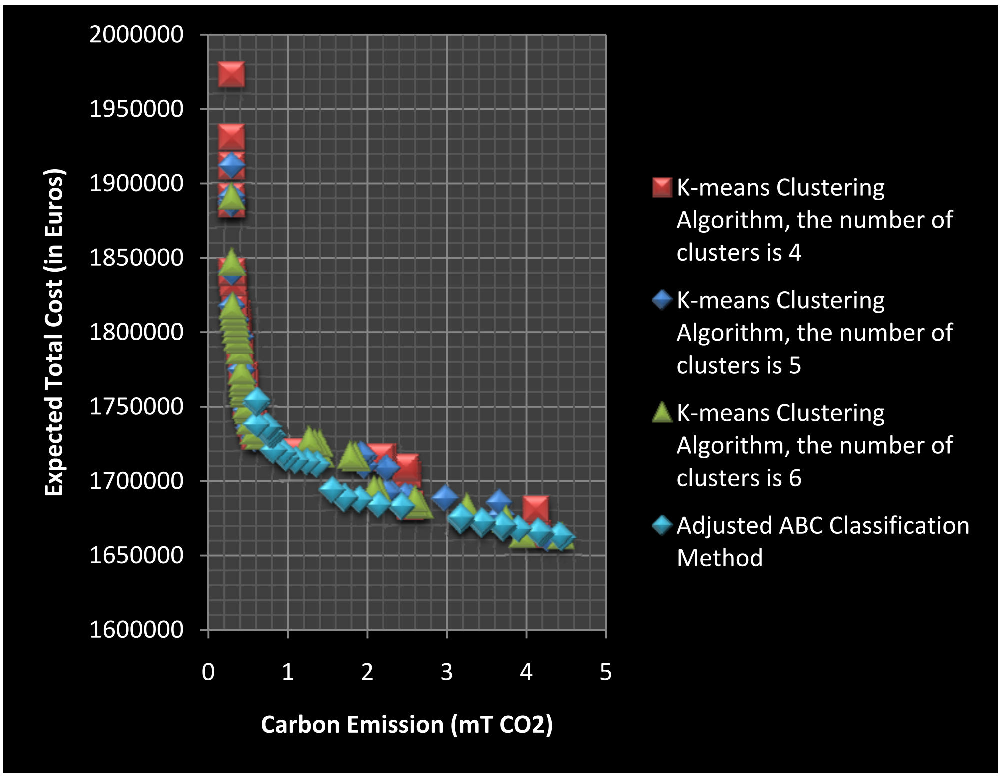


Figure 8 - Comparison between Efficient Solutions Obtained from k-means Clustering and Clustering with ABC Analyses

As it is seen in Figure 8, the efficient solutions of clustering with ABC analyses for Cisco dominate efficient solutions obtained from k-means clustering method in the range between 1 mT CO_2 and 4.6 mT CO_2. However below 1 mT CO_2, since the ABC analyses approach do not consider rail and water, in this range the efficient solutions of clustering with ABC analyses are dominated by efficient solutions of k-means clustering method that considers low carbon transportation modes and start from 0.6 mT CO_2, since with this transportation mode- cluster assignment lower carbon emissions cannot be obtained.

As a result, new adjusted ABC analyses method is suitable for partitioning the data by considering item characteristics of Cisco, although if the item characteristics are ignored, the solutions obtained from this method can be misleading. In addition, it is easy to implement and understand for the people who deal with inventory.

5.3.3 Greedy Algorithm

In the greedy algorithm, determining the item of which base stock level increases is based on the standardized weights assigned to aggregate fill rate and carbon emission constraints. Since the weights assigned to constraints are not determined certainly by the decision maker, the change in expected total costs, aggregate expected fill rates and expected carbon emissions are examined by considering different choices of weights. Therefore the weight assigned to aggregate fill rate constraint starting from 0 is increased by 0.02 each time. As it is mentioned in Section 4.4 the step size of 0.02 is found to be suitable in order to examine sufficient number of different expected carbon emission and expected total cost pair.

Firstly, we examine the efficient solutions according to different aggregate fill rates and then we scrutinize the solutions according to different emergency shipment costs that are equal to $t_{i4}, t_{i4} * 2, t_{i4} * 5$ and $t_{i4} * 10$, Appendix H.

In Figure 9, we present the efficient solutions for different aggregate fill rates that are 95, 98 and 99 per cent.

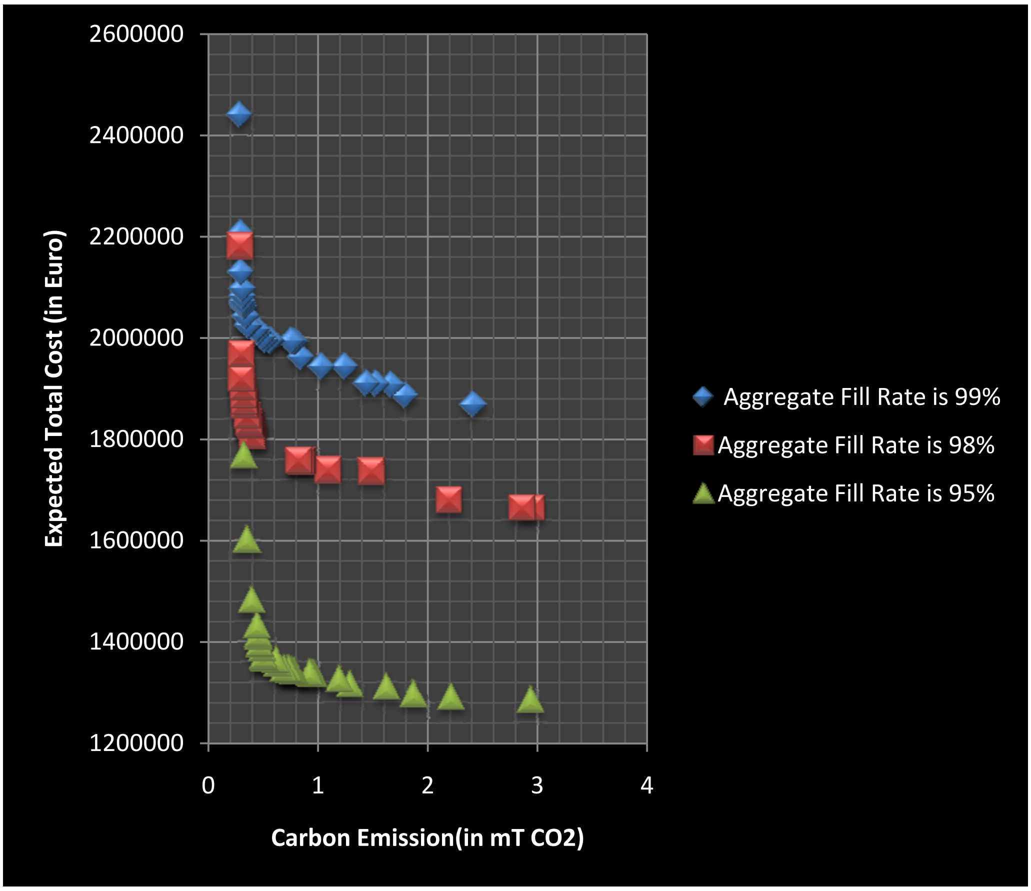


Figure 9 - Efficient Solutions for Greedy Algorithm Based on Aggregate Fill Rate of 95, 98 and 99 per cent and Emergency Shipment Cost

As it is seen in Figure 9, in the range between 0 mT CO_2 and 1 mT CO_2a steep drop in expected total cost is observed. In this range, as expected carbon emission increases, the expected total cost decreases significantly, therefore till 1 mT CO_2; the cost of decreasing carbon emission is very high. When the algorithm is examined in detail, it is seen that in the range between 0 mT CO_2 and 1 mT CO_2, the weight given to carbon emission constraint decreases from 1 to 0.32. In this range, greedy algorithm is giving more weight to carbon constraint and making use of slower and low-carbon transportation modes. As it is mentioned in Chapter 4, when base stock levels are zero, all items are transported by air. When we start to increase the base stock levels by determining the transportation modes, the carbon emission starts to decrease. As from the carbon emission level of 1 mT CO_2, the algorithm starts to give the more priority to meeting aggregate fill rate, because of this reason in this range mostly faster and high-carbon transportation modes start to be used.

