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Two-stage stochastic production and transportation planning under carbon cap-and-trade system

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Abstract

Under the current alarming climate change concern, more efforts have been put in academic studies to address the global warming issue in both public and private sectors. Particularly, managing greenhouse gas emissions in operational and/or supply chain activities has become a common practice among researchers. This thesis focuses on production and distribution planning of a two-level supply chain subjected to the carbon cap-and-trade regulatory mechanism. Cap-and-trade is a carbon managing system in which emitting entities are restricted by a carbon cap and are entitled to buy or sell allowances in the carbon trading market.

In this study, we formulate a two-stage stochastic Mixed Integer Linear Programming model (MILP) for a manufacturing firm with a single product facing stochastic market demand. The firm's operational decisions are made in two stages. The first stage decision refers to the initial emission allowances the firm needs to acquire to cover its overall uncertain level of emissions incurred during the planning horizon. The second stage includes major decisions on production planning, shipping schedule, inventory holding, and trading of emission allowances. The objective is to come up with optimal production and transportation plans and an emissions trading schedule to minimize i) the cost of the initially purchased emission rights (in the first stage) and ii) the expected total cost related to the production, transportation, inventory holding and emission trading (in the second stage) while complying with the total available emission rights that the firm has to cover its emissions from those major activities.

We address the stochasticity in demand by generating different random demand scenarios and instances under which the MILP model is correspondingly solved. A baseline parameter set is generated, the result of which serves as the benchmark case for our sensitivity analysis in a later section, in which we separately vary several key parameters of the model. In order to evaluate the impact of carbon price on the performance of the model, we vary the emission permits buying and selling prices at the first and the second stage, either simultaneously or separately. We also employ the concepts of Value of Stochastic Solution and Expected Value of Perfect Information, which are often used to assess the effectiveness of using the deterministic model to approximate the stochastic one when the model with uncertainty is hard to solve. In a later part of the study, to take into consideration different product types, we extend our planning problem by analyzing different types of demand pattern, i.e., stationary, random, sinusoidal, and life cycle patterns. A comparative analysis on the performance of these cases is also carried out.

Through these computational experiments, we have found out that operational decisions on production, inventory control, and transportation activities are highly correlated to one another, and there are inevitable trade-offs between cost and emissions indicators. Results also show that whether the approximation of the stochastic model by the deterministic mean-value model is a good one depends heavily on the importance of the emission cost in the total cost function. Although the total emission level is not influenced by the allowance trading prices, in our experiments, these carbon prices do have certain impacts on the firm's total cost and its emissions trading decisions. It is also shown that different demand patterns can significantly influence the model's computational time as well as the firm's performance.

Keywords: Stochastic programming, lot-sizing, heterogeneous vehicles, emissions, carbon cap-and-trade

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List of Abbreviations

Abbreviation	Full name
3PL	Third-party logistics provider
CDM	Clean development mechanisms
CO_2e	Carbon dioxide equivalent
CV	Coefficient of variation
DC	Distribution center
EEV	Expected result of using the Expected Value solution
EEX	European Energy Exchange Group
EOQ	Economic order quantity
EPQ	Economic production quantity
E-TDVRP	Emissions-based Time-Dependent Vehicle Routing Problem
EU ETS	European Union Emissions Trading System
EUAs	European Union Allowances
EV	Expected Value
EVPI	Expected Value of Perfect Information
FTL	Full truckload
GHG	Greenhouse gas
GVWR	Gross vehicle weight rating
HDD	Heavy-Duty Diesel
IPCC	Intergovernmental Panel on Climate Change
ISO	International Organization for Standardization
LTL	Less than truckload
LCY	Life cycle demand pattern
MILP	Mixed integer linear programming
MIP	Mixed integer programming
NAPs	National Allocation Plans
NGO	Non-governmental organization
NZ ETS	New Zealand Emissions Trading System
PPRP	Pollution Production-Routing Problem
PPR	Pollution-Routing Problem
RAND	Random demand pattern
SIN	Sinusoidal demand pattern
SLP	Stochastic linear programming
SP	Stochastic Problem
STAT	Stationary demand pattern
UN	United Nations
UNFCCC	United Nations Framework Convention on Climate Change
US EPA	United States Environmental Protection Agency
VRP	Vehicle Routing Problem
VSS	Value of Stochastic Solution
WS	Wait-and-see

Chapter 1. Introduction

1.1 Background

Over the past few decades, greenhouse gas (GHG) emissions have been widely acknowledged as one of the most harmful elements to the environment, which are majorly account for the global climate change (Chaabane *et al.*, 2010; Zhang & Xu, 2013). In 2007, the Intergovernmental Panel on Climate Change (IPCC) also reported that global warming, which is, according to a lot of research, caused by the growing concentrations of GHG emissions mostly resulting from human, is posing an immense threat to the world's ecological system and humankind (IPCC, 2007). Since then, there have been many reports and scientific studies specifying that if no action is taken, these GHGs will lead to significant changes and can devastate the earth's climate system. Given the potential threats of climate change, reducing emissions from greenhouse gases (CO_2, CH_4, CFCs, NOx, etc.), particularly carbon dioxide CO_2, has become a global public objective in recent years (Bai & Chen, 2016). For simplification purposes, hereafter in this paper, all types of GHGs will be represented as carbon dioxide equivalent (CO_2e).

Under the increasing public pressure and the substantial need for protecting the ecosystem from those man-made effects, the United Nations (UN), the European Union (EU), countries and authorities around the globe have enacted ambitious legislation. They have also established various mechanisms, whether they are incentives or mandatory targets, to enable companies and organizations to apply those that best suited their circumstances. Some of the common mechanisms include the environment management standards by the International Organization for Standardization (ISO 14000 family), the Kyoto Protocol, the Paris Agreement, government programs such as the EU Emissions Trading System (EU ETS), the New Zealand Emissions Trading System (NZ ETS), or the US's Regional Greenhouse Gas Initiative, private voluntary-membership organizations such as the Chicago Climate Exchange, the Montreal Climate Exchange, and other newly emerged emissions-offset companies (Chaabane *et al.*, 2010; Hua *et al.*, 2011; Zhang & Xu, 2013; Toptal *et al.*, 2014; Bai & Chen, 2016; Purohit *et al.*, 2016).

The ISO 14000 family is a set of practical tools developed by the ISO Technical Committee ISO/TC 207 for companies and organizations of any type to manage their environmental responsibilities. It encompasses requirements to be used in environmental systems, audits, communications, labelling and life cycle analysis, as well as environmental challenges like global climate change (ISO, n.d.).

Adopted by governments since 1997, the Kyoto Protocol is a global treaty where member states (currently 192 parties) have committed to scale back their overall greenhouse emissions by a minimum of 5 percent below 1990 levels within the first commitment period 2008 to 2012, and by a minimum of 18 percent below 1990 levels within the second commitment period 2013 to 2020 (United Nations Framework Convention on Climate Change - UNFCCC, n.d.). Those member parties, individually or jointly, have to ensure that their aggregated CO_2e emissions do not exceed their assigned number of tradeable credits (each credit represents the right to emit one metric ton of CO_2e), which are calculated based on their quantified emission limitation and reduction commitments.

Another agreement within the UNFCCC is the Paris Agreement. Entered into force on November 4, 2016, the Paris Agreement has brought all nations into common efforts to combat climate change, to adapt to its effects, and to build a sustainable future. Its core objective is to intensify global actions against climate change to limit the global temperature rise by below 2 degrees Celsius above the pre-industrial level by the end of this century. In addition, at the Paris 21st Conference of the Parties in the same year, all the agreed parties have also committed to generate zero net GHG emissions by the latter half of this century (UNFCCC, n.d.).

In Canada, the Pan-Canadian Framework on Clean Growth and Climate Change is a governmental plan with an aim to accelerate public and private entities to meet their emissions reduction targets, to boost economic growth, and to build resilience to a changing climate. It includes putting a price on carbon pollution, implementing emission reduction measures and other actions in enhancing the climate change adaptation across all sectors of the economy, to ensure Canadian businesses are well-prepared and competitive in the global low-carbon economy (Environment and Climate Change Canada, 2016). Readers can refer to the full publication of this framework for more detailed information.

Many studies on supply chains have concluded that supply chain decisions have a significant impact on the atmospheric carbon inventory (Purohit *et al.*, 2016), as carbon emissions can be generated from almost any kind of industrial and business activities. Supply chain operations such as production, freight transportation, warehousing, and inventory management are broadly believed as the dominant factors contributing to emissions from manufacturing, wholesale and retail, transportation, healthcare, and service industries (Konur, 2014). It is noticeable that carbon emissions from different activities are generated in varying ways. For instance, emissions from inventory control depends on the quantity of inventory and the holding time, while emissions from manufacturing processes are determined based on the lot-size. If the lot-size is small, more emissions can incur due to more frequent machine set-ups. On the contrary, if the lot-size is too large, inventory holding will experience a larger emission proportion incurred by keeping a large quantity in stock (He *et al.*, 2015).

In general, there are several ways for companies and organizations to reduce their carbon emission levels, either by re-planning their operations or investing in carbon emission projects. According to Benjaafar *et al.* (2013), the majority of firms tend to focus on mitigating GHG emissions from physical processes by employing effective yet more costly solutions, while neglecting emissions from other critical sources. With the carbon emission reduction targets, firms preferably make investments in replacing inefficient equipment, building energy-efficient facilities, switching production methods, and using greener energy from renewable sources like biomass, wind power, solar power, hydro power, or geo-thermal that can produce power with a much lower amount of fossil carbon emissions than conventional fossil fuels (Huisingh *et al.*, 2015). However, re-planning operational decisions for a business's major activities can also be a cost-efficient approach in curbing emissions (Toptal *et al.*, 2014). Provided the influence of supply chain decisions on carbon emissions, firms could possibly reduce their emission levels by incorporating environmental elements into their decision models (Benjaafar *et al.*, 2013; Toptal *et al.*, 2014; Purohit *et al.*, 2016). For example, firms can incorporate an emission factor into their traditional production and distribution planning models either by applying a carbon constraint as in Absi *et al.* (2013) and Zhang and Xu (2013), or by including the emission level and/or the emission cost in the objective function as employed in Bektas and Laporte (2011), Jabali *et al.* (2012), Darvish *et al.* (2017), etc., or applying both techniques as in Hua *et al.* (2011) and He *et al*. (2015).

One would ask why organizations and companies are willing to invest time, effort and capital in carbon emission abatement schemes. According to Hoen *et al.* (2014), there are two main reasons. The first one is the pressure from customers and environmental entities as there has been a considerable shift in consumer behavior in recognition of the potential impact of industry activities on the climate. Some consumers are willing to pay higher prices for environmentally friendly products. This can be demonstrated by the considerably higher growth rates of those greener products in the textile and food industries (Letmathe & Balakrishnan, 2005). If a firm's critical customers are environmentally inclined, demand of its products could possibly be influenced by their different carbon footprint levels. Therefore, to maintain a good corporate image and to retain consumers, firms are directed to apply green approaches in one or several of their operational activities. A second reason for firms to curb emissions is to serve as a response to the increasing governmental regulations on emission and environment protection. Apart from these two above-mentioned reasons, Van der Veen and Venugopal (2014) also point out a third reason for firms to do business in a sustainable way, which they call the *altruistic motive*. That is, in some cases, firms adopt green policies voluntarily just simply because they feel the urge to do good, as long as it does not conflict too much with their economic benefits.

Some of the most common prevailing carbon policies are:

- **Strict carbon cap**: Under the strict carbon cap policy, a company needs to ensure its total emission level does not exceed a predetermined level (a carbon cap). This level is set to comply with either the company's voluntary green objectives or the regulations imposed by government authorities (Chen *et al*., 2013).

- **Carbon cap-and-trade**: With the carbon cap-and-trade policy, a company's emission level is also restricted by a carbon cap, but it can buy additional credits in the case that its carbon footprint is higher than the initial carbon cap or it can sell the excessive permits if its emission level is ultimately lower than the cap. This means that under the cap-and-trade policy, emission allowances are tradable through a trading platform, such as the widely known EU ETS or the NZ ETS.

- **Carbon cap-and-offset**: Under cap-and-offset system, a company is subject to a predetermined carbon cap, in the meantime, it can also indirectly invest in carbon offset projects, which could compensate for its carbon emissions and be used to increase its emissions cap. Those projects, also known as clean development mechanisms (CDM) under the Kyoto Protocol, are, for instance, low-carbon energy projects (wind farms, solar arrays), rural electrification projects using more energy-efficient boilers, or afforestation and reforestation projects, with an aim to "*abate carbon emissions by compensating a company's emissions*" (Konur *et al*., 2014).

- **Carbon tax**: Carbon taxing means that a company is charged on every unit of emissions it generates with a fixed price (a tax). Carbon tax is levied on fossil fuels and related products such as coal, gas, jet fuel depending on their carbon contents, with an aim to reduce those fossil fuel consumption. European nations including Denmark, Norway, Finland, Sweden, Netherlands are among the first countries to implement carbon tax policy (Lin & Li, 2011).

Among these methods, carbon tax and carbon emissions trading are recognized as the most effective instruments in the emissions abatement scheme (Labatt & White, 2007; Hua *et al*., 2011). The basic idea of these policies is to put a price on carbon emissions to encourage firms to reduce their emissions, either by adjusting operational or investment decisions, in order to create new development opportunities and to generate funds for green technology and innovations.

We limit the scope of this thesis to consider only the emission trading mechanism (carbon cap-and-trade). A more detailed description of this system will be included in a later section.

1.2 Research objective

In the context where industrial processes, transportation, and other commercial activities are strongly linked to the increasing greenhouse effect by the release of GHGs, along with the growing pressure from governments and public concern (Harris *et al*., 2011), many questions arise on how firms make decisions under these environmental restrictions. What are the impacts of uncertainty in factors like demands or prices on these decisions? What are the trade-offs between the firm's economic objective and its carbon footprint?

To answer these questions, many researchers have incorporated carbon emission factors in traditional supply chain planning problems, either in the objective function or constraints of the model, by examining their problems under one or more emission control policies – carbon cap, carbon tax, cap-and-trade, cap-and-offset, etc. Lots of studies in the literature consider the emission element in their production, transportation, or inventory planning separately. However, less attention is paid to collectively consider emissions from all of these main activities. This study will investigate an integrated supply chain problem where cost and emission factors of production, inventory control, and transportation are all considered, but it will only focus on the carbon cap-and-trade mechanism in terms of the environmental regulation. As opposed to deterministic demands, this study will consider a more realistic context where demands are uncertain and change over time.

The basic problem setting can be briefly described as follow: We consider a two-level supply chain where a firm produces a single product at a factory to meet future market demand. When production is completed, the firm can choose to store its finished products either at a temporary storage space of the factory or to ship them directly to a central warehouse located further away using medium- or heavy-duty trucks or a combination of both. Each of the production, inventory holding, and transportation activities entails costs and emissions. As the firm is assumed to be subject to the carbon cap-and-trade policy, it needs to acquire the necessary number of emission rights to cover its carbon footprint. Operational decisions are made in two stages. The first-stage decision is related to how many emission credits to buy initially when the demand (and hence the actual level of emissions) is not yet known. The second-stage decisions are related to the manufacturing, inventory holding, transporting processes as well as the recourse decisions on further emission credits trading (if any). These second-stage decisions are made after the actual demand level is observed.

The objective of this study is to incorporate the carbon emission element into a two-stage stochastic model to help firms come up with an optimal production and transportation schedule and emission trading plan at the minimum cost while still comply with the carbon cap restriction. The proposed model can serve as a support tool for decision-makers to better understand the trade-offs between cost and emissions when facing stochastic demands under the emissions trading rule. It aims at examining how environmental factors (carbon emissions) could affect a firm's production and transportation planning decisions.

1.3 Methodology

To achieve the goals mentioned above, this thesis aims to build a two-stage mixed-integer linear programing model with stochastic dynamic demand over a finite planning horizon. It is developed for a two-level supply chain problem in which a firm manufactures a single product to satisfy uncertain dynamic demands. The setting is as follows. Products are produced at a factory and shipped to a central warehouse by different types of trucks (either medium- or heavy-duty or both). The firm's production, inventory control, and transportation activities are characterized by cost and emission features, which are then varied for the sensitivity analysis purpose. The firm is subject to a carbon cap-and-trade system where its initial emission allowances need to be purchased through auctioning. To accommodate the uncertainty in demand, different demand scenarios are randomly generated from the uniform and normal distribution.

The proposed model is solved using the optimizer CPLEX provided by IBM.

The structure of the thesis is as follows. In the next section, an overview of the literature on green lot-sizing and emissions trading is presented. Section 3 describes the basic case for the deterministic lot-sizing and transportation planning model and the new model for the case that incorporates the two-stage decision setting and emission factors. Section 4 presents numerical studies under different sets of parameters (including the discussion of results and sensitivity analysis addressing the trade-offs between costs and emissions). Section 5 presents an extensive experiment that takes into consideration the possibility of different demand patterns. Finally, the last section consists of a conclusion and a discussion on the limitations and possible future research directions.