According to European Climate Exchange, since maximum carbon price is € 30, it is difficult to offset the increase in the total expected cost by decreasing carbon emissions. As a result, according to Figure 9, for each aggregate expected fill rate the rightmost solution points that have minimum expected total costs among all efficient solutions are found to be more preferable points by giving priority to minimizing the expected total costs. These points and corresponding weights assigned to aggregate expected fill rate constraint are given in Table 12. As it is seen, the weights assigned to aggregate fill rates are not 1. This shows that assigning 1 to weight of aggregate expected fill rate, which is the current situation, does not lead to preferable solutions.

Table 12 - Appropriate Solution Points According to Different Aggregate Fill Rates

Aggregate Fill Rate	Solution Point	Weight Assigned to Aggregate Fill Rate
95 %	(2.94 mT CO_2, 1,285,696 Euro)	0.94
98 %	(2.93 mT CO_2, 1,662,879.9 Euro)	0.95
99 %	(2.42 mT CO_2, 1,867,421 Euro)	0.92

In the Figure 10, the expected inventory levels and expected carbon emissions are scrutinized according to different aggregate expected fill rates and it is seen that as aggregate expected fill rate increases, expected carbon emissions decrease, whereas expected inventory levels increase, and this increase in expected inventory levels cause increase in total expected total costs.

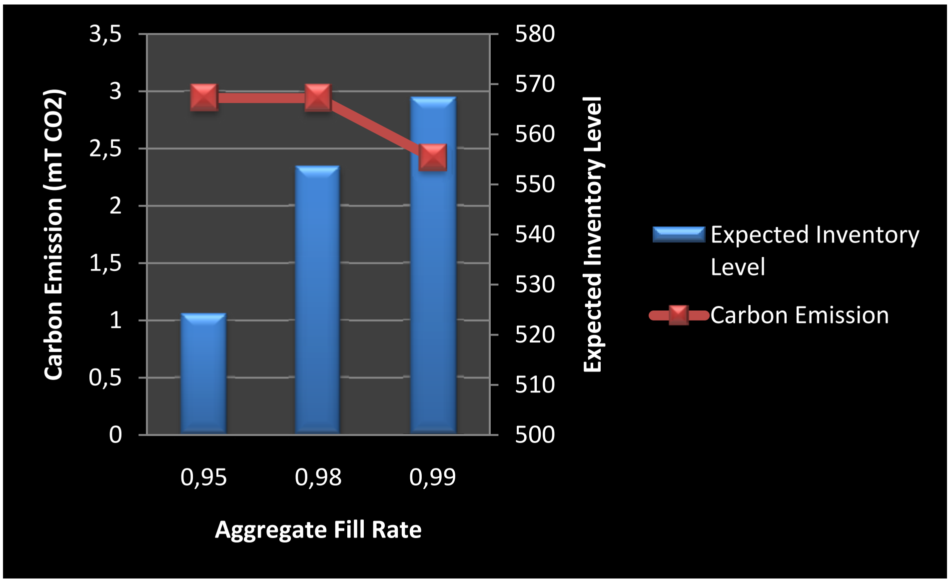


Figure 10 - Carbon Emissions and Inventory Levels According to Different Aggregate Fill Rates

5.3.4 Comparison of Solution Approaches

In the previous sections, results of methods developed for mode selection problem and greedy algorithm are examined. In this section, these are compared to each other.

In Table 11 methods for mode selection problem and greedy algorithm are compared according to computational times and it is seen that the computational time of greedy algorithm is comparably less.

Table 13 - Computational Times

	Cluster No	Computational Times(Second)
K- Means Clustering	4	4597
	5	7900
	6	57520
Clustering Based on ABC Analyses		6432
Greedy Algorithm		3201.69

The comparison between efficient solutions of mode selection methods based on k-means clustering, ABC analyses and greedy algorithm can be seen in Figure 11. In this comparison, we examine different carbon emission ranges in order to determine which methods can be suitable to implement under different carbon emission regulation scenarios.

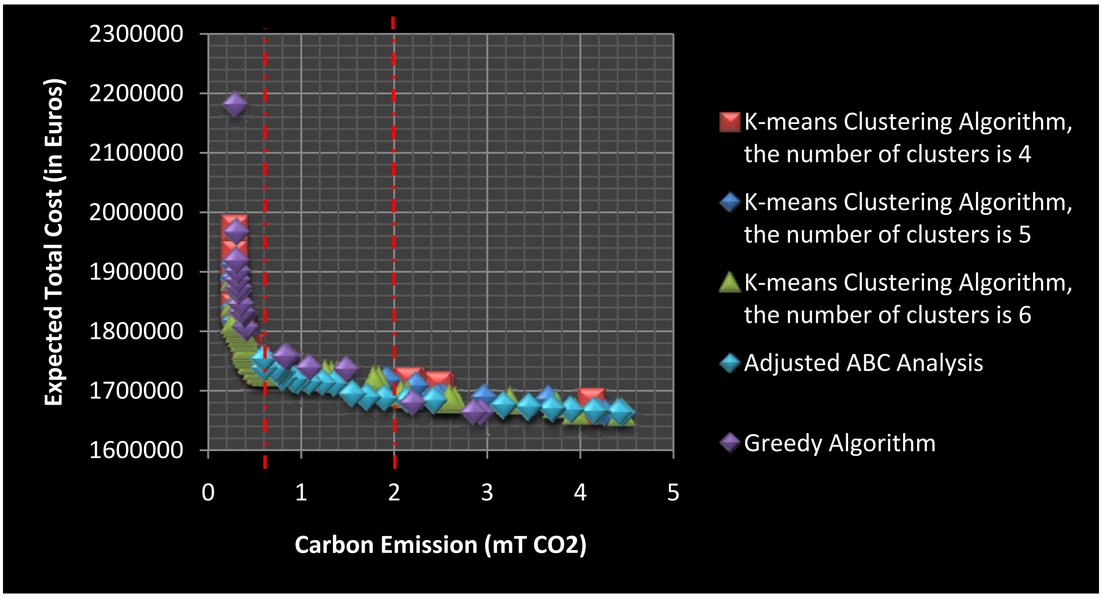


Figure 11 - Comparison of Efficient Solutions of Mode Selection Methods and Greedy Algorithm Based on Aggregate Fill Rate of 98 per cent

While examining, the Figure 11 is divided into three regions along the x-axis. In the first region (from 0 mT CO_2 to 0.6 mT CO_2), the efficient solutions of k-means algorithm dominate greedy algorithm and there is no efficient solution belong to adjusted ABC analysis due to assigned high-carbon transportation modes. In the second region (from 0.6 mT CO_2 to 2 mT CO_2), efficient solutions of adjusted ABC analysis method dominates the other efficient solutions. As first region, this region is also a low-carbon region, where slower and low-carbon transport modes are used, however since adjusted ABC analysis does not consider low-carbon transportation modes, lead times are not long and expected inventory levels are not as high as in other methods. Therefore the expected total costs of efficient solutions of adjusted ABC analysis are lower than efficient solutions of other methods. Since greedy algorithm gives high priority to reducing carbon emission in this region, the efficient solutions of greedy algorithm have lower expected carbon emissions but higher expected total costs. The third region (from 2 mT CO_2 to 5 mT CO_2), is comparably higher carbon region where mostly faster and high-carbon transport modes are used, although our adjusted ABC analysis method gives better results than k-means clustering method, efficient points of greedy algorithm dominates the other efficient points in the range between (2 mT CO2 to 3 mT CO2). The k-means clustering does not pay much attention to trade-off between expected carbon emission and total expected cost while assigning the transportation modes to clusters because it considers all possible mode-cluster assignments, whereas in our adjusted ABC analysis, by assigning fast and high-carbon transport modes to items, high priority is given to minimizing the expected total cost while satisfying target aggregate fill rate and ignoring the importance of carbon emission implicitly. Greedy algorithm performs better than the other two solution approaches in a specific range it is not possible to conclude that greedy algorithm performs better in the third region. However the computational time of algorithm is considered, the greedy algorithm can be preferred at least in the third region.