Chapter 2. Literature review

This chapter will provide a review of the various topics that are relevant for this thesis. Section 2.1 focuses on the methodology and presents a brief review on the general stochastic programming and on the stochastic lot-sizing literature. To provide a more comprehensive understanding on the approaches that have been investigated to cope with GHGs emissions in supply chain, the next sections present a review of those highly relevant studies, which can be divided into four streams. Section 2.2 focuses on green lot-sizing and Section 2.3 explores strategic and operational decision making in other major corporate activities with environmental elements. Section 2.4 studies the operational decisions of firms under the emission trading system as well as under other common regulatory mechanisms. Finally, Section 2.5 analyzes different applicable methods in measuring carbon emissions.

2.1 Stochastic programming

Early in 1999, Sen & Higle provided a fundamental tutorial on stochastic programming in which they discussed numerous models, ranging from single recourse policies to more general two-stage and multi-stage Stochastic Linear Programming (SLP) formulations. This section focuses only on the two-stage setting, given that this is the modelling approach used in this thesis.

- **Two-stage stochastic programming** is a modeling paradigm where decisions are made under one or more sources of uncertainty at two separate periods of time. Decision variables that are implemented before an outcome of the random variable is observed are classified as *first-stage decisions* – also regarded as the proactive decisions and are often associated with strategic or tactical planning activities such as capacity expansion. On the other hand, those decisions implemented after observing the outcome of a random variable are the *second-stage* or *recourse decisions*, which are often associated with operational decisions. In the second stage, for each of the possible observed outcomes of the random variables, corresponding recourse decisions are made to assist the organization to adapt to the realized outcome (Sen & Higle, 1999). This type of practice is also known as recourse planning. Readers interested in recourse planning models can refer to Higle (2005) for a more detailed description.

An example of applying the recourse planning concept is the work by Eppen *et al.* (1989). In their study, a stochastic programming problem with uncertain demand is considered, where the first-stage decisions are the capacity levels in a network of plants, and the production quantity decisions are the recourse decisions.

Within stochastic programming, an important stream to which much attention has been paid by researchers over the years is stochastic lot-sizing, which is often known as the lot-sizing problem with uncertain demand. This section will now present a review on the stochastic lot-sizing model.

- **Stochastic lot-sizing**

Lot-sizing and scheduling are widely acknowledged to be critical decisions in production planning, particularly for companies within the industrial sector. They could have direct impacts on a firm's total cost and efficiency level. In the past, production planning was often considered under deterministic settings as it is a lot simpler to resolve production problems without uncertainty. A general overview on deterministic lot-sizing can be found in Pochet and Wolsey (2006), Jans and Degraeve (2008), and Brahimi *et al.* (2017). However, uncertainties, either external or internal, such as those in demand, productivity, yield loss, etc., can highly affect a firm's production decisions. Therefore, imbedding stochasticity in lot-sizing and scheduling problems is important (Hu & Hu, 2016). In our production and transportation planning problem, we will involve the uncertainty in market demand. Other papers have looked at other sources of uncertainty like uncertainty in setup times (Tas *et al*., 2019) and yield (Helber *et al.*, 2018).

To the best of our knowledge, the early stochastic lot-sizing concept can be dated back to 1978 when Silver expressed that *"One should not necessarily use a deterministic lot-sizing rule when significant uncertainty exists. A more appropriate strategy might be some form of probabilistic modelling"*. In his study, he has suggested a heuristic approach for a stochastic lot-sizing problem, taking into consideration the normally distributed forecasting error. This non-stationary stochastic lot-sizing problem has not been extensively studied until the late 1990s and the start of the 21st century. A thorough review on the early stochastic lot-sizing literature can be found in Tarim and Kingsman (2004). A recent general review on stochastic lot-sizing can be found in Tempelmeier (2013).

Another aspect that has been studied is the capacitated lot-sizing and scheduling problem with sequence-dependent setups reviewed by Ramezanian and Saidi-Mehrabad (2013), Hu and Hu (2016, 2018). Ramezanian and Saidi-Mehrabad apply the chance-constrained programming theory to transform the stochastic models to the deterministic ones. Hu and Hu (2016) investigate a setting where baseline production decisions (production quantity and sequence of production) are made at the first stage, and possible updates on the production planning such as overtime production decisions are made at the second stage, with a goal to find the best sequence of production quantities under random demand with backorders allowed. In their study, demand uncertainty is explicitly modelled by applying scenario generation and the most representative scenarios are chosen to conduct further analysis. In another paper published in 2018, the authors have extended their original problem to a multi-stage stochastic problem which allows decisions to be revised at each period based on the previous realization of uncertainty and the decisions taken so far.

Other authors focus on stochastic lot sizing with a service level constraint (Tempelmeier, 2011; Tunc *et al*., 2014; Helber *et al*., 2013; Sereshti *et al*., 2020). Some research has been done to integrate stochastic demand in integrated lot-sizing and distribution planning problems (Adulyasak *et al*., 2015; Gruson *et al*., 2020; Alvarez *et al*., 2020). Also focusing on lot-sizing, Zhou and Guan (2013) extend the formulation of two-stage stochastic problem to allow backlogging and uncertainty in costs (cost parameters will increase or decrease after a given time period, following a discrete probability distribution). This uncertainty of cost can come from different sources –

fluctuations in purchasing costs of resources and materials, promotions and marketing activities, fluctuations in interest rate and currency exchange rate, etc.

At a more strategic level, Drake *et al.* (2016) employ a two-stage stochastic model for their technology choice and capacity investment problem of a firm under the carbon cap-and-trade or the carbon tax regulation. At the first stage (investment stage), the firm builds its capacity portfolio using 2 types of production technologies ("dirty" or "clean" technology) with corresponding investment costs and emissions intensity. After the uncertain demands are known, at the second stage, the firm makes production decisions which are constrained by the capacity built at the first stage.

2.2 Green lot-sizing

In the literature on sustainable supply chains that studies lot-sizing problems with environmental concerns, many have considered a constant or time-varying deterministic demand, such as the work of Hua *et al.* (2011), Arslan and Turkay (2013), Toptal *et al*. (2014), Konur (2014), and Absi *et al.* (2013, 2016), etc. However, in recent years, there are rising sources of uncertainty in the global supply chain. This has made decision-making under the consideration of environmental sustainability increasingly complex. Therefore, more attention has been paid to include stochastic elements in green lot-sizing models, of which the uncertainty in demand is the most common topic discussed by researchers. They develop it either into a single-period or a multi-period (dynamic) stochastic model, e.g., the work of Song and Leng (2012), Hoen *et al.* (2014), Gong and Zhou (2013), and Purohit *et al*. (2016), etc.

Most of the current studies on green lot-sizing that consider carbon emission factors (either emission cost or emission intensity) incorporate them either in the constraints or directly in the objective function of the mathematical model. An overview of these studies will be provided in this section, which comprises three main parts. The first part discusses papers using the classical economic order quantity (EOQ) model, the second part introduces studies using the newsvendor problem, and the third part reviews papers using a Mixed-Integer Programming (MIP) model.

2.2.1 Green lot-sizing with economic order quantity model

Many studies in the literature use the economic order quantity model – a standard model in the classical inventory control theory, as an instrument to help firms come up with optimal lot-sizing decisions (either for the production or ordering processes) in order to minimize the total cost of replenishment under deterministic setting (Arslan & Turkay, 2013).

A study by Bonney and Jaber published in 2011 has included the social cost of vehicle emissions and the cost of disposing waste into a classical EOQ model to develop an environmentally enhanced inventory model. It has shown that the existing inventory management system using small batch sizes and short product life cycles can lead to a significant increase in transportation costs and CO_2 emissions. The authors thus suggest future inventory systems should move towards larger batch sizes, longer product life cycles, and higher quality products to save costs and to reduce emissions. Similarly, Arslan and Turkay (2013) also emphasize that in most cases, models with sustainability constraints tend to result in larger optimal order quantity than those without such constraints. Their work revises the traditional EOQ model to include environmental and/or social criteria to obtain their sustainability objectives by using different modeling approaches, i.e., direct accounting, carbon tax, direct cap, cap and trade, etc. The study of Van der Veen and Venugopal in 2014 has collectively used a multi-objective approach and an energy cost-included EOQ model to test the validity of the two different schools of view: whether there are inevitable trade-offs or weather there exists a feasible synergy between the economic and environmental performance. Their findings indicate that both views are not incompatible but valid depending on the values of specific parameters of the emission regulations.

As there are increasing environmental regulations being put into place by legislative bodies, researchers tend to focus on incorporating one or several of these policies into their models, with an aim to investigate how these instruments affect their decision makings. A study by Hua *et al.* in 2011 examines how firms react under the carbon emission trading mechanism by involving the well-known European ETS and New Zealand ETS. They analyze how carbon related regulatory parameters (carbon cap and carbon trading price) affect their optimal EOQ quantities, carbon emissions and the total cost level. In their work, the permits buying and selling prices are assumed to be equal. Benjaafar *et al.* (2013) study several simple economic lot-sizing models in which the firm faces different environmental regulations (strict carbon cap, carbon tax, carbon cap-and-trade, carbon cap-and-offset). In the same year, Chen *et al.* also analyze the primary factors that influence the extent of emission reduction versus the increase in cost under these four carbon policies. They further propose essential conditions under which carbon emissions could possibly be reduced by adjusting the order quantity without considerable increase in costs.

Toptal *et al.* (2014) extend the EOQ model to jointly consider decisions on inventory control and investment in carbon reduction of a retailer under different carbon schemes, with an aim to provide guidance for companies to make better inventory decisions while utilizing the available environmental technologies. He *et al.* (2015) consider an EOQ-based lot-sizing problem of a carbon-intensive firm under carbon tax and carbon cap-and-trade systems where annual market demand is fixed. Their study compares the effectiveness of the two policies in terms of cost and their impacts on the firm's operational decisions. They find out that under cap-and-trade regulation, the firm's optimal emissions level as well as its allowances trading plan are contingent on the allowances trading prices.

A recent study by Malik and Kim (2020) involves both direct and indirect emissions from the production process in their proposed economic lot-size and production rate model for a single vendor-buyer supply chain. In calculating production costs, unlike other studies, they consider the possibility to reduce the fixed production setup cost with additional upfront investments in the production system. They even apply a changeable unit production cost which can vary depending on the quantity of products produced (decreases when production rate is large).

Tayyab *et al.* (2019) build a multi-objective model for a multi-stage production system by employing the Economic Production Quantity (EPQ) model, the concept of which is similar to the conventional EOQ model. By simultaneously considering two conflicting objectives - minimizing cost and minimizing emissions, the optimal sustainable lot-size that they obtain is expected to improve both the economic and environmental performances of the system. It is noticeable that with the application of analytical optimization technique and a metaheuristic approach, their study has successfully involved both the uncertain demand and the highly uncertain defective rate, which are acknowledged to be the imperfect nature in the manufacturing process.

2.2.2 Green lot-sizing with newsvendor problem

As opposed to the EOQ inventory control model, some researchers have studied the emissions restricted lot-sizing problem when demands are unknown, either in a single-period or multi-period setting. In this section, we will first provide an overview on the studies in which one single lot-sizing decision is made to cover the stochastic future demand for the whole planning horizon, which is commonly known as the newsvendor problem. A review of the studies with a stochastic dynamic structure will be presented in a later section.

The **newsvendor problem** (also called as newsboy problem) is a single-period lot-sizing model for a product with limited shelf life and uncertain future demand, often associated with a fixed acquisition price, an item selling price, and a salvage price. When market demand is higher than the order quantity, financial losses are incurred and unsatisfied demand is considered lost sales. When market demand is lower than the lot-size, losses also occur in the form of excessive inventory but the owner is often able to retrieve a portion of revenue from each unsold unit through the salvage price. The objective of this type of problem is to come up with an optimal order quantity to maximize its expected profit.

A work by Manikas and Godfrey in 2010 has combined the classical newsvendor model with the consideration of carbon emissions by including not only the emission permit purchasing cost but also the penalty cost of violating the upper emission limit into their stochastic lot-sizing model. It is noted that in their study, substitute products from other suppliers are assumed to exist, but the firm has limited authority on how much it can charge to offset the incremental costs resulting from the permit prices and penalties.

Song and Leng (2012) consider a single-period problem for a perishable product under three carbon policies, i.e., mandatory cap, cap-and-trade, and emissions tax. Their research provides important insights for policy makers in determining the appropriate emission capacity or in adjusting the profit structure based on different carbon price levels. Likewise, Hoen *et al.* (2014) examine the impacts of these regulations on a transportation mode selection problem in which they focus on the emissions of different transportation modes. Zhang and Xu (2013), however, extend the conventional model to a multi-item setting under carbon cap-and-trade regulation. They address a common production capacity and an emission quota that will be shared among different product types. In Bai and Chen (2016), two distributional robust newsvendor models with dual sourcing strategy are built. Dual sourcing is a common approach in supply chain management to deal with volatile market demand. They obtain the optimal order quantities by applying the

Maximin solving approach, which has been shown to remain effective even under the worst demand scenario.

Similar to many of the studies we have discussed so far, this thesis focuses on the production planning of a single product with stochastic demand, yet the main difference is that we consider a multi-period setting as opposed to the single-period lot-sizing. It is noticeable that, in our model, production quantities can be determined only after the uncertain market demands are realized.

2.2.3 Green lot-sizing with Mixed-Integer Programming model

Another major area in the literature of green lot-sizing is the stream of studies that employ mixed-integer programming techniques in deriving the optimal lot-sizing decisions under environmental considerations. This section will present an overview of those related papers.

An early work by Letmathe and Balakrishnan in 2005 was considered among the first attempts to develop models that integrate environmental concerns (e.g., carbon emission upper limits, taxes or penalties, tradable emission allowances) into production planning problems along with those traditional impediments (raw materials, machine capacity, labor hours, storage space, etc.) and environmental issues in production planning. They describe two separate mathematical models, i.e., a linear programing model for products with only one operating process and a mixed-integer linear programing model for products that need more than one operating process, with the objective to help firms solve their product mix and production quantity problem under the presence of emission thresholds (or taxes) and tradable emission allowances.

Following the idea of incorporating carbon emission constraints into decision-making models, Absi *et al.* (2013) study a single-item uncapacitated dynamic lot-sizing problem under 4 types of carbon emission constraints: periodic, cumulative, global or rolling emission constraint. With a multi-sourcing setting (there are various production facilities and transportation modes available to satisfy a given demand), carbon emissions in their study are aggregated by each supplying mode, i.e., a combination of a production location and a transportation mode. Unlike other studies, the upper limit of emission in their research is imposed on the average emission per product rather than on the overall emission quantity. This approach is highly relevant and applicable to firms that are strategically willing or mandatorily required to display the carbon footprint of their products explicitly. In a later study in 2016, the authors further investigate the above problem with an extension on the periodic carbon emission constraint, in which a fixed amount of carbon emission is associated to the use of a specific supply mode, in addition to the regular unit carbon emission (Absi *et al*., 2016). Helmrich *et al*. (2015) consider a global emission constraint, which also includes emissions from inventory holding.

Gong and Zhou (2013) employ a stochastic dynamic model to determine the optimal production and emission trading strategy in the case of a cement manufacturing company subject to emission trading policy. Similarly, Purohit *et al.* (2016) use an MIP model to fulfil non-stationary stochastic demands of a buyer firm and to analyze the impacts of emissions, product, and system related parameters on the supply chain performance through extensive computational experiments.

Instead of including the emission element in constraints, Darvish *et al.* (2017) imbed it directly into the objective function of their dual integrated production-routing and inventory-routing problems under three different objectives – minimization of total costs, routing costs only, or total emissions. Their study also provides useful insights on the costs and emissions in an integrated supply chain as well as on the cost of being environmentally friendly.

Recently, Castellano *et al.* (2019) study a single-vendor multiple-buyer supply network to minimize its total expected cost of transportation and emissions in the long term. In the same year, Turkensteen and van den Heuvel conduct a realistic assessment of the trade-offs between operational costs and carbon emissions with their novel bi-objective lot-sizing model, under a deterministic dynamic setting. The most distinguished feature of this study is that they focus on the realistic values of the emission parameters acquired from empirical studies as opposed to the generic parameters as often employed in historical studies.

From a broader perspective, Chaabane *et al.* (2010) use an MIP model to investigate the characteristics of a closed-loop supply chain network structure. They study multiple decisions on facility location, production lot-sizing, distribution/recycling centers, transportation and carbon credits management. One major remark provided by the study is that under the emergence of emission trading schemes, it is critical to explicitly consider environmental costs within supply chain design. There are a great number of studies on closed-loop supply chain and reverse supply chain within the sustainable lot-sizing domain but there will not be mentioned as they are considered outside the boundaries of this study.

A summary of the related studies in green lot-sizing is presented in Table 2.2-1.

Table 2.2-1: Summary of the literature in green lot-sizing

Authors	Demand	Model	Emission sources			Other features
			Ordering/ Production	Inventory holding	Transport ation	
Letmathe and Balakrishnan (2005)	Stochastic	MIP	✓			-Multi-item -Product mix
Manikas and Godfrey (2010)	Stochastic	Newsvendor	✓			-Emissions penalty cost -Disposal fee for unsold units
Hua *et al.* (2011)	Deterministic	EOQ		✓	✓	
Bonney and Jaber (2011)	Deterministic	EOQ			✓	-Costs of emissions and disposing waste
Song and Leng (2012)	Stochastic	Newsvendor	✓			
Arslan and Turkay (2013)	Deterministic	EOQ	✓	✓		-Environmental and social criteria
Benjaafar *et al.* (2013)	Deterministic	EOQ	✓	✓		-Single firm or multiple firms -Multi-period
Chen *et al.* (2013)	Deterministic	EOQ	✓	✓		
Zhang and Xu (2013)	Stochastic	Newsvendor	✓			-Multi-item with a common production capacity and emission quota
Gong and Zhou (2013)	Stochastic	MIP	✓			-Production technology selection -Stochastic allowance prices
Absi *et al.* (2013)	Deterministic	MIP	✓		✓	-Multi-sourcing -Four types of emission constraints
Toptal *et al.* (2014)	Deterministic	EOQ	✓	✓		
Van der Veen and Venugopal (2014)	Deterministic	EOQ	✓	✓		-Multi-objective -Consider energy usage
Hoen *et al.* (2014)	Stochastic	Newsvendor			✓	-Transportation mode selection
He *et al.* (2015)	Deterministic	EOQ	✓	✓		-A carbon-intensive firm
Helmrich *et al.* (2015)	Deterministic	MIP	✓	✓		-Bi-objective
Absi *et al.* (2016)	Deterministic	MIP	✓		✓	-Periodic emissions constraints
Purohit *et al.* (2016)	Stochastic	MIP	✓	✓		-Service level constraints
Bai and Chen (2016)	Stochastic	Newsvendor	✓	✓		-Dual sourcing
Darvish *et al.* (2017)	Deterministic	MIP			✓	-Three types of objective functions
Turkensteen and van den Heuvel (2019)	Deterministic	MIP		✓	✓	-Bi-objective
Castellano *et al.* (2019)	Stochastic	MIP	✓		✓	-Single item -Single vendor-multiple buyers
Tayyab *et al.* (2019)	Stochastic	EPQ	✓	✓		-Single item -Bi-objective -Uncertain product defective rate
Malik and Kim (2020)	Deterministic	EOQ	✓			-Direct and indirect production emissions
This study	Stochastic	MIP	✓	✓	✓	-Single item -Multi-period

2.3 Other types of operation problems incorporating environmental consideration

Apart from lot-sizing, environmental elements have also been integrated into other areas of operations and supply chain management such as transportation, technology selection, facility location, network design, etc.

Dated back to 1998, Gray and Shadbegian conducted an empirical study to discover the connection between environmental regulations and the productivity of a firm through its production technology selection and capital allocation investment problem in the pulp and paper industry.

In supply chain network design, Bauer *et al.* (2010) incorporate costs of greenhouse gases into a linear multicommodity and capacitated network design planning model to minimize emissions from the intermodal freight transport activities. Their study also presents computational results of an empirical case of a rail freight network in Eastern Europe. A study by Harris *et al.* in 2011 has examined two objectives, i.e., cost minimization and emissions minimization, in their supply chain network design problem. Their findings suggest that different objectives could result in different optimal network solutions, thus it is essential to address the economic and the environmental objectives explicitly in the design of a supply chain. Mallidis *et al.* (2014) develop two new periodic inventory planning models to evaluate the impact of jointly optimizing strategic network design decisions (the number and the type of distribution centers and transportation modes to use) and tactical inventory planning decisions (the optimal order delivery frequencies and stock levels) on the total cost and carbon emissions of a multi-echelon logistics network.

Transportation makes up about 21% of carbon emissions globally, in which road transportation has constituted a large portion, particularly freight transport (Jabali *et al.*, 2012). Given the significant contribution of the transportation sector to the total emission inventory as well as the critical role of trucking among supply chains, more efforts have been made by researchers to include transportation in their optimization models (Castellano *et al.*, 2019). A study in 2012 by Jabali *et al.* has provided a framework to model carbon emissions in a time-dependent vehicle routing problem in road freight distribution, which is used to minimize the sum of travel time, fuel usage and CO_2 emission costs. As fuel consumption is related to emissions, their study illustrates that reducing emissions could bring about potential cost reductions, and that minimizing CO_2 emissions by limiting the number of vehicles used can be costly in terms of travel time, but *"limiting it to a certain extent might be both cost and emission effective*". Similarly, when dealing with transportation related activities, Castellano *et al.* (2019) focus more closely on the transporting flows and vehicle routing issues with the consideration of GHG emissions from transportation.

From the perspective of fleet management, a study by Konur in 2014 is considered as the first in the literature that explicitly discusses heterogeneous truck types (each associated with a distinct cost and an emission factor) in an integrated inventory control and transportation problem with carbon emission constraint. Similar to most of the previous studies, his problem considers a deterministic inventory control system (classical EOQ model) but it applies Full-truckload (FTL) as opposed to Less-than-truckload (LTL) transportation. The experimental results of this study illustrate that when the carbon cap becomes tighter, firms tend to increase the number of truck types that are in use, and that using a configuration of different truck types not only reduces cost but also emissions. In the same year, the author has extended his scope of research to consider both FTL and LTL trucking practices, as being presented in Konur and Schaefer (2014). In the case of using an LTL carrier, the firm is subject to a per unit transportation cost and carbon emissions per unit shipped.

It can be seen that, in order to curb emissions from freight transportation more effectively, the trend is shifting towards considering different types of vehicles of one transport mode (as in Konur, 2014) or among different transport modes (as in Hoen *et al*., 2014). Therefore, vehicle configuration and fleet management has become a prevalent issue to consider in order to find the most appropriate solution with respect to cost and emissions under environmental policies. With that saying, this thesis will look into a two-level supply chain with a transportation system where two different types of truck, i.e. medium-duty and heavy-duty truck, are considered.

2.4 Studies incorporating emissions trading and other regulations

2.4.1 Introduction to emissions trading system (carbon cap-and-trade)

As early as mid-1970s, the United States Environmental Protection Agency (EPA) began to enforce some rules related to the emissions of greenhouse gases, which has triggered the emergence of several environmental initiatives, particularly in dealing with the emissions of carbon dioxide (Tietenberg, 2006). In the 1990 Clean Air Act Amendments of the United States, the very first large-scale sulfur dioxide (SO_2) emissions trading system was instituted for the electric sector under the framework of the Acid Rain program (Zhao *et al.*, 2010). Since then, this tradeable allowance approach has been extended to new geographic areas including Chile and the European Union, where a cap-and-trade policy for CO_2 (known as the Emission Trading System) came into effect in 2005. Meanwhile in the United States, although there was no federal carbon reduction requirement, numerous states have launched their own carbon trading system, most notably are the Regional Greenhouse Gas Initiative and the Western Climate Initiative, the latter also includes four Canadian provinces. These carbon control programs have brought back many positive economic impacts in the global effort of curbing greenhouse gases emissions (Zhao *et al.*, 2010).

Emissions trading, also known as cap-and-trade, is a market-based policy that controls the emissions of GHG pollutants to the air, under which emitting entities are required to possess an equivalent amount of emission allowances (a carbon cap) to cover the quantity of emissions they generate (He *et al.*, 2012). Under cap-and-trade system, if a firm's actual carbon emission level exceeds its carbon cap, it can buy extra emission allowances (permits) on a carbon trading market such as the widely acknowledged European Union Emissions Trading System. On the other hand, if the firm's actual amount of emissions is less than the cap, it can keep the spare allowances to cover its future needs or else sell them on the same market. These emission allowance prices are volatile and determined either by the regulators or by the trading market itself (Drake *et al*., 2016).

Under a cap-and-trade regime, there are many aspects in the design of the system that can affect its economic efficiency and consumer costs. One of the most critical and controversial elements is the initial allocation of emission allowances (Zhao *et al.*, 2010). In principle, initial allowances are allocated yearly through a regulatory agency, either by auctioning (where polluters purchase emission rights from regulators), by giving away fixed amounts free of charge (also known as grandfathering), or by allocating based on the present or recent investments and decisions. Nevertheless, in all cases, the total amount of emission allowances is limited by a cap, i.e., a pre-determined upper limit imposed by the regulator either at the industrial, regional or national level, which will be gradually tightened over time in order to reach the ultimate emission abatement target (He *et al*., 2012).

2.4.2 The European Union Emissions Trading System

Among the more than 20 carbon trading platforms worldwide, the emissions trading system of the European Union is known as the largest multi-national greenhouse gas emissions trading market (Bai & Chen, 2016).

Being launched by the Directive 2003/87/EC of the European Parliament and the Council on October 13, 2003, the EU ETS is intended to guarantee the reduction of greenhouse gas emissions from major industrial sectors within the EU, and to serve as an instrument for the EU to meet its emission targets in the Kyoto Protocol (Carmona *et al*., 2009). The system currently operates in all European Union countries plus Iceland, Norway and Liechtenstein, covering around 45% of the EU's greenhouse gas emissions from power sector to manufacturing industry and aviation. It imposes mandatory participation of more than 11,000 energy-intensive entities (including power stations, industrial plants, etc.) and over 500 airlines operating between these countries (European Commission, 2019). For these installations, carbon emission allowances (also called EUAs), which are used to cover their annual carbon footprint, are allocated annually by the responsible governments based on the National Allocation Plans (NAPs). By the end of April 30th each year, if they do not submit enough allowances to cover their total emissions of the preceding year, a penalty payment will be applied for each ton of excessive emission, e.g., the penalty price is €40 per ton in the first phase and is €100 in the second phase (Carmona *et al*., 2009). In 2019, the average allowance price on the EU ETS primary auction market is €24.72 per ton of CO_2e emissions.

The EU ETS system is now in its third phase that covers the years 2013 to 2020. Compared to its two prior phases – Phase 1 (2005-2007) and Phase 2 (2008-2012), several crucial changes have been carried out in Phase 3. Starting from 2013, a specified cap for each nation has been replaced by a single, EU-wide emissions cap which declines linearly each year by around 1.74%. Table 2.4-1 shows the annual caps for the stationary installations and the number of aviation allowances put into circulation from 2013 to 2020 provided by the European Commission (2019). Another noticeable change is that auctioning is now the default method of allowances allocation as opposed to the previous free allocation method. Additionally, more sectors and gases have been involved in Phase 3.

In April 2018, the EU ETS revised its legislative framework to prepare for its next trading period – Phase 4 from 2021 to 2030 (European Commission, n.d.). In a report to the European Parliament and the Council in 2019, the EU ETS has proved that putting a price on carbon and then trade it can help curb emissions. This is illustrated by the fact that, compared to 2017, the emissions from those installations covered by the system in 2018 had decreased by 4.1% (approximate 73 million tons CO_2e), except for the aviation sector where emissions continue to grow by 3.9% or about 2.6 million tons CO_2e (European Commission, 2019).

Table 2.4-1: EU ETS carbon cap in the 2013-2020 period

Year	Annual cap (installations)	Annual aviation allowances put into circulation
2013	2 084 301 856	32 455 296
2014	2 046 037 610	41 866 834
2015	2 007 773 364	50 669 024
2016	1 969 509 118	38 879 316
2017	1 931 244 873	38 711 651
2018	1 892 980 627	38 909 625
2019	1 854 716 381	35 172 897
2020	1 816 452 135	N/A

Source: European Commission (2019)

2.4.3 Studies with emissions trading system (carbon cap-and-trade)

Given the rising popularity of emissions trading systems and their important role in the global emissions abatement scheme, there is an increasing number of studies looking into various aspects of this carbon controlling mechanism.

Early in 1996, a study by Laffont and Tirole (1996) analyzed how the trading prices of pollution permits in the spot and futures markets could impact a firm's compliance strategies and production planning in a two-period deterministic setting. In their study, polluters can either buy emission permits, invest in pollution reduction projects, merely stop production, or outsource their polluting activities. Their findings indicate that under the spot market, overinvestment of firms is likely to be induced because the permit price exceeds the marginal pollution cost. Companies would rather pollute or invest in green technologies than buy emission permits. Meanwhile, the launch of futures markets can curtail this situation, as with the futures markets, firms have more incentives to buy permits in advance at a lower price that they can use in the future.

Shortly after the EU ETS went into effect in 2005, more research has been devoted to analyzing its effectiveness. A book by Tietenberg in 2006 discusses the role of the emissions allowance trading approach in environment protection schemes. By reviewing the accumulated successes of emissions trading over the years, it points out the weaknesses and challenges faced by this mechanism. The author also emphasizes that not all the emissions trading programs are equal, some are better designed than others, and each trading program should be adjusted for each specific application. This is followed by the research of Zhao *et al.* (2010) which focuses on analyzing the impacts of different permits allocation rules (auctioning, grandfathering, output, and investment based) on the economic efficiency of the electric power sector. Their arguments indicate that among those allocation rules, free allocation could possibly lead to market price distortion while the contingent allocation system (also called "output-based" or "input-based" allocation) could also distort decision making in production and technology investment. However, despite its potential misinterpretation, compared to the inefficiency of auctioning and grandfathering, output-based policies still receive strong support from political forces and are believed to actually improve the overall welfare. This is demonstrated by the fact that most of the national allowance allocation plans in the EU ETS are based on such schemes (Dissou, 2005; Fischer & Fox, 2007; Neuhoff *et al.*, 2006; Sterner & Muller, 2008, as cited in Zhao *et al.*, 2010). In the same year, Chaabane *et al.* introduce a multi-objective framework to assist firms in designing sustainable supply chains that integrate environmental factors. Their study also aims at providing decision makers with insights in the tradeoffs between economic and environmental performance.

At the operational level, Hua *et al.* (2011) study how firms manage their carbon footprint in inventory control by comparing the optimal order quantity derived from the modified carbon-constrained model with that of the traditional EOQ model. They show that the cap-and-trade mechanism does induce retailers to curtail their carbon levels but it ultimately increases their total costs, and the optimal lot-sizes under these two models are usually not equal.

Zhang and Xu (2013) formulate a linear programming model for their multi-item stochastic problem in which a single emission quota is shared among different product types. They find out that in the presence of a cap-and-trade mechanism, low-emission products will be favored over high-emission ones, and total emissions will decrease as the carbon price increases. Gong and Zhou (2013), also with the uncertain demand setting, investigate a multiperiod problem of a cement company facing stochastic emission trading prices. In their study, the firm covers its emissions not only by the initial allowances but also by the amount it trades from the external market via forward contracts at the end of the planning horizon, and its optimal emission trading and production decisions are to be made before the uncertain demands are realized. Furthermore, their research also involves a tactical production technology decision by selecting the green or the regular technology or a combination of both for their production process, each of which is associated with a specific cost and emission level.

Purohit *et al*. (2016) impose cycle service level and emission constraints on their dynamic stochastic lot-sizing problem in which emissions generated from purchasing, ordering and inventory storing activities are recorded. By analyzing different demand patterns, their study shows that the cycle service level and the demand coefficient of variation could have significant impacts on total cost and total emissions while increasing the carbon price can eventually reduce total costs, total emissions and total inventory. Xu *et al*. (2017) extend the conventional cap-and-trade problem by considering a case when the firm can either buy extra credits or adopt green technology in production if its actual emissions exceeds the initial permits that are allocated. Their findings suggest that green technology is preferable as it can technically reduce the amount of emissions generated from production while carbon trade mechanism cannot. They also suggest applying a combination of both techniques could help firms survive and gain more market share.

Qiu *et al.* (2017) incorporate fuel consumption and CO_2 emissions into the pollution-routing and the production inventory and routing problems to form a model for the Pollution Production-Routing Problem (PPRP) under a cap-and-trade system. Along with production and inventory holding costs, their total cost function also covers the cost of lost sales, wages for driver, cost of fuel, and cost of emissions. Several carbon price related insights have been derived from the study: (1) Operational cost and emissions under this integrated optimization model are lower than those obtained from a separate optimization and are more sensitive to changes in the carbon price; (2) An increase of the carbon price can lead to a reduction in emissions but a growth in operational costs; (3) When transportation costs increase, companies operating under this integrated optimization setting or companies with shorter planning horizon are more sensitive to changes of the carbon price.

In most of the studies that entail a carbon cap-and-trade system, the permit trading prices are often assumed to be stationary throughout the planning period while only a few takes into account their fluctuations. An example is the research by Carmona *et al*. (2009) that proposes a model for the equilibrium price formation of emission allowances under the EU ETS setting when the price process is stochastic. Their work identifies the main drivers of variations in carbon prices and also provides foundations to help regulatory authorities in designing market rules when a new emission trading mechanism is being established. Another example is the work by Drake *et al*. (2016) that investigates the incorporation of both the cap-and-trade and carbon tax policies into their technology choice and capacity planning problem, in which a single stochastic emissions price and a constant tax rate is respectively considered. The study by Gong and Zhou (2013) mentioned above also considers stochastic trading prices.