CHAPTER 6

CONCLUSION

This study is one of the succeeding projects of the Carbon Regulated Supply Chains project (CRSC, 2009) initiated by the European Supply Chain Forum (eSCF), Eindhoven University of Technology (TU/e) and consists of two phases.

In the first phase, a carbon emission calculation study was carried out at Cisco Systems, Inc. according to different material flows in service supply chain and service supply chain design of the company is evaluated by considering carbon dioxide emissions and carbon emission reduction opportunities are explored. One way of reducing the carbon emissions is increasing the load factors. Our analysis reveals that increasing the load factor from 50% to 75% improves the CO_2 emission by 0.28% and 1.69% for the COMPANY B shipments in repair order flow and the excess pullbacks flow, respectively. The other carbon emission reduction opportunity is shipment consolidation for dedicated trucks. Consolidation opportunities have been examined for the repair order shipments and two scenarios have been developed. In the first scenario, the cargos of the trucks, which come from Szombathely and Budapest separately, are consolidated into one truck; this brings 0.7 percent reduction in the CO_2 emission. In the second scenario, two different outbound shipments carried out in a week are combined together. This consolidation brings 2.13 percent reduction in the CO_2 emission. In this study, it has been seen that the carbon emission reduction opportunity of changing transportation mode from high-carbon transportation mode (air) to lower-carbon transportation mode (road) for allocation order flow brings 10.25 percent carbon emission reduction on the average. This is a significant carbon emission reduction opportunity compared to other reduction possibilities, so a more detailed study has been conducted in the second phase of the study.

In the second phase of the study, the tradeoffs involved in replenishment and transportation mode choice decisions are examined. In order to scrutinize the trade-offs, two mathematical models are developed. The aim of the first model that minimizes expected total cost subject to aggregate expected fill rate constraint is to examine the effect of transportation mode change from air to road for allocation orders material flow. In the second model that minimizes expected total cost subject to aggregate expected fill rate and carbon emission constraints, the underlying assumption of the first model, all items are shipped with the same transportation mode, is relaxed. In this model transportation mode choice decision is integrated into inventory decisions. Since it is difficult to make transportation mode choice decisions for each item, the items are clustered and transportation mode choice decision is made for each cluster, therefore we propose two clustering methods that are k-means algorithm and classification with an adopted ABC analysis. In addition to classify the items in order to define the mode-selection variables, a greedy algorithm that minimizes expected total cost subject to aggregate expected fill rate and carbon emission constraints is provided. In this greedy algorithm, we do not only determine the base stock levels but also make the transportation mode choice decision.

In our study, we conduct computational studies. According to our computational studies, when the multi-item and single-item approaches are compared multi-item approach is more suitable for Cisco. The results of computational studies for first model show us that an increase in the lead time caused by transportation mode change from air to road leads to a significant decrease in carbon emissions. Although this transportation mode change causes increase in the number of emergency shipments, the difference between carbon emissions of regular shipments made by air and road transports dominates the increase in carbon emissions results from emergency shipments. In addition, when the lead time is increased from one day to three days, expected inventory levels, expected total inventory holding cost and as a result expected total costs increase.

For the second model, the aims of the computational studies are to generate efficient solutions and then assist the decision maker at Cisco in selecting the most preferred solutions that have less carbon emission and lower total cost among all efficient solutions. Although for the current situation where no regulation on carbon emissions exists, the efficient solution that has minimum expected total cost can be most interesting point, with legal regulations different carbon emissions become more interesting for the company. At this point according to efficient solutions, expected total cost can be estimated under different carbon emission regulation scenarios. In these computational studies, each expected carbon emission value can be considered as a different carbon emission regulation scenario.

According to results of computational studies, we conclude that

- with respect to k-means algorithm, when the number of clusters increases better results in terms of expected carbon emissions and total expected costs are obtained.
- with respect to adjusted ABC analysis, this analysis should be made by considering the characteristics of the company items, considering general facts for transportation such as transporting heavy and cheap items by water can cause misleading results.
- with respect to greedy algorithm, if the priority is given to carbon constraint greedy algorithm tries to minimize the carbon emission by not increasing the total cost much, however while doing this it makes concession on cost, whereas if the priority is given to aggregate expected fill rate constraint it tries to meet the aggregate fill rate again by not increasing the total cost

much and it makes concession on carbon emission. Therefore in the both situations greedy algorithm has different goals and it achieves its goals, however since currently low priorityis given to carbon emission constraint greedy algorithm is not preferred due to high cost, however the computational time of greedy algorithm is very low compared to clustering methods in other solution approach.

When the results of solution approaches are examined it is seen that if the regulations restrict the carbon emissions to very low levels k-means clustering algorithm, to medium carbon emissions adjusted ABC analysis and to high carbon emissions greedy algorithm can be preferred.

In the literature, a model that examine the effects of a mode change on carbon emissions and expected total cost and transportation mode selection model with carbon emission consideration do not exist. In addition, although greedy algorithms for base stock level determination under different constraints exist, there is no greedy algorithm that minimizes expected total cost subject to aggregate expected fill rate and carbon emission constraints in the literature to best of our knowledge.

6.1 Implementation- Carbon Emission Calculations:

The carbon emissions should be monitored by Cisco periodically. Carbon emission calculations can be done by Cisco or can be outsourced.

If Cisco decides to calculate its carbon emissions, the calculations can be done by using TERRA Access Tool; one person can be responsible for the tool and do the calculations periodically. However the calculation periods can change with respect to material flows.

- For repair order flow: Carbon emissions can be monitored on a half yearly basis. There is no ambiguity related to shipment data of COMPANY C, since

COMPANY C keeps the type of vehicle and origin and destination cities are shown for each lane in the current data.

- For excess inventory pullbacks flow: Carbon emissions can be monitored on a half yearly basis. The network structures of the local carriers and the load factors should be known. When the necessary data related to network structures and load factors cannot be obtained, the assumptions made in this study can be used. By considering the weights of the excess parts, type of transport mode assumption is logical, therefore the assumption can be used in the future carbon emission calculations.
- For RMA and allocation orders: Carbon emissions can be monitored on a quarterly basis. Since the carbon emission calculations are done with very large amount of data, doing the calculations on a half yearly or yearly basis is not suggested. Cisco should demand distance data from COMPANY D. When the data cannot be obtained, by doing customer- distribution center assignment, distance calculations should be done on monthly basis and after a while the calculations can be done on a quarterly basis, since a database will start to be created. The load factor is stated as approximately 80 percent by COMPANY D. Even if the load factors are not exactly 80 percent, change in the load factors in high values certain values does not affect the emissions as much as change in the low values. As it is seen in the Figure 12, changing the load factor for road transport from 20 percent to 30 percent results in a decrease in the emission factor of about 30.23 percent, while changing a load factor from 80 to 90 percent results in a decrease in the emission factor of 7.88 percent.

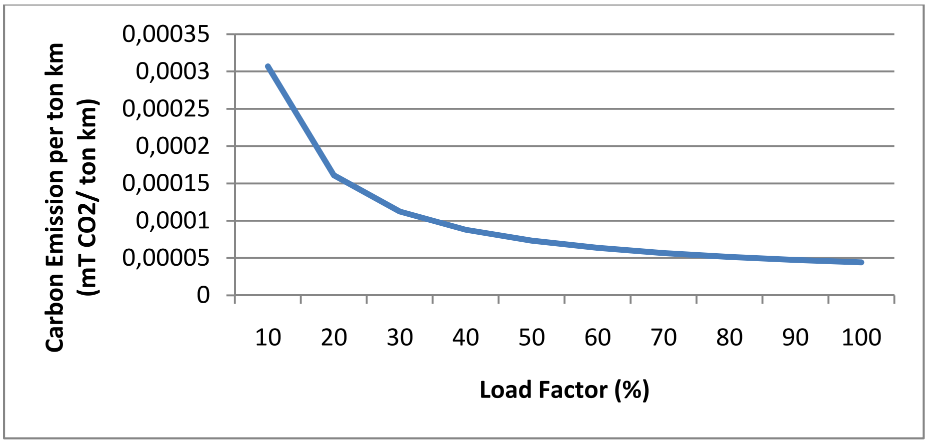


Figure 12 Carbon Emission (mT CO2) per ton km Values for Different Load Factors for Road Transport

In this study, the types of the transport mode are chosen considering COMPANY D fleet information, weight per shipment and distances.