Besides, it is worth to mention that carbon permits buying and selling prices are assumed to be the same in most of the historical studies, only a few studies in the literature differentiate between them, such as Letmathe and Balakrishnan (2005), Gong and Zhou (2013), Chen *et al.* (2013), He *et al.* (2015), Bai and Chen (2016). The rationale for this differentiation is due to (1) the different transaction costs incurred during the permits trading process, which are then reflected in the trading prices, (2) the discrepancy between the bid and ask prices in the trading market, as explained in Gong and Zhou (2013).

Similar to the studies that have been reviewed above, this thesis will examine a production and transportation planning problem under the carbon cap-an-trade system. However, unlike most of the studies, it will also include the cost and emissions of the production process along with those resulted from the inventory holding and transportation activities. Furthermore, we differentiate between allowances buying and selling prices.

2.4.4 Studies with multiple environmental regulations – Carbon tax, carbon cap, carbon cap-and-trade, and/or carbon offsetting

As mentioned in the introduction part, a variety of environmental systems have been designed and implemented by policy makers to curtail GHG emissions. Some of the most common policies are carbon emission tax, strict carbon cap, carbon cap-and-trade, and carbon cap-and-offset. Although they all serve to reduce carbon emissions, each of these regulations would bring about different impacts in terms of cost and emissions (Hoen *et al*., 2014). Therefore, many researchers have involved two or more of these regulations in analyzing different aspects of a supply chain.

Letmathe and Balakrishnan (2005) develop two mathematical models to determine the optimal product mix and production quantity in the textile and food industries under three different environmental conditions, i.e., threshold emission values, trading of emission allowances, penalties and taxes, corresponding to the carbon cap, carbon cap-and-trade, and carbon taxing policy. Benjaafar *et al*. (2013) have provided a general examination on a firm's reaction in the presence of different emission regulations by introducing a set of simple mathematical models involving emissions from production, transportation and inventory planning. Their study also investigates the possibility of collaboration among firms within the same supply chain and its potential impacts on the total cost and emission levels. Their experimental results disclose that reducing emissions could be tremendously less costly if firms within the same supply chain collaborate (e.g., by placing orders jointly) in their cost-minimizing operation structure.

Arslan and Turkay (2013) revise the standard EOQ model under five different environmental regulations (direct accounting, carbon tax, direct cap, cap-and-trade, and cap-and-offset) to analyze the effectiveness of these policies on the sustainability of the firm's supply chain. Their study shows that mechanisms involving a cap (direct cap, cap-and-trade, cap-and-offset) are most effective in driving organizations towards greener regulatory policies. Toptal *et al*. (2014) also investigate their integrated inventory control and emission reduction investment model using these emissions curbing policies, with an aim to assist policy makers in understanding the impacts of each regulation on the profitability of the company and the role of green technologies in its cost and carbon footprint level. They find out that, under carbon tax and cap-and-trade, the availability of carbon emission reduction investment can further reduce carbon emissions along with reducing costs. Therefore, they suggest governments to encourage green technology application when these two policies are in place.

Bai and Chen (2016) address a newsvendor model with a dual sourcing policy of a retailer under carbon tax and carbon cap-and-trade, respectively. Numerical solutions are analyzed and compared in terms of replenishment lead times and order quantities from the two supply sources. Their study has provided useful managerial insights for authorities in setting up the carbon tax rate or carbon cap in the reality.

In transportation mode selection problems, Hoen *et al.* (2014) have developed an emission-measuring methodology based on empirical data to analyze the trade-offs between inventory, transportation, and emission costs, with an aim to find the most appropriate transportation mode among air, road, rail, and water for a given product type. They also investigate the effect of various regulations in terms of emissions on the selected transport mode and its corresponding emission values. Nonetheless, in their study, emission related costs are found to have little influence on the firm's optimal decision, hence, adding those costs into consideration could barely change the selected mode. Similarly, Jin *et al.* (2014) investigate how different carbon policies influence the supply chain network design and transportation mode selection of major retailers, who are believed to account for a huge amount of freight movement. Their findings imply that involving multiple sourcing options and redesigning the supply chains of those retailers are essential to achieve a drastic decline in emissions, and merely shifting to a more energy-efficient transportation mode cannot effectively reduce emissions.

In analyzing the efficiency of carbon abatement policies, Mandell (2008) divides emitters within an economy into two groups (some are subjected to an emission tax and the others follow cap-and-trade rules) and then compares the efficiency of this structure to that of the uniform policy where all emitters are confronted to only one mechanism. His experiment reveals that applying two instruments simultaneously can be superior to adopting only one regulation. Similarly, He *et al.* (2012) compare the effectiveness and the efficiency of the two most common systems, i.e., carbon tax and carbon cap-and-trade, under a generation expansion planning framework in a competitive electricity market. According to them, the two systems are different in the sense that cap-and-trade focuses on policy effectiveness when it explicitly limits the total emission quantity by the cap but its carbon price is contingent on the market, while carbon taxing emphasizes policy efficiency with a predetermined tax rate but on the contrary, the extent of emission reduction has to depend on the market manipulation. Given the fact that cap-and-trade and carbon tax are the two most widely adopted schemes in practice (Bai & Chen, 2016), there exist contrasting points of view on their practicality. Supporters of the carbon tax regime (e.g., Metcalf, 2009, as cited in Jaber *et al*., 2013 and Drake *et al*., 2016) argue that the volatility in emission allowances price under cap-and-trade could negatively influence a firm's profit. However, in their own experiments, Drake *et al.* (2016) have contradictorily found out that the uncertain emissions price in cap-and-trade mechanism could generate greater expected profit than the constant carbon tax price.

In general, the main objective of these above-mentioned models is to measure the effectiveness and compatibility of each policy. Most of them have shown that different emission schemes can have distinct impacts on the total cost and emissions reduction, and how to choose policy parameters plays a critical role in determining the effectiveness of a carbon policy. They also imply there are certain challenges during the implementation of carbon policies, e.g., a high carbon tax rate could prevent businesses from adapting the policy, or it is difficult for companies and policy makers to obtain an agreement on the carbon caps (Jin *et al*., 2014).

A summary of these relevant studies considering one or more emission regulations can be found in Table 2.4-2.

Table 2.4-2: Studies with the carbon cap-and-trade and other emission legislations

Authors	Legislations				Allowance buying/selling prices	
	Carbon cap	Carbon tax	Cap-and-trade	Cap-and-offset	Equal	Differentiated
Letmathe and Balakrishnan (2005)	✓	✓	✓			✓
Mandell (2008)		✓	✓		✓	
Carmona *et al.* (2009)			✓		✓	
Hua *et al.* (2011)			✓		✓	
He *et al.* (2012)		✓	✓		✓	
Song and Leng (2012)	✓	✓	✓			✓
Arslan and Turkay (2013)	✓	✓	✓	✓	✓	
Benjaafar *et al.* (2013)	✓	✓	✓	✓	✓	
Zhang and Xu (2013)			✓		✓	
Gong and Zhou (2013)			✓			✓
Chen *et al.* (2013)	✓	✓	✓	✓		✓
Toptal *et al.* (2014)	✓	✓	✓		✓	
Hoen *et al.* (2014)	✓	✓	✓		✓	
Jin *et al.* (2014)	✓	✓	✓			✓
He *et al.* (2015)		✓	✓			✓
Purohit *et al.* (2016)			✓		✓	
Bai and Chen (2016)		✓	✓			✓
Drake *et al.* (2016)		✓	✓		✓	
Xu *et al.* (2017)			✓		✓	
Qiu *et al.* (2017)			✓		✓	
This study			✓			✓

2.5 Emissions measurement techniques

In recent years, many efforts have been made by firms and authorities to quantify the emissions from their activities as a response to the regulatory legislations by which they are confronted, or as an instrument to communicate the carbon footprint index of their products to consumers. Given the fact that more companies have been required to trim down their carbon emissions, the need for companies to monitor their carbon footprint is growing. As such, effective measuring tools play a critical role in a company’s efforts to evaluate its environmental impact. In a 2013 study, Absi *et al*. have mentioned several methodologies for calculating carbon emissions, such as Greenhouse Gas Protocol, ARTEMIS, EcoTransIT, etc., in which GHG Protocol is the most commonly used technique worldwide. The first part of this section will provide a brief introduction to the GHG Protocol while the latter parts will present a review of the emissions measuring mechanisms that have been employed in the academic studies, focusing on the production, inventory holding, and transportation activities. It should be noticed that before measuring emissions, one common implicit assumption to be made by every emission regulatory policy is that those carbon emissions are measurable and quantifiable.

2.5.1 Greenhouse Gas Protocol

Greenhouse Gas Protocol, run by the World Resource Institute and the World Business Council for Sustainable Development, is a Non-governmental organization (NGO) - business partnership with the aim to establish global standardized frameworks to measure and manage GHG emissions from the operations and value chains of the public and private sectors such as governments, industry associations, businesses and other organizations. The Protocol comprises various types of standards, among which Corporate Standard is aimed to help companies prepare their emissions accounting and reporting by providing a five-step calculating process as shown in Figure 2.5-1. Before calculating a company's emissions, it is critical to categorize the sources of GHGs within its boundaries. Emissions generally fall within the following four major sources: 1) stationary combustion – the combustion of fuels in stationary equipment such as boilers, turbines, engines, etc.; 2) mobile combustion – the combustion of fuels in transportation devices such as automobiles, trucks, buses, etc.; 3) process emissions – emissions from physical or chemical processes such as CO_2 from the calcination step in cement manufacturing or the PFC emissions from aluminum smelting, etc.; and 4) fugitive emissions – the intentional or unintentional releases such as equipment leaks from packing, joints, seals as well as fugitive emissions from coal piles, gas processing facilities, wastewater treatment, etc. (GHG Protocol, n.d.).

Under the GHG Protocol, emissions are classified into 3 scopes: Scope 1 emissions are direct emissions generated from owned or controlled assets/sources. Scope 2 emissions are indirect emissions from the consumption of purchased energy (e.g., electricity, heat, steam). Scope 3 emissions refer to all the other indirect emissions from a company's upstream or downstream activities as well as emissions from outsourced or contracted activities that are not included in scope 1 and 2. With the inclusion of scope 3 emissions, companies are able to expand their emissions inventory boundary along their value chain and to identify all of its relevant GHG emissions.

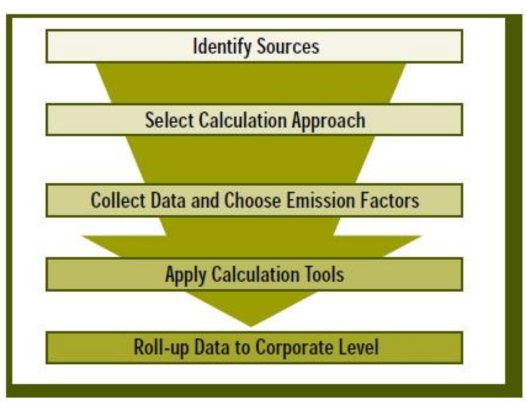

Figure 2.5-1: Steps in identifying and calculating GHG emissions
(Source: GHG Protocol, n.d.)

There are several techniques to measure emissions, ranging from the application of generic emission factors, fuel usage data, to direct monitoring. The method of measurement based on emission factors is the most common, in which GHG emissions are converted into carbon dioxide equivalent quantity CO_2e (Chaabane *et al*., 2010).

The **emission factor** is the estimated average emission rate of a certain pollutant released to the atmosphere associated with a particular activity (Mtalaa *et al*., 2009). They are usually expressed as the weight of pollutant divided by a unit weight, volume, distance or duration of the emitting activity. For instance, it can be the amount of CO_2 emitted by the combustion of one liter of fuel in a certain engine, or kilograms of particulate emitted per megagram of coal burned, etc.

Table 2.5-1 presents the CO_2 emission factors for the mobile combustion of major fuel types provided by the U.S. Environmental Protection Agency. Interested readers can refer to the website of EPA for the latest version of the full list of Emission factors for Greenhouse gas inventories (U.S. EPA, 2020).

Table 2.5-1: Mobile combustion CO_2

Table 2.5-1: Mobile combustion CO_2

Fuel type	Kg CO_2 per gallon
Residual Fuel Oil	11.27
Diesel Fuel	10.21
Kerosene-Type Jet Fuel	9.75
Biodiesel (100%)	9.45
Motor Gasoline	8.78
Aviation Gasoline	8.31
Ethanol (100%)	5.75
Liquefied Petroleum Gases (LPG)	5.68
Liquefied Natural Gas (LNG)	4.50
Compressed Natural Gas (CNG)	0.05444*

*per standard cubic foot (scf)

Source: U.S. EPA (2020)

2.5.2 Production and inventory emissions measuring techniques

Greenhouse gas emissions in **production activities** are usually associated with the amount of energy consumed in machine setups plus the variable emissions per unit produced. While production processes are believed to account for a certain proportion of a manufacturing firm's GHG emissions, only few papers have explicitly presented its measurement method.

The works by Jaber *et al*. (2013) and Castellano *et al.* (2019) both calculate emissions from their production processes (in ton per quantity unit) based on the function described in Bogaschewsky (1995), according to which a firm's energy consumption is correlated to its production rate. This calculation method has been backed up by several researchers as they have found similar patterns of energy consumption in different production processes (as referred in Jaber *et al*., 2013).

Apart from the direct emissions generated during the production process, a recent study by Malik and Kim (2020) also integrates the indirect emissions from the sources that are not directly controlled by the firm but related to its production system. They calculate these indirect emissions by estimating the electric energy consumptions (kWh), rate of loss energy (%), and the cooling/heating/steam energy consumptions (kWh) used to produce a production lot.

Regarding **inventory control** in logistics, emissions in storage buildings (depots, warehouses) arise from the direct burning of fossil fuels to generate heat and electricity that are used to facilitate their operations, hence, their energy consumption depends primarily on the type of product being stored. Storage of frozen or perishable goods would require specific space and equipment, involving a larger amount of energy required. In the literature, many studies have measured the emissions of a storage facility based on its electricity consumption rate and its capacity, measured by the size of the warehouse measured in square feet/m^2 (area) or m^3 (volume) (e.g., Harris *et al.*, 2011; Mallidis *et al.*, 2014; Turkensteen & van den Heuvel , 2019), while some others tend to focus on the energy usage (e.g., Bozorgi *et al*., 2014).

A research in 2011 by Harris *et al.* has examined the emissions of a firm's storage facilities by estimating the annual electricity consumption per warehouse, where specific storing conditions (heating or cooling) is not necessary. The amount of energy consumed is then converted into CO_2 emissions through a conversion factor:

$$CO_2 \text{ emissions (kg)} = \text{Electricity consumption} \times \text{Conversion factor} \times \text{Area of depot}$$

where, electricity consumption is in kWh/m^2, conversion factor is in kg CO_2/kWh and varies by country.

Mallidis *et al.* (2014) apply the same method in measuring the level of emissions for their distribution centers (DCs), with an assumption that emissions per time unit of a DC is non-linearly related to its capacity. However, instead of measuring the area of the DC (in m^2), they measure its capacity in volume (cubic meters m^3), therefore, in this case, the electricity consumption is in kWh/m^3. They have examined various sized DCs in the study, each with associated cost and emissions indicators as summarized in Table 2.5-2.

Table 2.5-2: Capacity and cost parameters for various sized DCs

Capacity (m^3)	Operating costs €/day	CO_2 emissions tons/day
100,000	2740	0.36
39,580	2192	0.26
32,400	1579	0.28
14,112	667	0.14
8400	700	0.08
2000	217	0.05
1000	150	0.04

Source: Mallidis et al. (2014)

More recently, Turkensteen and van den Heuvel (2019) relate their warehouse emissions to the storage space needed to store the items instead of its actual inventory level, this means no unit holding emissions is considered in their case. They come up with a median emission rate for an average warehouse by reviewing the emission indicators presented in various studies from different nations, which is approximate 33 kg per m^2 per year. Similar to the other studies, the authors do not consider specific storing requirements (freezing or heating) and according to them, up to their paper, there are no studies that explicitly consider the exact number of units in inventory as a key driver of carbon emissions.

With regard to temperature sensitive products, a study by Bozorgi *et al.* (2014) has proposed the use of modular temperature-control units in storing inventory. These units have been widely applied within the industrial sector in the form of segmented industrial freezers, partitioned cold rooms, walk-in coolers, etc. With this structure, the emissions generated from holding inventory is determined by the quantity of cold items held in inventory (or the number of freezers needed), the total energy consumption of a freezer within the planning horizon, and the total carbon footprint of 1 kW energy.

It is worth to mention that most of the studies only consider the direct emissions from operating the storage units (scope 2 of the emissions in the GHG Protocol), they do not include emissions from building the warehouse and the commuting of the staffs operating it. Considering the complication in accounting all the indirect emissions generated all the way upstream and downstream, this study will also consider the direct emissions falling within the scope 2 boundary of the protocol, interpreted as a unit holding emissions per time unit (which is assumed to include both the emissions from operating the warehouse and the emissions from holding one item of inventory from one period to the next).

2.5.3 Transportation emissions measuring techniques

In terms of the emissions from transportation, different transportation modes such as air, road, rail, or marine are bound to emit varying amounts of greenhouse gases (Bauer *et al*., 2010). A recent report by Wiginton *et al.* in 2019 shows that in Canada, 10.5% of greenhouse gases emissions are from freight transportation, a predominance of which are generated from heavy-duty trucks. Heavy-Duty Diesel (HDD) vehicles make up only a small proportion of the road transportation, yet with their built-in high durability and reliability along with the increasing volume in goods movement, they have become the major contributor to the overall emissions inventory (Barth *et al*., 2005). This section will focus on discussing the emissions measurement techniques employed in road transport.

An early work from 1997 by Marc Ross provided a greenhouse gases estimation method based on the amount of energy required to perform the related transportation operations. According to him, energy consumption is determined by the vehicle mass, total tractive power, and the efficiency of the vehicle powertrain (components that generate power like engine and transmission). For electrical vehicles, the total power needed can be directly converted into carbon emissions using a conversion factor of electricity supply. In the case of combustion engines, the emissions level is computed by multiplying the amount of power needed for the fuel combustion process and the CO_2 content of the fuel. This method has been used by many other researchers in the similar field.

Barth *et al.* (2005) model the emissions of Heavy-Duty Diesel vehicles as the product of three components: fuel rate, engine-out emission indices (grams of engine-out emissions per gram of fuel consumed), and any emission after-treatment pass fraction (the ratio of tailpipe to engine-out emissions). Their model enables the possibility to measure in-time emissions and to perform simulations on a wide variety of traffic scenarios.

A work by Mtalaa *et al.* in 2009 provides a comprehensive review of the prevailing measurements and models that are used to calculate carbon emissions from truck transportation. According to them, the two most popular types of model that have been widely applied in the literature are the "Average speed models", which account for vehicle dynamics using the concept of average speed and the "Micro-scale models", which apply second-by-second speed profiles of a vehicle to calculate its fuel consumption and emissions of a particular trip. In terms of calculation tools, direct methods that use emission factors are employed if the actual energy consumptions (of petrol, diesel, etc.) are known, otherwise, indirect methods will be used if at least one of these requisite indicators – the average fuel consumption and the overall distance driven, the traffic flow (in vehicles.km), or the total amount of freight transported over one kilometer for each vehicle type (in tons.km), is available. However, their study shows that even when many various models have been developed, their precision in computing the carbon emissions remains a concern. In the same year, a work by McKinnon *et al*. that examines different methods of carbon auditing within the road freight transportation sector of the United Kingdom also highlights the difficulty in collecting an accurate and consistent set of emissions data for trucking. The main reason why it is so complex to quantify carbon emissions linked to transportation is the high number of parameters that affect these emissions. These factors are often grouped into several categories: travel-related factors (driving patterns, distance travelled, average speed, degree of acceleration, load on the engine), driving behaviors (drag force, resistance, smoothness and consistency of vehicle speed), vehicle characteristics (fuels, devices, engine size and type, vehicle mass), and external conditions (temperature, humidity, altitude, wind speed and direction) (Mtalaa *et al*., 2009; Harris *et al*., 2011; Turkensteen & van den Heuvel, 2019).

In road transport, when calculating emissions, one common assumption used by numerous researchers is that each empty truck is associated with a fixed amount of emissions and the overall emissions generated by a truck depends on its load and the distance travelled (Konur *et al*., 2014; Hoen *et al*., 2014; Darvish et *al*., 2017). Therefore, the total number of trucks used along with their loads will determine the total emissions of the retailer's transportation activities. A similar emissions function has also been mentioned in Konur (2014) and Hoen *et al.* (2014).

The existing literature on a firm's transportation planning decisions comprises research that employs a single truck type or multiple truck types. From the perspective of considering a single truck type in transportation planning, the research of Bektas and Laporte (2011) introduces a Pollution-Routing problem (PRP), an extension of the traditional Vehicle Routing Problem (VRP), that accounts for greenhouse gas emissions, fuel, travel times and costs. The emission function in their study is determined by the vehicle load, speed and other factors, all of which generate the estimation of the energy requirement in joules ($J = kg.m^2/s^2$) which is then directly converted into fuel consumption (using an energy efficiency rate) and further into GHG emissions (using an emissions factor). Their emissions measurement is distinctive from other existing models in the sense that it reflects the change in vehicle load as the vehicle travels as opposed to an assumed constant load throughout the trip. The study by Qiu *et al*. (2017) also applies this formulation in measuring its emissions from vehicle routing activities in its single-vehicle Pollution Production-Routing Problem, where a single supplier produces a single product to serve a set of retailers who are visited only once by one truck (one tour per period).

Jabali *et al*. (2012) introduce an Emissions-based Time-Dependent Vehicle Routing Problem (E-TDVRP) where the vehicle speed changes throughout the day, i.e., when the vehicle experiences free flow speed periods and the periods with congestion, rather than a single constant speed that is commonly assumed by previous studies. In their model, the vehicle speed limit is explicitly a part of the optimization and the emissions per kilometer is formulated as a function of speed which is minimized at a certain speed value.

On the other hand, some authors consider multiple truck types in their transportation planning problems. In the analysis of a US beverage industry, Daccarett Garcia (2009) illustrates that fleet management (truck configuration) has potential significant influences not only on transportation costs but also on the carbon emissions it generates. In a study conducted in 2014, Konur shows that compared to single truck type shipment, multiple truck types shipment can not only reduce costs but also emissions. Harris *et al.* (2011) have provided a distance-based formula that calculates the carbon emissions for each vehicle type: *Total CO_2 (kg) = total distance travelled × fuel consumption rate × fuel conversion factor*, where the fuel consumption rate is calculated based on the vehicle type, speed, and payload. A fuel conversion factor of 2.63 kg/l is used for diesel fuel. Turkensteen and van den Heuvel (2019) compute the emissions of their medium and large trucks based on the assumption that emissions of a vehicle increase linearly with the weight of its load. They measure the emissions of the empty vehicle *e'* (fixed emissions per shipment) and of the fully loaded vehicle *f'* (with known maximum payload capacity) to derive the emissions related to the size of the shipment, which is *e' + U (f' – e')*, where *U = actual load/payload capacity* is the percentage of the vehicle's load. They also differentiate emissions generated between Highway and Urban driving conditions.

Apart from considering two vehicle types – heavy-duty and delivery trucks, Mallidis *et al.* (2014) also take into account the cost and the emissions of the truck's return trip in their transportation planning problem. The cost of the return trip is assumed to be 80% of the forward trip (due to the reduction of fuel consumed by an empty truck) whereas its emissions per km of an empty truck will be approximately 30% less (considering lower loading factors on the return trips).

This thesis considers a setting where the firm has different types of trucks available for its transportation from the factory to its storage facility, they are medium-duty trucks and heavy-duty trucks, each associated with a distinct capacity, per truck cost, and emissions indicators. For emissions measurement, we will apply the emission features provided by Turkensteen and van den Heuvel (2019) as presented later in Table 4.2-1.

Chapter 3. Model formulation

Before developing the two-stage stochastic lot-sizing model, a deterministic version of the model will be presented as the baseline model. Under the deterministic setting, demand per period is known with certainty while in the stochastic model, demands are uncertain and modelled by different scenarios, and the firm's decisions are made at two different stages. The goal of both models is to find the optimal lot-sizing schedule and the amount of emission permits to buy at the lowest level of cost while meeting demand and environmental constraints.

3.1 Problem definition and assumptions

This study considers a problem in which a firm manufactures a single product with stochastic demand over a planning horizon of m periods, and each period is associated with a demand level d_t. The scope of the study is limited to a two-level supply chain: a product is produced at a factory and shipped to a central warehouse. Afterwards, the goods will be delivered to the customers, but this is not part of the model. The problem defined comprises main activities from production, finished product shipping and inventory holding. Beside these operational decisions, the firm also needs to make decisions on the trading of emission allowances as we consider our firm is subject to the carbon cap-and-trade system. Under this system, the firm's carbon footprint from all the main operations needs to be recorded and reported. It is necessary for the firm to own enough emission allowances (which it can purchase from an emissions trading market) at the end of the planning horizon to cover its total emission level. Each of the major operational activities, i.e., production, transportation, and inventory holding, entails costs and emissions. The firm's objective is to find the optimal production, distribution, and emissions trading schedule to minimize its expected total cost over the planning horizon. A more detailed problem description for each activity will be given next.

- **Production**

We consider a single product problem. At the factory, whenever there is production, a machine setup needs to be conducted at a fixed cost and the production system can produce up to its available capacity per period. Yet the machine setup condition cannot be carried over to the next period, meaning that if the firm wishes to produce in the next period, another setup is required. In addition to the fixed production cost (for each setup), a unit variable cost is incurred per unit of produced item. The production quantity at a given period is not necessarily equal to the demand of that period, meaning that the firm may produce a certain quantity of products in advance and keep it as inventory to satisfy future demands. However, no backorders are allowed as we assume that demand in each period must be satisfied on time.

- **Inventory control**

After the manufacturing process, finished products are either stored temporarily at the storage area of the factory (referred to as factory warehouse) or transported directly to a central warehouse. Each of the storage facilities is characterized by a capacity level (in units) and an inventory holding cost. In this study, the inventory holding cost refers to the variable cost of holding one unit of product in inventory per time period. It consists of the physical handling cost, opportunity cost, utility and maintenance costs, insurance, and cost of obsolescence, etc. Other fixed costs such as facility acquisition or rental fee, labor cost, are considered sunk costs and will not be included in the scope of this study.

- **Transportation**

There are two types of vehicles being used in this study: medium-duty trucks and heavy-duty trucks, each with an associated load capacity and fixed cost. We assume that the firm has its own fleet and either type of the vehicles or a combination of both can be used to transport goods from the factory to its central warehouse. The load capacity of a truck type is determined based on several factors, i.e., the gross vehicle weight rating (GVWR) (the maximum allowable total weight of the vehicle including its empty mass, fuel, and any load carried), curb weight (the empty weight or the total vehicle mass with all the necessary equipment and fuel except for passengers and cargo), the unit weight of the product. This load capacity is measured as a maximum number of units of product carried. The fixed cost per truck, which comprises depreciation costs, driver's expenses, maintenance fee, fuel and toll costs per trip, is always applied regardless of whether the truck is fully loaded or not. In other words, our model applies full truck-load rate in calculating costs for transportation.

- **Carbon cap-and-trade system**

Different from the traditional lot-sizing problem, this study considers a firm subjected to the carbon cap-and-trade system where the total emission level of the firm is constrained by a carbon cap. In practice, this carbon cap can be obtained from the free allocation of the government and/or by obtaining emission rights through auctions in the emission trading market. To facilitate our emission trading model, we assume that our firm belongs to the industry sector where initial emission rights need to be bought through the auctioning process, at a market-determined price, to cover all of its emission activities. At the end of the planning horizon, the firm can make further decisions on buying or selling additional/excessive allowances in the market to ensure that its carbon footprint complies with the carbon cap restriction. At the end of the planning horizon, the firm needs to keep a non-negative balance in its allowance account to avoid penalties. Unlike most studies in the literature where one single carbon trading price is considered, we assume three different trading prices: 1) a buying price in the first stage (corresponding to buying the permits upfront in a long-term market), 2) a buying price in the second stage (corresponding to buying additional permits at the end of the horizon in a spot market) and 3) a selling price in the second stage (corresponding to selling excessive permits at the end of the horizon in the spot market). We also assume that these prices are known in advance and not subject to any uncertainty. Furthermore, to guarantee the feasibility in implementing the cap-and-trade system, it is necessary to assume that there is no limit on the amount of emission allowances that the firm can buy or sell, and there is always sufficient supply and demand of emission allowances in the market.

- **Emission measurement**

Regarding the measurement of emissions, aside from the two common factors considered in the literature - the ending stock level in inventory control and the vehicle dispatching decisions in transportation, our research, similar to Qiu *et al*. (2017), also considers the emissions generated from machine setups and production processes. However, due to the wide range of potential factors that can influence these emission patterns, it is often complex for firms to provide accurate measurements on their actual emission levels. A key principle in calculating a firm's carbon footprint is thus to limit its emissions to the most relevant sources that are closely related to the decisions it takes (Harris *et al*., 2011; Turkensteen & van den Heuvel, 2019). Therefore, in our model, the function of total emissions (*TE*) only comprises the fixed and variable emissions from production and transportation, and the variable emissions from holding inventory at both storage facilities. The fixed emissions are calculated based on the number of machine setups in production as well as the number of vehicles used in transportation. Meanwhile, the variable emission levels are respectively modelled as a function of the quantity of items produced, the number of finished goods being delivered, and the inventory level being stored at warehouses.

More precisely, in production, we limit the emissions to those directly generated from the machine setups and the production processes, which are generally powered by the "purchased electricity" from an electricity supplier. This corresponds to scope 2 of the GHG Protocol. Similarly, in stock keeping, we only consider the emissions generated from the use of electricity in operating the warehouse and storing products, excluding the emissions due to warehouse construction and the commuting of the personnel operating it. At the same time, for the base case, we assume that the product being considered does not need specific storing conditions (cooling, freezing or heating) which, otherwise, would create a major increase in the emission level due to the significant extra amount of energy required. In transportation, we consider the direct emissions from the combustion of purchased fuel and ignore the emissions related to extraction and production of fuel. In our study, the transportation fleet is owned by the company, thus these transportation related emissions will be reported as scope 1 emissions of the company (i.e., the direct emissions from sources owned or controlled by a company according to the GHG Protocol) and are counted as part of the emission Cap. In the case that the transportation activity is outsourced to a third-party logistics provider (3PL), the company will report these emissions in scope 3 (indirect emissions) and they will not be included in its emission quota. This scenario will not be included in the scope of this study.

To enable the model's feasibility and for simplification purposes, there are some further assumptions being made:

- The demands in different time periods are independent and identically distributed random variables, meaning that the realization of demand in a period does not depend on the realization of the previous period.
- Within a planning period, first the production is done. The demand is satisfied at the end of the period and the inventory is calculated as the ending inventory after production and demand satisfaction.
- The buying and selling prices for the emission permits are different and deterministic. Similar to the work of Hua *et al*. (2011), Chen *et al*. (2013) and He *et al*. (2015), uncertainty in selling and buying prices is not considered.
- The buying price for the emission permits in the spot market (stage 2) is more expensive than the buying price in the long-term (or future) market (stage 1). Otherwise, it would be optimal to buy no permits in stage 1 and buy all the additional permits in stage 2. Furthermore, the selling price for the emission permits in the spot market (stage 2) is lower than the buying price in the long-term market (stage 1). Otherwise, it would be optimal to buy as many permits as possible in the first stage.
- There is a sufficient number of vehicles available to be used whenever a dispatching decision is made.
- All the cost and emissions parameters are known and remain constant over time and in different demand scenarios.
- Some factors related to transportation emissions such as driver behavior, road conditions, traffic, etc. are ignored.
- Lead times due to production, inventory handling and transportation are not considered.
- The initial inventory levels at both warehouses are assumed to be 0.

3.2 Mathematical notation

The mathematical notation for the deterministic model is presented in Table 3.2-1. These parameters are fixed and known in the deterministic model. In the stochastic model, the demand is stochastic and will depend on the scenario.