- For direct shipments from RFDs: Carbon emissions can be monitored on a quarterly basis. The distances given by COMPANY D and COMPANY C should be controlled and if it is needed, the distances should be calculated. Since there are time restrictions caused by service level agreements, the vehicles should be considered as dedicated vehicles. By considering time restrictions and weights of parts, vehicle type assumption can be used in the future calculations.

For these carbon emission calculations, except COMPANY D shipments, one person can be sufficient; however for carbon emission calculations of COMPANY D shipments the number of people who will work on calculations should be increased.

If Cisco does not want to calculate its own carbon emissions, Cisco can also cooperate with a consultancy company for carbon emission calculations and analyses. Most of the carriers offer consultancy services for measuring carbon footprint and monitoring carbon emissions throughout the supply chain. However, this study shows that NTM is the most suitable methodology among current methodologies, therefore making deal with a company that uses NTM methodology is suggested.

For carbon emission calculations, collecting all the necessary data for a detailed calculation is very labor intensive. To determine whether all these data are needed the sensitivity analysis was conducted (see Schers, (2009) to get more detail information). Based on sensitivity analysis it is concluded that it is not necessary to collect all data. In many cases, the assumptions can be used to calculate the emissions. It is suggested using all the available data if possible. The following data are certainly needed to get an accurate result,

- Mode of transport
- Distance per transport mode
- Weight of shipment

6.2 Implementation- Transportation Mode Selection Model with Carbon Emission Consideration

Currently for allocation order material flow, the company has pilot studies to change the transportation mode from air to road, however our studies show that the other transportation modes need to be considered and instead of using the same transportation mode for all items, transportation mode choice decision should be made for each item. The transportation mode choice decisions can be made for each item by implementing greedy algorithm. In addition to this, clustering methods can be used, however if the k-means algorithm is found to be complex to implement, adjusted ABC analysis is very easy to understand and implement for the people who deal with inventory.

These solution approaches in this study are proposed by considering allocation order material flow and these are not very suitable for RMA order material flow, because of the time based service level agreements. However since there are no time restrictions, for repair order and excess pullback material flows these approaches can be considered.

Even if the computational times seems to be very high to implement the clustering methods and greedy algorithm in practice, it should be noted that these studies needs to be done once to determine the base stock levels and transportation modes. It is highly recommended to consider the results of these studies, because based on our results it can be concluded that the current system is not efficient.

6.3 Further Studies

To understand the impact of some reduction possibilities, further studies should be carried out by obtaining more data. Consolidating the shipments of nearby RFDs, especially in the excess inventory pullbacks material flow, should be considered in order to decrease the carbon emissions. Since the network structure of excess inventory pullbacks are not known, possible consolidation improvements cannot be examined. This improvement area can be examined in detail in the further studies.

Similarly, carbon emission reductions by reducing the number of empty returns or the positioning distance can be examined in detailed in the further studies. Empty returns can be reduced by cooperating with other companies that need to ship their cargos in the opposite direction. For reducing the positioning distances, the carriers that are close to pick-up locations can be chosen.

In the second phase, the study is conducted at Cisco Systems Inc. and the items of the company have specific characteristics such as being very expensive and slow moving. The results of this study are subject to these characteristics, therefore the same studies can be conducted under different circumstances and the results under different circumstances can be examined in detail.

REFERENCES

"Article 2", The United Nations Framework Convention on Climate Change, 15 November 2005.

Artemis, "ARTEMIS: Assessment and reliability of transport emission models and inventory systems, Final report", TRL limited, 2007.

Axsater S., "Continuous review policies for multi level inventory systems with stochastic demand", Handbooks in OR&MS, Vol. 4, North Holland, Amsterdam, The Netherlands, pp. 175 -197, 1993.

Boyd S., Vandenberghe L., "Convex Optimization", Cambridge University Press, 2004.

Chen Y., Li K. W., Levy J., Hipel K. W. and Kilgour D. M., "Rough-Set Multiple-Criteria ABC Analysis", Lecture Notes In Computer Science, Transactions on rough sets VIII, Springer-Verlag, Berlin Heidelberg, pp. 35–52, 2008.

Christofides N., Mingozzi A., "The vehicle routing problem" In Christofides, N., Mingozzi, A., Toth, Paolo, Sandi, C. (Eds.), Combinatorial Optimization. John Wiley & Sons Ltd., Chichester, pp. 315–338, 1979.

Cohen M.A., Kleindorfer P.R., Lee H.L., "Near-optimal service constrained stocking policies for spare parts", Operations Research 37, pp. 104–117, 1989.

Daganzo CF., “Logistics Systems Analysis”, 3rd edition, Springer, Heidelberg, Germany, 1999.

EcoTransIT, “EcoTransIT: Ecological Transport Information Tool, Environmental Method and Data”, EcoTransIT, 2008.

Eurostat, “Database“, http://epp.eurostat.ec.europa.eu/portal/page/portal/transport/data/database, July 2010.

Fahim A. M., Salem A. M., Torkey F.A., Ramadan M.A., “An efficient enhanced k-means clustering algorithm”, J Zhejiang Univ SCIENCE A, 7(10), pp. 1626-1633, 2006.

Feeney G. J. and Sherbrooke CC., “The (S - 1, S) Inventory Policy under Compound Poisson Demand”, Management Science, Vol. 12, No. 5, Series A, Sciences, Informs, pp. 391-411, January 1966.

GHG Protocol, “Calculating CO_2 Emissions from Mobile Sources”, GHG Protocol, 2005.

Gross O., “A Class of Discrete-Type Minimization Problems” RM-1644-PR, The Rand Corporation, Santa Monica, California, 1956.

Harris I., Naim M., Palmer A., Potter A., Mumford C., “Assessing the impact of cost optimization based on infrastructure modelling on CO_2 emissions” , International Journal of Economics, 2010.

Hoen K.M.R., Tan T. ,Fransoo JC. , Houtum van G.J.J.A.N., “Effect of carbon emission regulations on transport mode selection in supply chains”, Eindhoven Technology University, 2010

Hopp W., Spearman M., “Factory Physics”, 3rd Edition, The McGraw- Hill, Singapore, 2008

IntercontinentalExchange, “European Climate Exchange”, www.ecx.eu, July 2010.

Joseph G., Zuo-Jun Max S., Akin E., “Planning and approximation models for delivery route based services with price-sensitive demands”, European Journal of Operational Research 183, pp. 460–471, 2007.

Cavinato J. L., “Supply Chain and Transportation Dictionary”, 4th Edition, Business & Economics, 2000.

Kessel D.G., “Global warming — facts, assessment, countermeasures”, Journal of Petroleum Science and Engineering, Volume 26, Issues 1-4, pp. 157-168, May 2000

Kiehl, J.T., Kevin E. Trenberth “Earth’s Annual Global Mean Energy Budget”, Bulletin of the American Meteorological Society 78 (2), pp. 197–208, February 1997.

Kocağa Y.L., Şen A., “Spare parts inventory management with demand lead times and rationing”, IIE Transactions, September 2007.

Kranenburg A.A., “Spare parts inventory control under system availability constraints”, Cip-Data Library Technische Universiteit Eindhoven, 2006.

Likas A., Vlassis N., Verbeek J.J., “The global k-means clustering algorithm”, Pattern Recognition, 36, pp. 451 – 461, 2003.

Mitchell J.C., “Multi-item (s, S) inventory systems with a service objective” Operational Research, 36, pp. 747-755, 1988.

Muckstadt J.A., “A model for a multi-item, multi-echelon, multi-indenture inventory system”, Management Science 20, 472–481, 1973.

Muckstadt J.A., “A three-echelon, multi-item model for recoverable items”, Naval Research Logistics Quarterly 26, 199–221, 1979.

NTM Air, “Environmental data for international cargo and passenger air transport”, NTM, 2008.

NTM Rail, “Environmental data for international cargo transport – rail transport”, NTM, 2008.

NTM Road, “Environmental data for international cargo transport – road transport”, NTM, 2008.