Table 3.2-1: Notation for the deterministic model

Notation	Description
Sets	
T	Set of time periods {1, 2, 3, …., m}
K	Set of vehicles {medium-duty = 0, heavy-duty = 1}
I	Set of facilities {0 = factory, 1 = warehouse}
Parameters	
d_t	Demand at time period t
$Pcap$	Production capacity at factory in each period (units)
$Icap_i$	Inventory storage capacity at facility i (units)
$Vcap_k$	Capacity of vehicle type k (units)
r	Buying price of emission allowances
pfc	Production fixed cost (machine setup)
pvc	Production variable cost per unit produced
hc_i	Cost of holding one unit of product at facility i for one period
vfc_k	Fixed cost per trip of using one vehicle of type k
vvc_k	Variable cost per unit carried by vehicles of type k
pfe	Production fixed emissions (from machine setup)
pve	Production variable emissions per unit produced
he_i	Emissions from holding one unit of product at facility i for one period
vfe_k	Fixed emissions of using one vehicle of type k
vve_k	Variable emissions per unit carried by vehicles of type k
TE	Total emissions from production, inventory holding and transportation
TC	Total cost from production, inventory holding and transportation
Decision variables	
R'	Emission allowances to buy at the beginning of the planning horizon
x_t	Production quantity at time period t
v_{kt}	Quantity transported by vehicle(s) of type k from the factory to the warehouse at period time t
inv_{it}	Inventory kept at facility i at the end of time period t
z_{kt}	Number of vehicles of type k to use at time period t
y_t	Production setup decision at time period t (equals to 1 if there is production in period t, 0 otherwise)

3.3 Deterministic model

We first model the above-mentioned problem as a Mixed-Integer Linear Program with deterministic demands, with the objective to minimize the total operational cost while complying with the predetermined emissions quota. The deterministic demand data are assumed to be the results of forecasting. In the objective function (1), the first term is the cost of buying emission allowances at the beginning of the planning horizon. In the deterministic model, since demand is known with certainty, the firm simply purchases the exact amount of emission permits needed upfront. Therefore, we do not model the possibility of the firm buying or selling allowances at the end of the planning horizon. The second and the third term in the objective function is the fixed and unit variable production cost, respectively. The fourth term represents the total cost of holding products in inventory. The last two terms are the transportation fixed and variable cost, respectively.

$$\text{M}inimize\text{:}\ TC = rR' + \sum_{t\in T}[\,pfc\ y_t +\ pvc\,x_t + \sum_{i\in I} hc_i\,inv_{it} + \sum_{k\in K}(vfc_k\,z_{kt} + vvc_k\,v_{kt})\,] \quad (1)$$

In production, a machine setup is required for the manufacturing process to be activated, represented by the binary variable y_t. Furthermore, the production quantity per period is limited by the capacity of the production line, denoted by *Pcap*, as well as the total remaining demand over the rest of the planning horizon, as integrated in constraint (2). With this constraint, if a setup decision is made (y_t = 1), the number of products produced in period *t* should not exceed either the production capacity or the remaining demand accumulated from that period to the end of the planning horizon, whichever is the smaller value. Otherwise, if no setup is conducted in period *t* (y_t = 0), there will be no production at all.

$$x_t \le min\left(Pcap, \sum\nolimits_{l=t}^{m} d_l\right) y_t \qquad \forall t \in T \qquad (2)$$

Constraint (3) and (4) represent the product flow conservation (or inventory balance) constraint at the factory warehouse and the central warehouse, respectively. At the factory warehouse, the total production quantity in period *t* plus the inventory amount from the preceding period is equal to the quantity shipped to the main warehouse plus the inventory level kept at the end of that period. Similarly, at the central warehouse, the incoming number of products transported from the factory plus the ending inventory in the previous period is equal to the customer demand plus the ending inventory at that time period. These constraints are to ensure that within one storage facility, its inflow and outflow are balanced, and demand is satisfied.

$$inv_{0,t-1} + x_t = \sum_{k\in K} v_{kt} +\ inv_{0t} \qquad \forall t \in T \qquad (3)$$

$$inv_{1,t-1} + \sum_{k\in K} v_{kt}\ = d_t + inv_{1t} \qquad \forall t \in T \qquad (4)$$

Constraints (5) and (6) impose the limitations on the storage capacity of the warehouses. For any given period *t*, the sum of the ending inventory from the preceding time period and the input quantity of that period, i.e., the production lot-size in the case of factory storage or the total amount being delivered from the factory in the case of central warehouse, can never exceed the upper limit of that storing facility, denoted by $Icap_0$ and $Icap_1$, respectively.

$$inv_{0,t-1} + x_t \leq Icap_0 \qquad \forall t \in T \tag{5}$$

$$inv_{1,t-1} + \sum_{k\in K} v_{kt} \leq Icap_1 \qquad \forall t \in T \tag{6}$$

Similarly, in transportation, the total number of units being transported by a certain vehicle of type *k* is restricted by its total available capacity, which is the multiplication of the load capacity of that vehicle type $Vcap_k$ and the actual number of vehicles utilized in that period z_{kt}, as shown in constraint (7).

$$v_{kt} \leq Vcap_k \, z_{kt} \qquad \forall k \in K, \forall t \in T \tag{7}$$

Constraint (8) sets a limit on the total amount of carbon being emitted from all of its production, inventory and transportation activities. This upper limit is also known as the carbon cap in the cap-and-trade system and corresponds in this case to the total amount of permits purchased. On the left-hand side of the inequality (the *TE*), the first two terms represent emissions from the production process, including the total fixed emissions generated from machine setups and the variable emissions from producing each unit of item. The third term corresponds the total emissions resulting from keeping products in inventory at the two facilities. The summation of emissions from transportation activities is displayed through the last two terms, which respectively represent the total fixed emissions in truck-dispatching and the incremental emissions based on the actual vehicle load. The total number of emission permits purchased *R'* (carbon cap) is on the right-hand side of the constraint.

$$TE = \sum_{t\in T} [\, pfe\, y_t + pve\, x_t + \sum_{i\in I} he_i\, inv_{it} + \sum_{k\in K} (vfe_k\, z_{kt} + vve_k v_{kt}) \,] \leq R' \tag{8}$$

The remaining constraints impose the domain of those decision variables mentioned above. Constraint (9) states that the production quantity, the number of items being transported, and the emission allowances purchased are real numbers with positive values. Constraint (10) ensures that the numbers of vehicles utilized are positive integers. Finally, constraint (11) imposes the binary characteristic of the production setup decision.

$$x_t, v_{kt}, inv_{it}, R' \in R \text{ and } \geq 0 \qquad \forall k \in K, \forall t \in T, \forall i \in I \tag{9}$$

$$z_{kt} \in Z \text{ and } \geq 0 \qquad \forall k \in K, \forall t \in T \tag{10}$$

$$y_t \text{ binary} \qquad \forall t \in T \tag{11}$$

3.4 Two-stage stochastic model

Next, we transform the deterministic model in Section 3.4 into a two-stage stochastic MILP model, where demand in each period is unknown and varies throughout the *m* periods. The first-stage decision R_1 relates to the number of emission allowances that the firm needs to buy (through auctioning) in the long-term market at the beginning of the planning horizon in order to cover its emitting activities. The first stage buying price is denoted as *s1b*.

In this two-stage model, we assume that the demands for all *m* periods are revealed simultaneously, which is in line with other studies on stochastic lot-sizing (Adulyasak *et al.*, 2015; Sereshti *et al.*, 2020; Gruson *et al.*, 2020). At the second stage after uncertain demands are realized, the firm decides on the production and transportation plan, depending on the realized demands. At this stage, there are also recourse decisions on the trading of emission allowances that the firm needs to make in order not to violate its emission right. More specifically, the company determines whether it needs to buy or sell extra allowances on the spot market and how many to trade. Depending on the realized demands and the firm's lot-sizing and distribution schedule, there are three possible scenarios in the allowances trading: (1) The firm has initially bought the exact quantity of permits needed for its operational activities, thus no trading occurs in the second stage; (2) the firm did not purchase a sufficient number of permits at stage 1 to cover its carbon footprint, hence it needs to purchase the missing permits at stage 2 at a higher market price; (3) the firm bought more than the level of permits needed, so it sells the excessive units at the end of the planning horizon, albeit accepting a partial loss due to the lower selling price. Therefore, in the stochastic model, the total cost function will include the cost (or the revenue) from buying (or selling) the extra emission permits in the second stage.

To model the uncertainty in demand, we use a set of scenarios $S = \{1, 2, \ldots, n\}$. Each scenario is associated to a different set of random demands, the values of which are assumed to follow a uniform distribution. In each scenario, a total of *m* demand realizations is generated, corresponding to the demands for *m* time periods. With this stochastic element, all the decision variables in the deterministic model (except for stage 1 allowances R_1) need to be modified with an additional scenario index *s*. We also add two new variables R_{2+}^s, R_{2-}^s which represent the emission allowances to buy and the number of allowances to sell at the second stage for each scenario *s*. These two new variables are associated with the market buying price *s2b* and the selling price *s2s*, respectively.

The two-stage stochastic programming model is then formulated as follows:

Minimize :

$$TC = s1b\, R_1 + \frac{1}{n} \sum_{s \in S} \sum_{t \in T} [\, pfc\, y_t^s + pvc\, x_t^s + \sum_{i \in I} hc_i\, inv_{it}^s + \sum_{k \in K} (vfc_k\, z_{kt}^s + vvc_k v_{kt}^s) + s2b\, R_{2+}^s - s2s\, R_{2-}^s \,] \tag{11}$$

$$Subject\ to: \quad x_t^s \leq min\left(Pcap, \sum_{l=t}^{m} d_l^s\right) \times y_t^s \qquad \forall t \in T, \forall s \in S \tag{12}$$

$$inv_{0,t-1}^s + x_t^s = \sum_{k \in K} v_{kt}^s + inv_{0t}^s \qquad \forall t \in T, \forall s \in S \tag{13}$$

$$inv_{1,t-1}^s + \sum_{k \in K} v_{kt}^s = d_t^s + inv_{1t}^s \qquad \forall t \in T, \forall s \in S \tag{14}$$

$$inv_{0,t-1}^s + x_t^s \leq Icap_0 \qquad \forall t \in T, \forall s \in S \tag{15}$$

$$inv_{1,t-1}^s + \sum_{k \in K} v_{kt}^s \leq Icap_1 \qquad \forall t \in T, \forall s \in S \tag{16}$$

$$v_{kt}^s \leq Vcap_k\, z_{kt}^s \qquad \forall k \in K, \forall t \in T, \forall s \in S \tag{17}$$

$$TE^s = \sum_{t \in T} [\, pfe\ y_t^s + pve\, x_t^s + \sum_{i \in I} he_i\, inv_{it}^s + \sum_{k \in K} (vfe_k\, z_{kt}^s + vve_k v_{kt}^s)\,]$$

$$\leq R_1 + R_{2+}^s - R_{2-}^s \qquad \forall s \in S \tag{18}$$

$$x_t^s, v_{kt}^s, inv_{it}^s, R_1, R_{2+}^s, R_{2-}^s \in R\ and \geq 0 \qquad \forall k \in K, \forall t \in T, \forall i \in I, \forall s \in S \tag{19}$$

$$z_{kt}^s \in Z\ and \geq 0 \qquad \forall k \in K, \forall t \in T, \forall s \in S \tag{20}$$

$$y_t^s\ binary \qquad \forall t \in T, \forall s \in S \tag{21}$$

The objective function of the stochastic model (11) includes the cost of buying the emission allowances in the first stage and the expected value of the total second-stage operational cost over *n* scenarios. Similar to the deterministic model, the second-stage operational costs also comprise production setup and variable costs, inventory holding costs, and transportation fixed and variable costs. Yet it also includes the cost (or revenue) from emission permits trading in the second stage, denoted by $s2b\, R_{2+}^s - s2s\, R_{2-}^s$. Constraints (12) to (21) are built based on those of the deterministic model, with an additional scenario index *s* embedded. Specifically, constraint (18) imposes that the firm's total carbon emissions resulted from its operating activities in each scenario cannot exceed the total emission right it possesses, that is, the sum of allowances it purchased at stage 1 and 2 minus those sold at the end of stage 2 (if any).

Chapter 4. Numerical experiments

Based on the deterministic and the two-stage stochastic lot-sizing models incorporating carbon emissions that are proposed in the previous section, a number of computational experiments have been conducted. We first generate different scenarios of random demand data and determine an initial set of parameters (the base case) to serve as the inputs for our computational tests. The optimal solution of the base case is examined. We then compare the effectiveness of the deterministic and the stochastic models by analyzing the Value of Stochastic Solution and Expected Value of Perfect Information measures. Next, we conduct a sensitivity analysis to investigate the impact of different factors on the performance of our model by varying key parameters related to costs, emissions, and capacity. In addition, we analyze how the variations in allowance trading prices affect the firm's performance.

All the computational experiments have been modeled in Python 3 script and solved with the IBM ILOG CPLEX Optimization Studio 12.10.0.0. These computations are run on a 64-bit operating system with an Intel® Core™ i5-3337U CPU of 1.80GHz and an installed RAM of 4GB. In running these optimization problems, we set the maximum solving time to one hour per instance. We set the relative MIP gap tolerance to 0.0 instead of the CPLEX's default value at 1e-04 and keep the other parameters at their default levels.

4.1 Scenario generation

To accommodate the uncertainty in market demand, we first generate demand for each period with values assumed to randomly fall within the range of [0, 5000] units. This also means that demand per period is independent and uniformly distributed, with a minimum of zero units and a maximum of 5000 units. A set of random demands for *m* periods (*m* is equal to 12 in this study) is considered as one demand scenario. We solve our stochastic model using 50 different demand scenarios (n = 50), which we consider as one instance. We then repeatedly conduct the computations for 10 different demand instances. Readers can refer to Appendix 1 for an example of the periodical random demand over 50 scenarios of instance 1, in which the highest total demand is in scenario 10 with 40697 units while the lowest total demand is in scenario 12 with 22613 units. Table 4.1-1 presents the minimum, maximum, as well as the average value of the total demand over 50 scenarios for each instance, in which the scenario with lowest demand (16359 units) is instance 6 whereas the one with highest demand is instance 2 (with 43578 units), the average total demand over 12 periods per scenario is variated around 30000 units. For the detailed total demand data per scenario, readers can refer to Appendix 2.

Table 4.1-1: Total demand data for different instances

Instance	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
Min	22613.00	16705.00	20354.00	18658.00	19845.00	16359.00	17666.00	19264.00	17002.00	18339.00
Max	40697.00	43578.00	41561.00	40399.00	42368.00	40040.00	42189.00	43431.00	43442.00	42279.00
Average	30970.08	31169.32	29846.8	29453.44	30476.30	30251.90	30150.48	30457.42	29690.80	31295.94

4.2 The base case

To conduct numerical experiments, we first determine a set of parameters which serves as the base case for our analysis. We initially planned to incorporate real data with an aim to provide a better picture for decision makers in real situations. However, as far as we know, in the literature, there is no complete real parameter set that encompasses the three main operations (production, transportation, inventory control) being considered in this study, we thus design a mixed parameter set with some figures extracted from published studies and others determined by preliminary tests. In this study, one planning period corresponds to a month and there are total of 12 periods considered in our planning horizon, thus this model is over a span of one year.

4.2.1 Data description

This section will present the assignment of values for each parameter of the mathematical model in the base case setting.

- **Production**

In production, firms need to make a setup to facilitate their manufacturing processes, which is generally associated with a fixed level of cost (Malik & Kim, 2020). In this study, fixed cost in production refers to the expense incurred in setting up machines if a production decision is made at that period. The production fixed cost *pfc* in the base case is set to $200 per setup. We assume that once the production line is turned on, it can operate for the whole period with a maximum capacity of *Pcap* = 5000 units. This is reasonable as the maximum demand per period is assumed to be 5000 units. However, another setup is required if the firm wishes to produce in the next period. It is noticed that other operating costs within the factory such as facility and equipment acquiring or renting cost, electricity and lighting, staff personnel are all considered sunk costs and not included in our model.

Variable production cost refers to the resources needed to produce an additional unit of item. As we assume that no backlog is allowed, the total variable production cost will be determined by the total demand level and therefore is not contingent upon different operational decisions. The total amount produced will always be equal to the total demand since no backlogging or lost sales are allowed, and there is no incentive (in the current model) to have inventory left over at the end of the horizon. Therefore, the total variable production cost is a fixed demand (per demand scenario) and will be hence omitted by assuming *pvc* = 0.

Along with cost, every machine setup will emit a certain amount of GHGs resulting from the use of machine-running electricity, named as the production fixed emissions *pfe*. In the base case, the fixed emissions per production setup *pfe* is set to 0.25 kilograms (kg) CO_2e. Similarly, every single unit of product also accounts for a certain extra amount of emissions during its production process, known as the variable unit emissions *pve*, which is set to 0.02 kg per unit of item produced. These values are determined based on preliminary tests.

- **Inventory control**

In inventory management, operating costs and carbon intensity of a storage facility depend principally on its size, location and equipment, therefore, determining its capacity is essential (Mallidis *et al*., 2014). In this study, capacity of the central warehouse and the factory warehouse is initially set to $Icap_1$ = 8000 and $Icap_0$ = 5000 units, respectively.

Generally, operating costs of a storage depot (warehouse or distribution center) include rental or depreciation costs, salary and handling costs, as well as other expenses such as electricity, taxes and insurance, etc. These operating costs, together with the opportunity cost, are incorporated in a commonly used measure – inventory carrying (or holding) cost, the annual value of which is normally set at about 10 to 30% of the inventory value. In this study, we set the unit sales price of the product to \$20 and the annual holding costs at both the factory and the central warehouses are 20% of the item value, meaning that the costs of holding one unit for one period are $hc_0 = hc_1 = 20\% \times 20 / 12 = \$0.033$. For simplification purpose, we assume holding costs at both storage facilities are equal, ignoring their prospective differences in rental, utilities, operating and labor cost, etc.

In terms of holding emissions, we use the figure employed in Turkensteen and van den Heuvel (2019), which is 33 kg emissions per m^2 per year. We assume that the number of units per m^2 is 50 items, this gives an emission rate of 33/50 = 0.66 kg CO_2e per unit per year. The resulting emissions level of storing one unit of product for a month is hereby $he_0 = he_1 = 0.66/12 = 0.055$ kg. As the emissions per item held in inventory is considered mainly due to its electricity usage, equalizing the unit holding emissions at both warehouses appears to be rational.

- **Transportation**

Another primary source of costs and emissions in our lot-sizing and distribution model is transportation. There are two types of vehicles considered in this study: medium trucks with a GVWR of 15 ton (corresponding to a 9-ton payload capacity) and a 40-ton GVWR heavy-duty trucks (with a payload capacity of 25 ton). For the base case, product weight is set at 10 kg per item, meaning that a medium truck can carry a maximum of $Vcap_0$ = 900 units of product and a heavy truck has a capacity of up to $Vcap_1$ = 2500 units. Travel distance between factory and the central warehouse is assumed to be 100 km.

Unlike most of the existing studies in the literature that consider LTL shipments, which are usually applied when a firm outsources its transportation activities to external carriers, we use FTL shipments as the firm in our study is assumed to own vehicle fleets with sufficient capacity to serve its transportation needs. In FTL shipments, costs of transport are often based on the distance travelled and the weight carried, thus they generally do not consider the amount delivered. This also means that a fixed cost is incurred whenever a truck is scheduled for dispatch regardless of whether its payload is fully utilized or not. Therefore, in this case, the per unit transportation costs of both truck types are ignored $vvc_0 = vvc_1 = 0$. We set vfc_0 and vfc_1 to take the value of $122 and $203, respectively.

Regarding emissions in truck transportation, there is a common assumption among researchers in published studies, that is, a fixed amount of carbon emissions is generated by each empty truck, and this emission level increases with the load that the truck carries. Therefore, to determine the emissions per unit transported by a particular vehicle type, we set the fixed emissions per truck equal to its empty-load emissions level, then the unit variable emissions is derived from the difference between the vehicle's full-load emissions and empty-load emissions over its capacity.

As opposed to using the theoretical values for emission parameters as in most of the previous studies, we apply the empirical emissions data provided by Turkensteen and van den Heuvel (2019) with an aim to reflect the real-life situation more accurately. In particular, we employ their carbon emission rates for heavy-duty trucks and medium-duty trucks under two road types, as presented in Table 4.2-1. We assume that the 100 km distance between the factory and the central warehouse comprises 5.5% urban road (an equivalent distance of 5.5 km) and 94.5% highway driving condition (an equivalent distance of 94.5 km). The fixed emission rate of our medium truck vfe_0 is thus around 0.396 kg CO_2/km and the full truckload emission rate is around 0.5 kg CO_2/km. The variable emissions per unit transported by the medium truck will have a value of $vve_0 = 1.16 \times 10^{-4}$ kg CO_2/km. Correspondingly, the fixed emission level of a heavy-duty truck is $vfe_1 = 0.687$ kg CO2/km and the emissions of transporting one unit of product by the heavy truck is $vve_1 = 1.11 \times 10^{-4}$ kg CO_2/km.

Table 4.2-1: Carbon emissions in grams per km for urban and highway road segments of the selected trucks

Truck (GVWR)	Road type	Empty load	Full load
Heavy-duty (40t)	Urban	1034.8	1518.4
	Highway	668.2	907.4
Medium-duty (15t)	Urban	408.2	605.8
	Highway	395.2	483.6

Source: Turkensteen and van den Heuvel (2019)

- **Prices for emissions rights**

There are three independent emission related costs (also known as allowance trading prices) being considered in this study: first-stage allowance buying price, second-stage allowance buying price, and second-stage allowance selling price. According to the empirical data from the EU Allowance Primary Market Auction Report 2020 provided by European Energy Exchange Group (EEX), the average carbon allowances auctioning price has an approximate value of $24 per permit (which allows to emit one ton of CO_2), equivalent to $0.024 per kg of CO_2e emitted. However, if we apply this empirical price level into our problem, the resulting total emission cost will take up an insignificant portion in our objective function (only less than 1% of the total cost based on our preliminary tests). For the case when emission costs are very low, there is hardly any trade-off between the emission costs and the operational costs, and hence just minimizing the operational cost will give a near-optimal solution. Therefore, to observe a more noticeable impact of the carbon trading activity, we decided to set the emission credit buying price at the first stage as *s1b* = \$0.24 per kg of GHGs emissions, which is 10 times higher than the actual rate. Regarding the second stage emission credit buying price, we realize that the actual price in the spot market provided by the EEX is similar to that of the primary market. However, with an aim to differentiate the benefits (losses) resulted from trading these allowances at different stages, we assume that the second stage allowance buying price from the spot market is 50% higher than the first stage level, this means *s2b* = \$0.36 per kg CO_2e emitted. The selling price of emission allowances at this stage is accordingly set to only *s2s* = \$0.12 per kg CO_2e emitted.

A summary of the assigned parameters is given in Table 4.2-2.

Table 4.2-2: Summary of the base case setting parameters

Capacity (units)	*Pcap*	$Icap_0$	$Icap_1$	$Vcap_0$	$Vcap_1$						
	5000	5000	8000	900	2500						
Costs (\$)	*pfc*	*pvc*	hc_0	hc_1	vfc_0	vfc_1	vvc_0	vvc_1	*s1b*	*s2b*	*s2s*
	200	0	0.33	0.33	122	203	0	0	0.24	0.36	0.12
Emissions (kg CO_2e)	*pfe*	*pve*	he_0	he_1	vfe_0	vfe_1	vve_0		vve_1		
	0.25	0.02	0.055	0.055	0.396	0.687	0.116×10^{-3}		0.111×10^{-3}		

4.2.2 Result for the base case

Solving the two-stage stochastic model under the baseline parameter set mentioned in Section 4.2.1 with 10 different demand instances, each of which comprises 50 demand scenarios, we obtain the average optimal results as presented in Tables 4.2-4 to 4.2-6. The notation used in our tables of solutions is described in Table 4.2-3.

Under the base case, our model is solved to optimality for all 10 instances, this is illustrated by the equality in the value of the objective function (upper bound) and the lower bound at the end of the computation, the relative MIP gap is thus equal to 0. It is noticeable that the model is solved to optimality within a very short period of time, only 33.51 seconds on average. The optimal result (total expected cost) is quite stable over different instances, with an average of around \$5948, of which the two main components are the costs from transportation and production activities, respectively accounting for over 50% and 35% of the total cost. Inventory holding takes up only about 5% of the total cost, while the firm's trading of emission allowances to cover its carbon footprint costs about 8.6%.

Table 4.2-3: The notation used in the solution tables

Notation	Description
MIP time	The solving time of the MIP model, measured in seconds
Upper bound	The valid upper bound on the optimal solution of the MIP model at the end of the computation (also known as the Objective function value)
Lower bound	The valid lower bound of all the nodes in the computation (denoted as Best bound in CPLEX solver)
Optimality	Optimal status of the computation (= 1 if solved to optimality within the time limit, = 0 otherwise)
MIP gap	The relative MIP gap: the difference between the Upper bound and the Lower bound, = 0 if solved to optimality
Prod_c	Average total production cost
Trans_c	Average total transportation cost
Inv_c	Average total inventory holding cost
Emis_c	Average total emission allowance cost
Total_e	Average total emissions
Prod_e	Average total emissions of production
Trans_e	Average total emissions of transportation
Inv_e	Average total emissions of inventory holding
% with s2 buy	The percentage of scenarios that involve allowances buying at the second stage
% with s2 sell	The percentage of scenarios that involve allowances selling at the second stage
s1 buy	Quantity of emission allowance bought at the first stage
s2 buy	Average quantity of emission allowance bought at the second stage
s2 sell	Average quantity of emission allowance sold at the second stage
Setup	Average total number of setups
Prod quant	Average total production quantity
Vehi light	Average total number of light vehicles used over the planning horizon
Vehi heavy	Average total number of heavy vehicles used over the planning horizon
Inv fact	Average total amount of inventory stored at the factory warehouse
Inv ware	Average total amount of inventory stored at the central warehouse

The solution also reveals that the firm only produces the exact quantity to meet market demand. This is not surprising, since the objective is to minimize cost, so there is no incentive to produce more than the quantity needed. The average machine setup frequency is between 10 and 11 times within the planning horizon, this means that production takes place in almost every period. With respect to vehicle utilization, heavy-duty vehicles are preferable over medium vehicles as there are five times as many more 25t trucks being used. Regarding inventory control, most of the finished products are shipped directly to the central warehouse as opposed to being stored in the factory affiliated warehouse. Over the entire planning horizon, there are approximately 900 units of item kept in the central warehouse while the other is hardly used. This is understandable as we consider holding costs at both storing facilities are equal, with a storage capacity of 8000 units, the central warehouse is apparently sufficient to keep products in inventory.

In terms of emissions, on average, the total amount of carbon emissions generated is around 2017 kilograms per planning horizon. Transportation is the main factor as it is responsible for up to 67.2% of the firm's carbon footprint, while production process takes up around 30%. Inventory holding is the least polluting activity since it creates only an approximate amount of 50 kg CO_2e (around 2.4% of the total emissions). The firm purchases most of its emission rights at the first stage of the planning horizon. At the second stage, on average, the firm needs to buy extra emission rights in 49.2% of the 50 scenarios while in 48.8% of the scenarios, it has excessive rights that are sold in the carbon market. This phenomenon can be explained when we relate this allowance trading setup to the newsvendor problem in which the decision maker needs to face an overage or an underage cost, and an order quantity at the critical ratio is purchased to maximize profit. With our symmetric allowances cost structure (the firm pays $0.12 more when buying or loses an additional $0.12 when selling at the second stage), the critical ratio will be 50%. Therefore, it is reasonable for the firm to buy (sell) in around half of all scenarios.

Table 4.2-4: Computational results of the 10 instances under the base case setting (C0)

Instance	Computational status				
	MIP time	Upper bound	Lower bound	MIP gap	% Optimality
1	24.91	5984.59	5984.59	0%	100%
2	29.09	6045.72	6045.72	0%	100%
3	35.94	5887.28	5887.28	0%	100%
4	26.44	5829.31	5829.31	0%	100%
5	51.38	5954.39	5954.39	0%	100%
6	27.05	5920.75	5920.75	0%	100%
7	26.83	5934.08	5934.08	0%	100%
8	32.69	5990.56	5990.56	0%	100%
9	32.61	5863.65	5863.65	0%	100%
10	48.17	6076.40	6076.40	0%	100%
Average	33.51	5948.67	5948.67	0%	100%

Table 4.2-5: Average total cost and total emissions under the base case setting (C0)

Instance	Costs				Emissions			
	Prod_c	Trans_c	Inv_c	Emis_c	Total_e	Prod_e	Trans_e	Inv_e
1	2140.00	3061.00	267.62	515.97	2042.52	622.08	1375.84	44.60
2	2132.00	3101.64	279.87	532.21	2064.23	626.05	1391.53	46.64
3	2088.00	2974.94	319.13	505.21	1986.96	599.55	1334.22	53.19
4	2092.00	2929.40	314.29	493.62	1958.91	591.68	1314.84	52.38
5	2088.00	3032.56	318.36	515.46	2026.09	612.14	1360.89	53.06
6	2104.00	3013.10	294.63	509.02	2008.40	607.67	1351.63	49.11
7	2132.00	3020.44	272.54	509.10	2003.89	605.67	1352.79	45.42
8	2124.00	3031.00	321.64	513.92	2025.15	611.80	1359.74	53.61
9	2068.00	2958.70	330.09	506.86	1978.34	596.40	1326.93	55.01
10	2108.00	3135.70	306.79	525.91	2084.46	628.55	1404.77	51.13
Average	2107.60	3025.85	302.50	512.73	2017.89	610.16	1357.32	50.42

Table 4.2-6: Average optimal decisions under the base case setting (C0)

Instance	% of scenarios		Decision variables								
	with s2 buy	with s2 sell	s1 buy	s2 buy	s2 sell	Setup	Prod	Vehi medium	Vehi heavy	Inv fact	Inv ware
1	48%	50%	2070.94	93.15	121.57	10.70	30970.08	2.86	13.36	0.00	810.98
2	50%	48%	2015.08	177.90	128.76	10.66	31169.32	3.06	13.44	0.00	848.08
3	50%	48%	1976.31	123.43	112.78	10.44	29846.80	2.92	12.90	0.00	967.06
4	50%	48%	1971.79	91.39	104.28	10.46	29453.44	2.58	12.88	1.30	951.10
5	50%	48%	1989.10	140.16	103.17	10.44	30476.30	2.76	13.28	0.00	964.74
6	48%	50%	2027.31	103.08	121.98	10.52	30251.90	2.90	13.10	0.52	892.30
7	48%	50%	1963.80	137.39	97.31	10.66	30150.48	3.06	13.04	0.00	825.88
8	50%	48%	2015.27	121.14	111.26	10.62	30457.42	3.08	13.08	0.00	974.66
9	48%	50%	1977.70	133.91	133.27	10.34	29690.80	2.92	12.82	0.00	1000.26
10	50%	48%	2062.76	117.67	95.97	10.54	31295.94	2.84	13.74	0.00	929.68
Average	49.2%	48.8%	2007.01	123.92	113.04	10.54	30376.25	2.90	13.16	0.18	916.47

4.3 Deterministic model versus Stochastic model analysis

This section will examine the optimal results provided by the deterministic and the stochastic models to verify the potential impact (if any) of uncertainty on a firm's operational performance.

As stochastic problems are often computationally difficult to solve, it is a common practice for decision makers to solve simpler problems first. There are several ways to simplify a complex stochastic problem: a firm could replace the unknown elements in its system with the expected value (or average value) of those random variables and then solve the resulted deterministic model, or it could solve all the deterministic sub-models (each corresponds to one realization scenario of the uncertain factor) and then compute the expectation value of these solutions. However, the solutions provided by these alternatives cannot always effectively represent the stochastic problem, they can be nearly optimal, totally inaccurate or even infeasible in some cases (Moraza, 2016).

In order to determine whether the simplified model is good enough to represent the approximation of the stochastic model, assessment indicators such as the Expected Value of Perfect Information, the Value of Stochastic Solution, as well as the concepts of Wait-and-See solution, Expected Value, and the Expected result of using the Expected Value solution are commonly applied, as mentioned in Escudero *et al*. (2007). These measures are mainly used to quantify how valuable the Stochastic Problem is, with respect to the other models. These concepts are explained as follows:

- **Expected Value (EV)** model refers to the simplified deterministic problem obtained by replacing the random variables in the original stochastic model with their expected values. It is also known as the *mean value* problem.

- **Expected result of using the Expected Value solution (EEV)** refers to the result of applying the solution provided by the EV problem. In two-stage stochastic model, this means solving the model with a fixed first-stage decision derived from the deterministic EV model.

- **Wait-and-see (WS)** solution value is the expected value obtained from using the optimal solution for each scenario of uncertainty. This approximation is based on the perfect information (information known with certainty) along the planning horizon. In our case, wait-and-see solution is derived by taking the average value of the optimal results from solving 50 separate scenarios, each with known and certain demands.

- **Stochastic Problem (SP)** value, also known as the *here-and-now* solution, denotes the optimal solution of the stochastic model.

- **Value of Stochastic Solution (VSS)** is defined as the difference between the Expected result of the EV problem and the result of the stochastic problem. In minimization problems, this value is equal to VSS = EEV – SP. It represents the cost of ignoring uncertainty in decision-making or the expected loss of using a deterministic solution. A small VSS means that the approximation of the stochastic problem by the model with expected values of the random variables is a good one, while in other cases when VSS is equal to 0 (the values of EEV and SP are the same), solving the hard stochastic problem becomes unnecessary.

- **Expected Value of Perfect Information (EVPI)** is defined as the difference between the solutions of wait-and-see and the stochastic problem. It represents the highest level of investment that a decision-maker would be willing to make (the highest cost he wants to pay) in order to obtain the perfect information about the future. In minimization problems, EVPI is derived from SP – WS. The higher the EVPI, the more important role the uncertain element has in the model.

In minimization problems, the relation among them is WS ≤ SP ≤ EEV.

Particularly, in our case, the EV problem is the deterministic model with known demands calculated as the average values of the 50 different demand scenarios. Solving the EV problem, we obtain the first-stage decision R_1 of how many emission allowances to buy at first. We then solve the two-stage stochastic model with this fixed R_1 decision, the optimal result derived is the EEV value. On the other hand, the WS value is obtained by first solving the deterministic model individually (model with predetermined demands) for each of the 50 demand scenarios, then compute the expected value over these 50 solutions. Finally, we can obtain the SP value by simply solving our original two-stage stochastic model with uncertain demands.

4.3.1 Different sets of parameters

When comparing the optimal solutions provided by the Stochastic problem and the Expected results of using the Expected Value (the SP problem with fixed first-stage decision) under the base case, we found that in all of the 10 instances, the majority of differences in the decision variables between the solutions of the SP model and the EEV model are the decisions related to the trading of emission allowances, i.e., the quantity to buy at the first-stage and the quantity to buy or sell at the second stage. Therefore, we vary some principle cost- or emission-related parameters of the model to verify whether a different share of emission cost in the total cost value has any impact on the VSS value. Seven parameter sets have been generated, as shown in Table 4.3-1.

In Case 1 (C1), increasing the machine setup cost of the production line (production fixed cost) can vary the setup frequency and the quantity of items kept in inventory. Cases 2 and 3 refer to the situations when less energy-efficient vehicles are used and when the production line is carbon intensive, respectively. Case 4 to 7 vary the proportion of emission allowance cost (from low to high) in the total cost value.