NTM Sea, “Environmental data for international cargo transport – sea transport”, NTM, 2008.

Ramanathan R., “ABC inventory classification with multiple-criteria using weighted linear optimization” Computers & Operations Research Volume 33, Issue 3, pp. 695-700, 2006.

Rustenburg J.W., Van Houtum G.J. and Zijm W.H.M., “Exact and approximate analysis of multi-echelon, multi-indenture spare parts systems with commonality”, In: Shantiku-mar JG, Yao DD and Zijm WHM (eds), Stochastic Modeling and Optimization of Manufacturing Systems and Supply Chains, Kluwer, Boston, 2003.

Schers R., “Determining a method for calculating CO_2 emissions in transport and the effect of emission regulations on supply chain design for a chemical company”, Master of Science in Operations Management and Logistics, Eindhoven University of Technology, Department Technology Management, 2009.

Sherbrooke, C.C., "A multi-echelon technique for recoverable item control", Operations Research 16, pp. 122–141, 1968.
Sherbrooke, C.C., "VARI-METRIC: Improved approximations for multi-indenture", multi-echelon availability models, Operations Research 34, 311–319, 1986.

Sherbrooke CC., "Optimal Inventory Modeling of Systems", Kluwer, Boston, 2004.

Slay, F.M., "VARI-METRIC: An Approach to Modeling Multi-Echelon Resupply When the Demand Process is Poisson with a Gamma Prior", Report AF301-3, Logistics Management Institute, Washington D.C., 1984.

Srivastava S.K.,"Network design for reverse logistics", Omega Volume 36, Issue 4, pp. 535-548, 2008

Srivastava S. K., "Green supply-chain management: A state-of the-art literature review", International Journal of Management Reviews, Volume 9, Issue 1, pp. 53–80, 2007

Te Loo R., "A methodology for calculating CO2 emissions from transport and an evaluation of the impact of European Union emission regulations", Master of Science in Operations Management and Logistics, Eindhoven University of Technology, Department Technology Management, 2009.

Thonemann UW., Brown AO., Hausman WH., "Easy Quantification of Improved Spare Parts Inventory Policies", Management Science, Vol. 48, No. 9, Informs, pp. 1213-1225, September 2002.

Van den Akker, I.J.G., Loo, R. te, Ozsalih, H., Schers, R., “General report CRSC Project”, Eindhoven University of Technology, 2009.

Van den Akker Inge, “Calculating and reducing carbon dioxide emissions for an eye health company”, Master of Science in Operations Management and Logistics, Eindhoven University of Technology, Department Technology Management, 2009.

Vliegen I.M.H., and Van Houtum G.J., “Approximate evaluation of order fill rates for an inventory system of service tools”, International Journal of Production Economics, Volume 118, Issue 1, pp. 339-351, March 2009.

Weart S., "The Carbon Dioxide Greenhouse Effect", The Discovery of Global Warming, American Institute of Physics, 2009.

Wong H., Van Houtum GJ., Cattrysse D. and Van Oudheusden D., “Multi-item spare parts systems with lateral transhipments and waiting time constraints”, European Journal of Operational Research Volume 171, Issue 3, pp. 1071-1093, 2006.

Zipkin, P. H. “Foundations of Inventory Management”. McGraw-Hill, Burr Ridge, Illinois, 2000.

APPENDICES

APPENDIX A – THE MAIN MATERIAL FLOWS OF THE SERVICE SUPPLY CHAIN

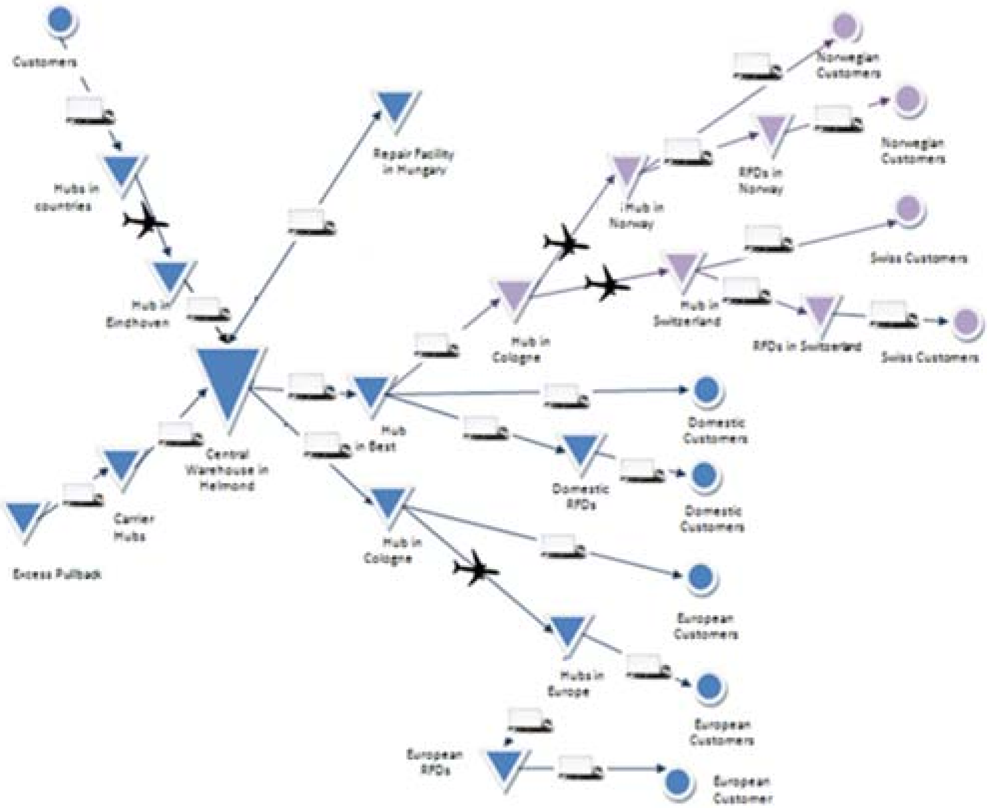
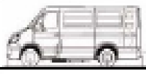
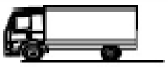
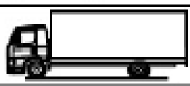
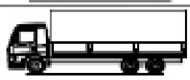
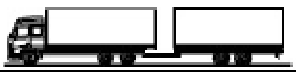
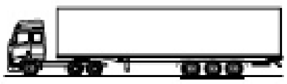
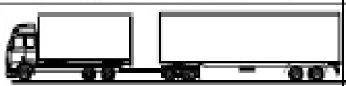


Figure 13- The Main Material Flows of the Service Supply Chain

APPENDIX B – TYPE OF VEHICLES

Table 14 - The Overview of the Vehicle Types

No	Illustration	Nomenclature	Max weight[1]	Vehicle length (approx.)	Cargo capacity (typical values, inner dimensions)				
			[tonne]	[m]	[tonne]	pallets	[m]	[m3]	TEU
1	(no picture)	(LCV) Pick-up	< 2,5	5	0,6	1	1,8	3 - 6	0
2		(LCV) Van	< 3,5	7	1,5	3 - 5	3 - 4	10	0
3		(MDV) Light lorry/truck	3,5–7	8	5	14	4 - 6	35	0
4		(MDV) Medium lorry/truck	7-18	12	7	24	7,7	44	0
5		(MDV) Heavy lorry/truck	16–26	12	15	24	7,7	44	1
6		(HDV) Tractor + 'city-trailer'	16 - 26	12 - 15	15 - 16,5	20-28	8 - 12	50-64	1
7		(HDV) Lorry/truck + trailer	≤ 40	18,75	22	36	7,75 + 7,75	104	2
8		(HDV) Tractor + semi-trailer	≤ 40	16,5	26	33	13,6	92	2
9		(HDV) Tractor + MEGA-trailer	40 ≤ 50	16,5	33	33	13,6	110	2
10		(HDV) Lorry/truck + trailer or semi-trailer on dolly	≤ 60	24 - 25,25	40	51	7,7 + 13,5	140	3

APPENDIX C- THE FORMULAS USED IN THE DISTANCE CALCULATIONS

These formulas entered into the Google Spreadsheet are as follows

- =INDEX(importXML("http://maps.google.com/maps?saddr="&SUBSTITUTE(TRIM(SUBSTITUTE(SUBSTITUTE(A2;CHAR(13);" ");CHAR(10);" ")); " "; "+")&"&daddr="&SUBSTITUTE(TRIM(SUBSTITUTE(SUBSTITUTE(B2;CHAR(13); " ");CHAR(10);" ")); " "; "+")&"&ie=UTF8&hl=en&output=mobile&f=d&btnG=Get+Directions" ; "//b[1]");3;1)
- =("http://maps.google.com.de/maps?saddr="&SUBSTITUTE(TRIM(SUBSTITUTE(SUBSTITUTE(A41;CHAR(13);"");CHAR(10);"")); " "; "+")&"&daddr="&SUBSTITUTE(TRIM(SUBSTITUTE(SUBSTITUTE(B50;CHAR(13);"");CHAR(10);"")); " "; "+")&"&ie=UTF8&hl=en&output=mobile&f=d&btnG=Get+Directions")

APPENDIX D - PROOFS OF CONVEXITIES FOR FIRST MODEL

Convexity of Objective Function:

For a convex problem that has convex objective function and constraints, any local optimum must be a global optimum. (Boyd and Vandenberghe, 2004)

$$\sum_{i=1}^{n}\sum_{x=S_i}^{\infty} p_i\,(x - S_i)P(X = x) + \sum_{i=1}^{n}\sum_{x=0}^{S_i} h_i(S_i - x)P(X = x)$$

$$\Delta f(S_i) = f(S_i + 1) - f(S_i)$$

$$\Delta' = \sum_{i=1}^{n} h_i\left[\sum_{x=0}^{S_i} P(X = x)\right] - \sum_{i=1}^{n} p_i\left[\sum_{x=S_i+1}^{\infty} P(X = x)\right]$$

$$\Delta" = \Delta f(S_i + 1) - \Delta f(S_i)$$

$$\Delta" = \sum_{i=1}^{n} p_i P(X = S_i + 1) + \sum_{i=1}^{n} h_i P(X = S_i + 1) \ \geq 0$$

Convexity of Constraint:

$$\sum_{i=1}^{n} \frac{m_i}{m}\left(1 - \frac{\sum_{x=S_i}^{\infty}(x - S_i)P(X = x)}{\theta_i}\right) \geq \beta_0$$

We will check the convexity of g(S)

$$\beta_0 - \sum_{i=1}^{n} \frac{m_i}{m}\left(1 - \frac{\sum_{x=S}^{\infty}(x - S_i)P(X = x)}{\theta_i}\right) \leq 0$$

$$\Delta f(S_i) = f(S_i + 1) - f(S_i)$$

$$= -\sum_{i=1}^{n} \frac{m_i}{m\theta_i}\left[\sum_{x=S_i+1}^{\infty} P(X = x)\right]$$

$$\Delta'' = \Delta f(S_i + 1) - \Delta f(S_i)$$

$$= \sum_{i=1}^{n} \frac{m_i}{m\theta_i} P(X = S_i + 1) \geq 0$$

APPENDIX E- MULTIPLIER UPDATE FOR ALGORITHM 1

The multiplier is updated by considering distance to feasible region, since at the beginning the distance is large; the increment in the multiplier is determined as a large value. After the distance to feasible region becomes smaller, the increment is reduced. The distance to feasible region is divided into three. The pseudo code for algorithm 1 is given for the aggregate fill rate of 98 % as follows

```
if aggregate fill rate ≤ 0.94
    increase the multiplier λ 1000000;
else if 0.94<aggregate fill rate ≤ 0.96
    increase the multiplier λ 1000;
else if 0.96<aggregate fill rate ≤ 0.98
    increase the multiplier λ 100;
end
```

APPENDIX F- PROOFS OF CONVEXITIES FOR SECOND MODEL

$$f(S_{ij}) = \sum_{i=1}^{n}\left[\sum_{j=1}^{4}\sum_{x=S_{ij}}^{\infty} p_{ij}y_{ij}(x - S_{ij})P(X = x) + \sum_{j=1}^{4}\sum_{x=0}^{S_i} h_i(S_{ij} - x)\,P(X = x) + \sum_{j=1}^{4} t_{ij}y_{ij}m_i\right]$$

$$\Delta f(S_{ij}) = f(S_{ij} + 1) - f(S_{ij})$$

$$\Delta' = \sum_{i=1}^{n}\left[\sum_{j=1}^{4} h_i\left[\sum_{x=0}^{S_{ij}} P(X = x)\right] - \sum_{j=1}^{4} p_{ij}y_{ij}\left[\sum_{x=S_{ij}+1}^{\infty} P(X = x)\right]\right]$$

$$\Delta" = \Delta f(S_{ij} + 1) - \Delta f(S_{ij})$$

$$\Delta" = \sum_{i=1}^{n}\left[\sum_{j=1}^{4} p_i y_{ij} P(X = S_i + 1) + \sum_{j=1}^{4} h_i P(X = S_i + 1)\right] \geq 0$$

Convexity of Aggregate Fill Rate Constraint:

$$\sum_{i=1}^{n}\sum_{j=1}^{4}\frac{m_i}{m}\left(1 - \frac{\sum_{x=S_{ij}}^{\infty}(x - S_{ij})P(X = x)}{\sum_{j=1}^{4} y_{ij}\,\theta_{ij}}\right) \geq \beta_0$$

We will check the convexity of g(S)

$$\beta_0 - \sum_{i=1}^{n}\sum_{j=1}^{4}\frac{m_i}{m}\left(1 - \frac{\sum_{x=S_{ij}}^{\infty}(x - S_{ij})P(X = x)}{\sum_{j=1}^{4} y_{ij}\,\theta_{ij}}\right) \le 0$$

$$\Delta g(S_{ij}) = g(S_{ij} + 1) - g(S_{ij})$$

$$= -\sum_{i=1}^{n}\sum_{j=1}^{4}\frac{m_i}{m\sum_{j=1}^{4} y_{ij}\,\theta_{ij}}\left[\sum_{x=S_{ij}+1}^{\infty} P(X = x)\right]$$

$$\Delta'' = \Delta g(S_{ij} + 1) - \Delta g(S_{ij})$$

$$= \sum_{i=1}^{n}\frac{m_i}{m\sum_{j=1}^{4} y_{ij}\,\theta_{ij}} P(X = S_{ij} + 1) \quad \ge 0$$

Convexity of Aggregate Fill Rate Constraint:

$$\sum_{j=1}^{4}\sum_{i=1}^{n}\left[e_j y_{ij} w_i m_i + e_a w_i \sum_{x=S_{ij}}^{\infty}(x - S_{ij})P(X = x)\right] \le EM_{max}$$

We will check the convexity of h(S)

$$\sum_{j=1}^{4}\sum_{i=1}^{n}\left[e_j y_{ij} w_i m_i + e_a w_i \sum_{x=S_{ij}}^{\infty}\left(x - S_{ij}\right)P(X = x)\right] - EM_{max} \leq 0$$

$$\Delta h(S_{ij}) = h\left(S_{ij} + 1\right) - h(S_{ij})$$

$$= -e_a w_i \left[\sum_{x=S_{ij}+1}^{\infty} P(X = x)\right]$$

$$\Delta'' = \Delta h\left(S_{ij} + 1\right) - \Delta h(S_{ij})$$

$$= \sum_{i=1}^{n} e_a w_i P\left(X = S_{ij} + 1\right) \geq 0$$

APPENDIX G- MULTIPLIER UPDATE FOR ALGORITHM 2

The pseudo code for algorithm 2 is given for a given aggregate fill rate as follows

```
epsilon=0
while epsilon<epsilon_u
     while agg_fill_rate<target_agg_fillrate
         call model
     end
    epsilon=epsilon + stepsize_epsilon
end
```

Updating of the multiplier λ is done as in Appendix E. For epsilon step sizes can change however in this study, the step sizes are taken as $10^{iteration\_number}$.

APPENDIX H- GREEDY ALGORITHM RESULTS ACCORDING TO DIFFERENT AGGREGATE FILL RATES AND EMERGENCY SHIPMENT COST

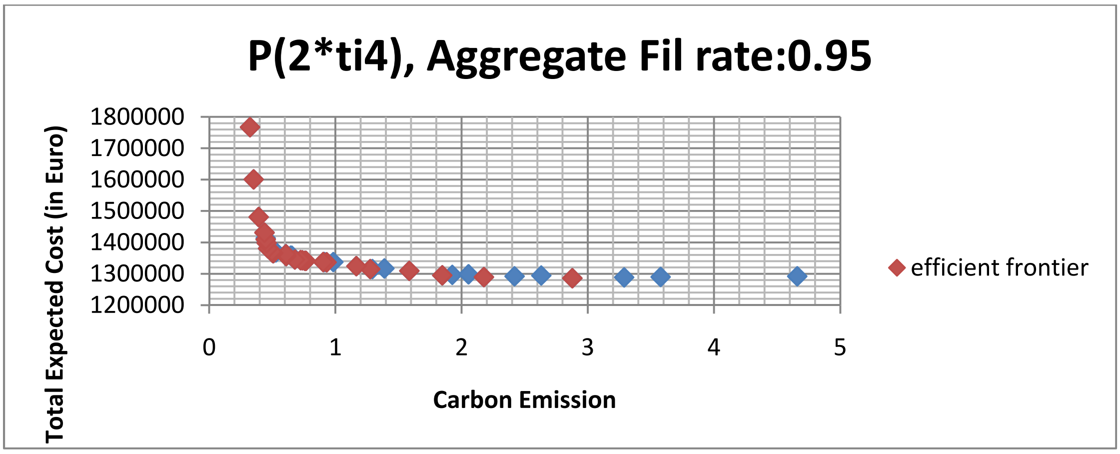


Figure 14 - Efficient solutions when aggregate fill rate is 95 per cent and emergency shipment cost is equal to 2*ti4

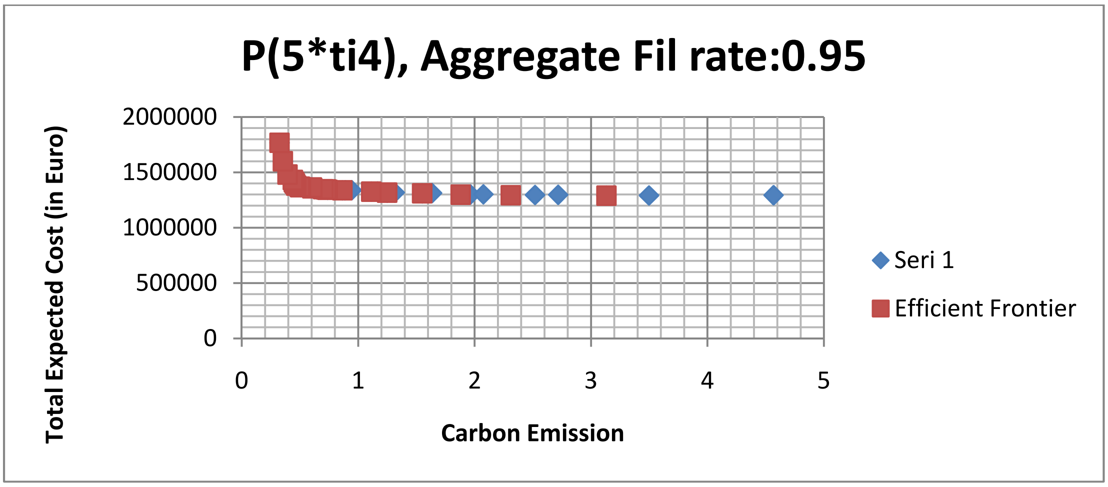


Figure 15 - Efficient solutions when aggregate fill rate is 95 per cent and emergency shipment cost is equal to 5*ti4

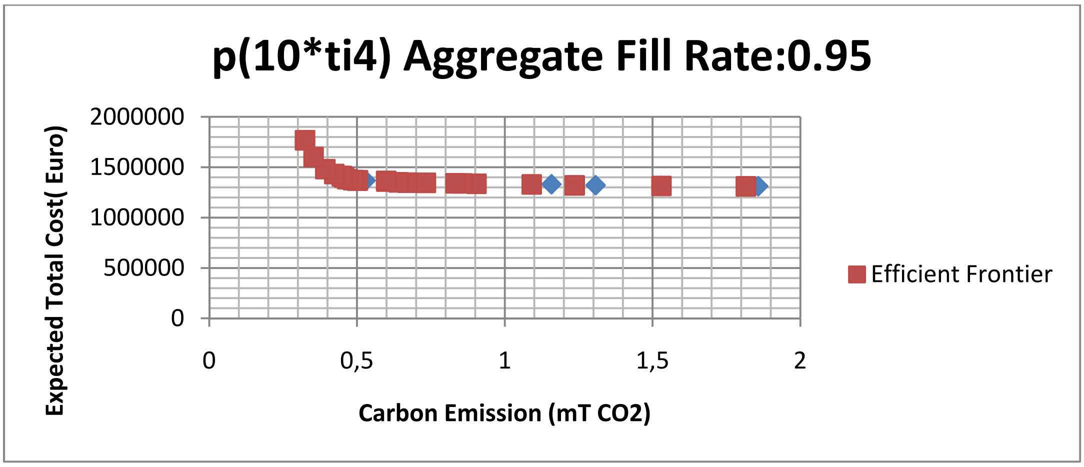


Figure 16 - Efficient solutions when aggregate fill rate is 95 per cent and emergency shipment cost is equal to 10*ti4

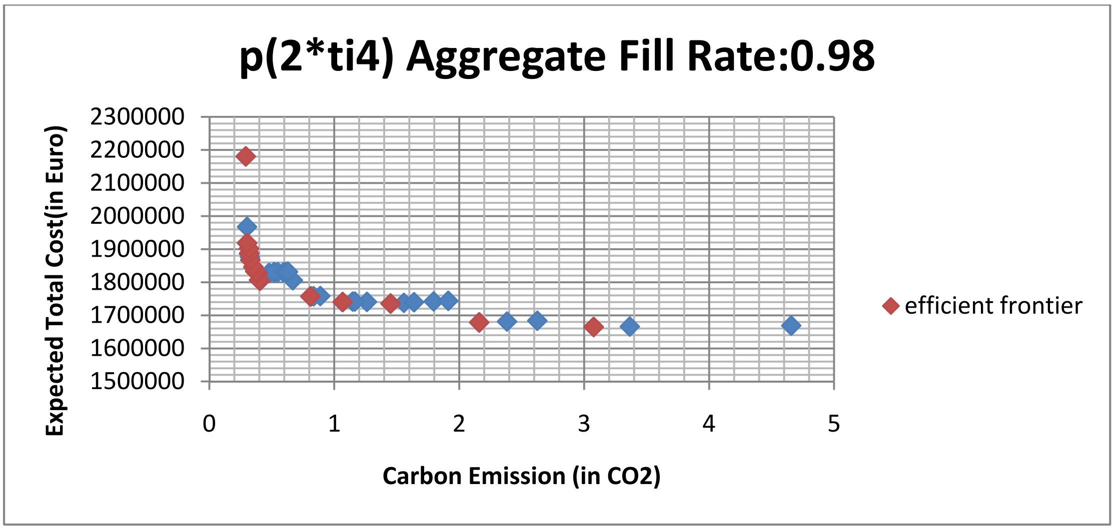


Figure 17 - Efficient solutions when aggregate fill rate is 98 per cent and emergency shipment cost is equal to 2*ti4

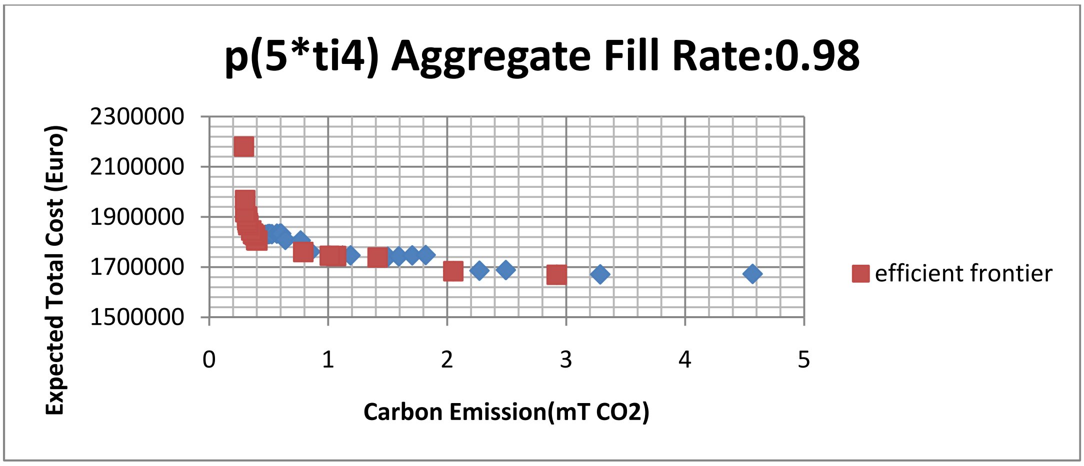


Figure 18- Efficient solutions when aggregate fill rate is 98 per cent and emergency shipment cost is equal to 5*ti4

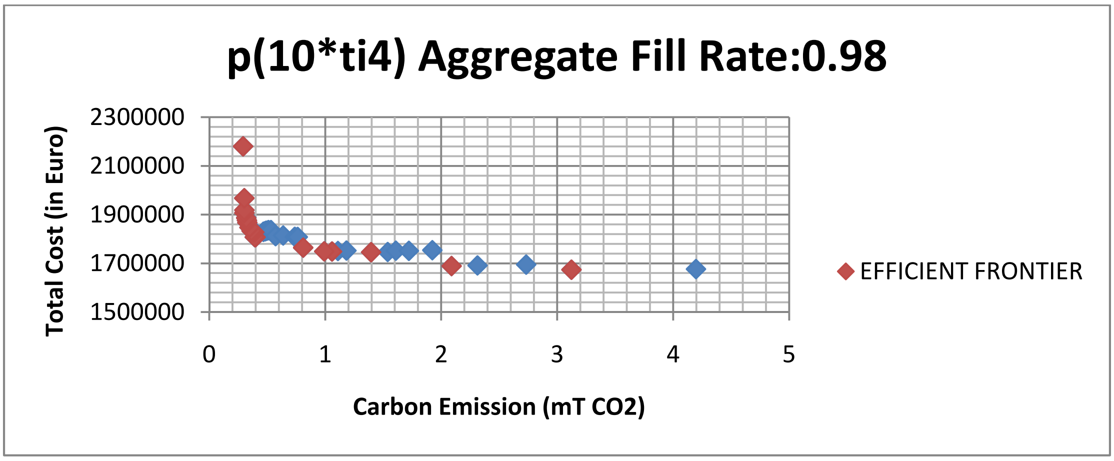


Figure 19- Efficient solutions when aggregate fill rate is 98 per cent and emergency shipment cost is equal to 10*ti4

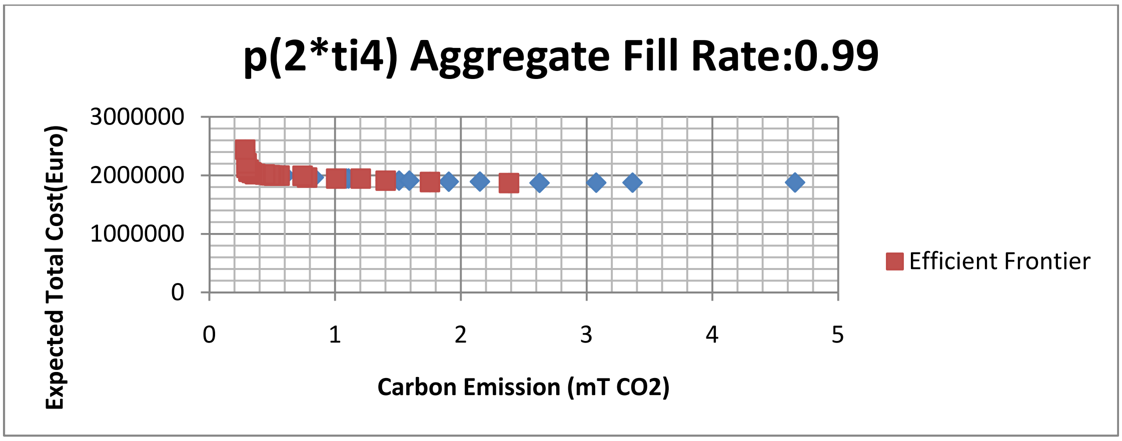


Figure 20- Efficient solutions when aggregate fill rate is 99 per cent and emergency shipment cost is equal to 2*ti4

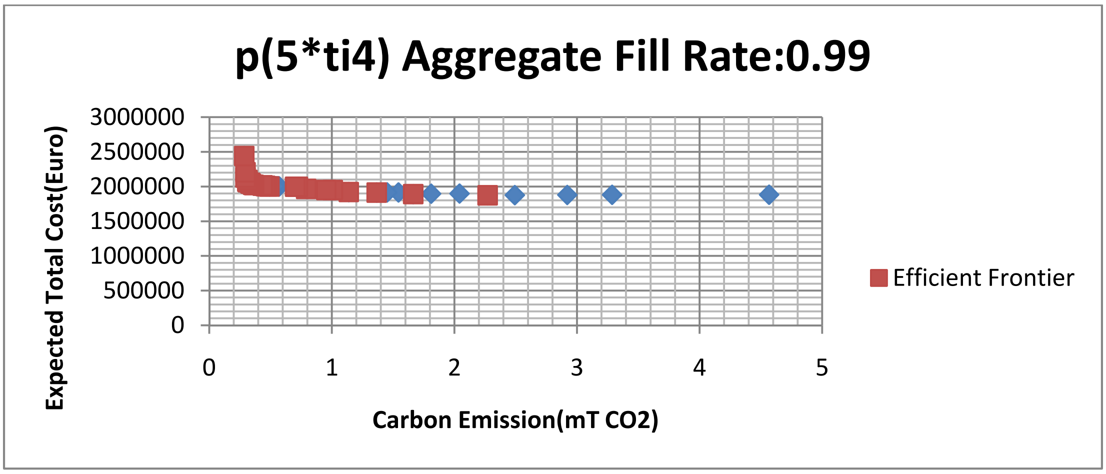


Figure 21- Efficient solutions when aggregate fill rate is 99 per cent and emergency shipment cost is equal to 5*ti4

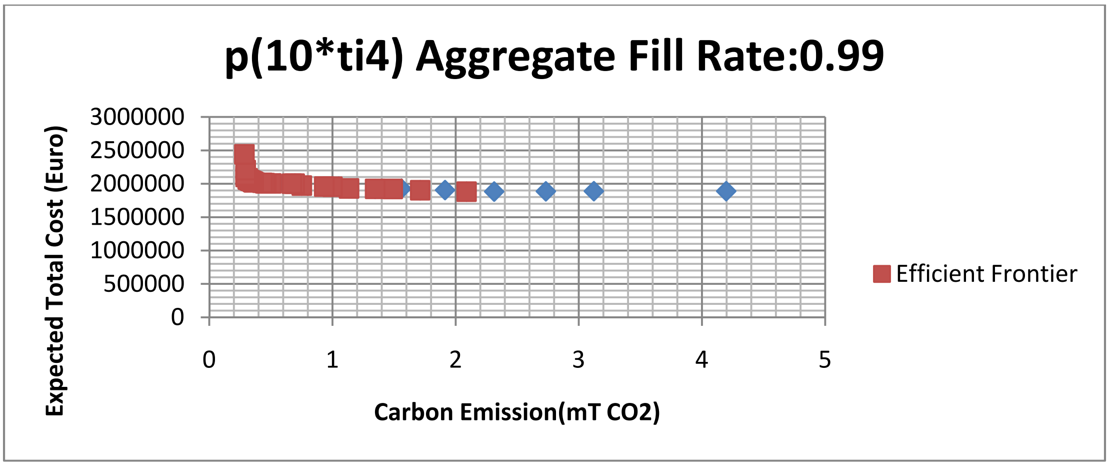


Figure 22- Efficient solutions when aggregate fill rate is 99 per cent and emergency shipment cost is equal to 10*ti4