Table 4.3-1: Cases considered in the experiments

Case	Change(s) description	Corresponding parameter(s)
C1	Production fixed cost increases 50%	pfc = 300
C2	Emissions from transportation double	vfe_0 = 0.792, vve_1 = 0.000232 vfe_1 = 1.374, vve_1 = 0.000222
C3	Emissions from production 10 times higher	pfe = 2.5, pve = 0.2
C4	Emission prices are 10 times lower	$s1b$ = 0.024, $s2b$ = 0.036, $s2s$ = 0.12
C5	Emission prices halve	$s1b$ = 0.12, $s2b$ = 0.18, $s2s$ = 0.06
C6	Emission prices double	$s1b$ = 0.48, $s2b$ = 0.72, $s2s$ = 0.24
C7	Emission prices are 5 times higher	$s1b$ = 1.2, $s2b$ = 1.8, $s2s$ = 0.6

The variation of these parameters would ultimately result in different percentages of the cost indicators, including production cost, transportation cost, inventory cost and emission cost in the total cost structure, as illustrated in Table 4.3-2. The results presented in Table 4.3-2 are calculated as the average over 10 instances. Our model is solved to optimality easily under these different cases, with a computing time of less than 1 minute. Compared to the base case, an increase in total cost is seen in most of the cases, mainly due to the rise in either cost or emission factors. It is also observed that with these parameter variations, the cost of emissions can take up as low as 0.94% (in case 4) or as high as 32% (in case 7) of the total cost.

Table 4.3-2: Distribution of different cases operational costs (%) in different cases

Case	MIP time (s)	MIP gap (%)	Total cost	Cost (%)			
				Prod_c	Trans_c	Inv_c	Emis_c
C0	33.51	0%	5948.67	35.43	50.87	5.09	8.62
C1	58.27	0%	6975.81	43.03	42.83	6.74	7.40
C2	32.55	0%	6293.73	33.40	47.90	5.09	13.62
C3	35.06	0%	7356.03	28.65	41.13	4.12	26.10
C4	35.27	0%	5487.08	38.35	55.23	5.48	0.94
C5	37.67	0%	5692.28	37.03	53.20	5.27	4.50
C6	38.82	0%	6461.27	32.69	46.80	4.65	15.86
C7	39.75	0%	7997.55	26.50	37.71	3.80	32.00

We then solve the stochastic, wait-and-see, and the expected value problems under these parameter settings. Their average optimal total costs over 10 instances are presented in Table 4.3-3. The average VSS and the average EVPI under different cases are also included. Interested readers can refer to Appendix 3 for the detailed results of each instance.

Table 4.3-3: Average value of the WS, SP, and EEV solutions under different cases

Case	WS	SP	EEV	EVPI	% of SP	VSS	% of SP
C0	5920.20	5948.67	5950.67	28.47	0.4786	2.00	0.0336
C1	6947.65	6975.81	6978.31	28.16	0.4037	2.50	0.0358
C2	6245.55	6293.73	6297.86	48.19	0.7656	4.12	0.0655
C3	7238.15	7356.03	7356.81	117.88	1.6025	0.78	0.0106
C4	5484.23	5487.08	5487.27	2.85	0.0520	0.19	0.0035
C5	5678.03	5692.28	5693.27	14.25	0.2503	0.99	0.0175
C6	6404.33	6461.27	6465.26	56.94	0.8813	3.99	0.0618
C7	7855.49	7997.55	8007.50	142.06	1.7763	9.94	0.1243

4.3.2 The Value of Stochastic Solution under different cases

In this section, we will present a more detailed comparison among the VSS values of various parameter cases that are mentioned in Section 4.3-1. As the total cost levels incurred in different cases are different, for comparison purpose, we convert these VSS values into a relative form, i.e., the percentage of VSS compared to the optimal total cost of the Stochastic problem. We first compare the relative VSS values among cases C0 to C4, as presented in Table 4.3-4. These cases appear in the ascending order of percentage of emission cost in the total cost (spanning from 0.94% to 26.1% of the total cost), resulting from varying the parameter of production fixed cost, production emissions, transportation emissions, etc.

Table 4.3-4: Relative VSS values (in percentage of the SP's solution) among case C0 to C4

Case	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
C4	0.0026	0.0000	0.0047	0.0084	0.0032	0.0056	0.0009	0.0050	0.0032	0.0017
C1	0.0340	0.0006	0.0420	0.0731	0.0286	0.0494	0.0252	0.0467	0.0343	0.0258
C0	0.0327	0.0000	0.0335	0.0770	0.0291	0.0513	0.0189	0.0456	0.0338	0.0154
C2	0.0577	0.0010	0.0556	0.1380	0.0375	0.1019	0.0522	0.0736	0.1109	0.0311
C3	0.0281	0.0055	0.0022	0.0162	0.0018	0.0215	0.0059	0.0113	0.0055	0.0076

Through Table 4.3-4, we can see that the variations of those parameters entail changes in the VSS values. However, from C4 to C3, over the 10 instances, no unified impact or directed tendency is seen, an increase in emission cost can either trigger a rise or a decline in the relative VSS value.

In the next step, we conduct a similar comparison for the results among cases C0 and C4 to C7. These cases appear in the ascending order of the emission cost/total cost ratio in Table 4.3-5. However, these increases of emission cost are derived from varying the allowances trading prices only, as already specified in Table 4.3-1. Looking at the relative VSS among these cases (as shown in Table 4.3-5) over the 10 instances, there is a positive correlation between the share of emission cost in the total cost and the VSS value: the larger proportion of carbon emissions cost, the higher the VSS value. It is noticeable that in instance 2, the difference between the solution of our SP problem and EEV problem is insignificant in most of the cases that are considered, between [0.0001~ 0.4168]. This explains why its relative value to the SP's solution is almost 0.0 (between [3.41E-09, 1.16E-07]).

Table 4.3-5: Relative VSS values (%) among case C0 and case C4 to C7

Case	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
C4	0.0026	0.0000	0.0047	0.0084	0.0032	0.0056	0.0009	0.0050	0.0032	0.0017
C5	0.0171	0.0000	0.0184	0.0404	0.0156	0.0268	0.0099	0.0239	0.0154	0.0081
C0	0.0327	0.0000	0.0335	0.0770	0.0291	0.0513	0.0189	0.0456	0.0338	0.0154
C6	0.0582	0.0000	0.0584	0.1406	0.0512	0.0915	0.0349	0.0826	0.0768	0.0274
C7	0.1130	0.0000	0.1175	0.2781	0.0986	0.1792	0.0983	0.1620	0.1540	0.0512

Through these comparisons, it can be concluded that the carbon trading prices have substantial impact on the approximation of the stochastic problem by using the expected value solution models. The higher the carbon allowance prices, the less accurate the Expected Value solution is in estimating the uncertain elements. It is also worth to mention that, in most of the cases, the Value of Stochastic Solution is relatively small. We can again refer to the concept of critical ratio in the newsvendor problem for a possible rationale for this behavior. As explained in the previous section, the symmetric structure in our emission prices has led to a critical ratio of 0.5, meaning that the firm can make operational decisions with demand values at the 50 percentiles of the distribution of total demand.

Generally, this experiment has implied that the approximation of the stochastic problem by the expected value of the mean value model is a good one for the current parameter setting. Under the circumstances when the stochastic problem is hard to solve, decision-makers can simplify their problems by employing the average value of the uncertain demand in finding the optimal solution.

4.3.3 Expected Value of Perfect Information under different cases

In this section, a similar experimental setting as in Section 4.3.2 is conducted. With the Expected value of perfect information being analyzed, we aim to verify if different cost structure in the total cost function have an influence on the EVPI value. The relative EVPI values (i.e., the EVPI expressed as a percentage of the Stochastic problem's solution) for different cases are presented in Table 4.3-6 and 4.3-7.

Table 4.3-6: Relative EVPI values (%) among case C0 to C4

Case	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
C4	0.0469	0.0662	0.0522	0.0438	0.0533	0.0496	0.0517	0.0506	0.0595	0.0458
C1	0.3626	0.5101	0.4084	0.3497	0.4128	0.3878	0.3998	0.3943	0.4608	0.3506
C0	0.4308	0.6095	0.4821	0.4030	0.4911	0.4561	0.4748	0.4668	0.5482	0.4222
C2	0.6855	0.9728	0.7824	0.6458	0.7862	0.7424	0.7422	0.7457	0.8750	0.6759
C3	1.4413	2.0524	1.6129	1.3446	1.6133	1.6041	1.5843	1.5668	1.8011	1.3971

Table 4.3-7: Relative EVPI values (%) among case C0 and case C4 to C7

Case	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
C4	0.0469	0.0662	0.0522	0.0438	0.0533	0.0496	0.0517	0.0506	0.0595	0.0458
C5	0.2253	0.3192	0.2515	0.2109	0.2567	0.2383	0.2489	0.2433	0.2867	0.2212
C0	0.4308	0.6095	0.4821	0.4030	0.4911	0.4561	0.4748	0.4668	0.5482	0.4222
C6	0.7928	1.1188	0.8903	0.7460	0.9052	0.8445	0.8736	0.8593	1.0035	0.7764
C7	1.5980	2.2465	1.8019	1.5035	1.8266	1.7135	1.7543	1.7325	2.0159	1.5628

Under both settings, in all the 10 instances, it is observed that there exists a positive correlation between the proportion of emission cost in the total cost and the EVPI value: the bigger proportion the emission cost, the higher the EVPI value. This finding implies that decision-makers are willing to pay more to obtain the perfect information when emissions play a more important role in their total budget.

4.4 Parameter sensitivity analysis

Sensitivity analysis (also known as post-optimality investigation of the solution) is used as an attempt to study the robustness of the solution to a linear programing model. To measure the impact of different factors on the performance of our two-stage stochastic model, we separately change several key parameters, including production fixed cost, vehicle fixed transportation cost, inventory holding cost, production emissions rates, inventory holding emissions rates, capacity of vehicle, and the number of periods in our planning horizon. We resolve our model under each of the variated set of parameters over 10 demand instances, each of which also comprises 50 demand scenarios as in the base case. The results of these parameter settings are then compared to those of the base case.

4.4.1 Production fixed cost

We first investigate the impact of production fixed cost (*pfc*) on the optimal solution and the model's performance by reducing the machine setup cost by 50% or increasing it to two times higher, *pfc* ϵ {100, 400}. Their respective results are then compared to the base case where *pfc* has a value of 200. The average optimal results over 10 instances and the computational status are presented in Table 4.4-1.

Table 4.4-1: Average results under variations of the production fixed cost

Case	Computational status					Costs				Emissions			
	MIP time	Upper bound	Lower bound	MIP gap	% Optimality	Prod_c	Trans_c	Inv_c	Emis_c	Total_e	Prod_e	Trans_e	Inv_e
100	22.14	4866.77	4866.77	0%	100%	1108.00	3073.24	174.03	511.50	2011.80	610.29	1372.50	29.01
200	33.51	5948.67	5948.67	0%	100%	2107.60	3025.85	302.50	512.73	2017.89	610.16	1357.32	50.42
400	175.62	7954.33	7954.33	0%	100%	3837.60	2955.31	641.59	519.83	2051.20	609.92	1334.34	106.93

Case	Percentage of scenarios		Decision variables								
	with s2 buy	with s2 sell	s1 buy	s2 buy	s2 sell	Setup	Prod	Vehi light	Vehi heavy	Inv fact	Inv ware
100	49.0%	49.0%	1999.08	125.83	113.10	11.08	30376.25	3.55	13.01	0.00	527.36
200	49.2%	48.8%	2007.01	123.92	113.04	10.54	30376.25	2.90	13.16	0.18	916.47
400	49.2%	48.8%	2036.06	122.35	107.21	9.59	30376.25	2.20	13.24	75.15	1869.06

Under these variations, all of the instances are solved to optimality, but there is a fivefold increase in the computational time when production fixed cost is doubled compared to the base case. This longer solving time may be explained by the consideration between setup frequency and inventory level and it seems harder to find the optimal trade-off between these two decisions. Indeed, with low setup costs, it is optimal to setup in almost every time period, whereas with a much higher setup cost, it is optimal to conduct a setup less frequently. In this latter case, the exact timing of the setup periods becomes critical and the search for these optimal setup periods might explain the increased CPU times. There is also an effect on the inventory levels. Since it costs two times more to conduct a production setup, the firm may consider producing in bigger batches and store finished products in inventory to reduce its setup frequency. This is reflected in the considerably higher quantity of products being stored in inventory, i.e., an average of 1944 units compared to 916 units of the base case (which is more than double), and the less frequent setup (9.59 times compared to 10.54 times). Figure 4.4-1 presents a negative correlation between production fixed cost and setup decision. Fewer setups correspond to more items being produced in advance and held in inventory. On the contrary, when *pfc* is halved, the firm has an incentive to conduct more setups as it becomes a more cost-effective option.

Figure 4.4-2 indicates the value of objective function (total expected cost) and the overall emissions level varies according to the decrease or increase in the production fixed cost. As the firm must satisfy all demands, it needs to conduct machine setups for the production process regardless of how expensive it is. Total cost rises when production fixed cost increases because the small reduction in setup frequency cannot offset the higher rate of increase in setup cost itself. Moreover, the significantly higher total inventory cost also contributes to the rise in total cost. Compared to the base case, total cost increases by 33.7% when *pfc* is 400, whereas it reduces by 18% when *pfc* is 100.

In terms of emissions, there is a slight increase in the total emission level when production fixed cost increases. This is mainly due to the additional emissions from holding more products in inventory.

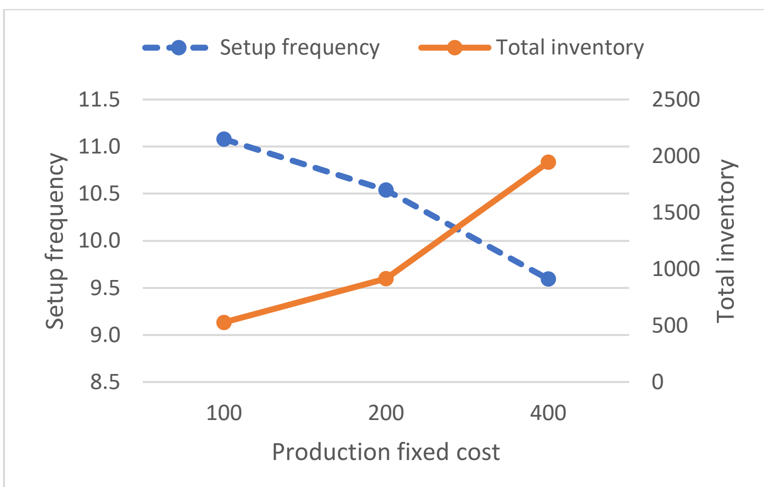

Figure 4.4-1: Effect of production fixed cost on setup frequency and inventory level

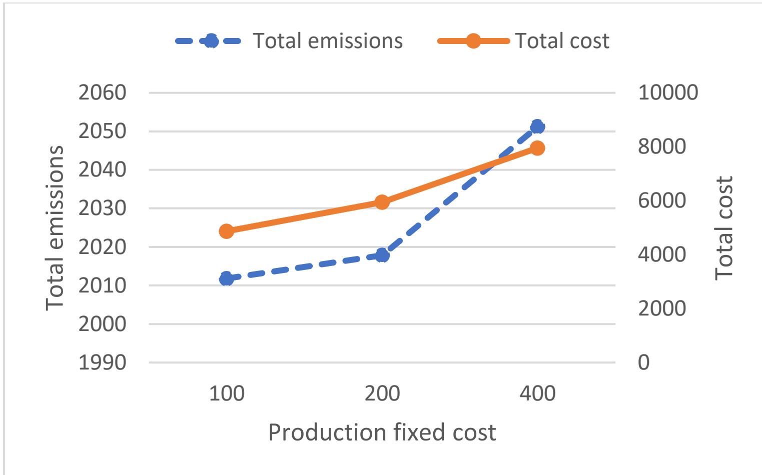

Figure 4.4-2: Effect of production fixed cost on total cost and total emissions

4.4.2 Vehicle fixed cost

In freight transportation, the vehicle shipping rate of each vehicle type is a major factor in determining its own utilization rate as well as the relative rate of usage among different types of vehicles. To observe the effect of variations in vehicle costs on the relative utilization rate of our medium- and heavy-trucks, we vary the fixed delivery cost of the medium-duty truck while keeping that of the heavy truck unchanged. We consider the scenarios when it costs 20% less to use a medium truck and when it is 20% more expensive compared to the base case. Table 4.4-2 presents the average results under 3 different shipping rates of medium trucks, $vfc_0 \in \{98, 122, 147\}$.

Table 4.4-2: Average results under variations of the medium-vehicle fixed cost

Case	Computational status					Costs				Emissions			
	MIP time	Upper bound	Lower bound	MIP gap	% Optimality	Prod_c	Trans_c	Inv_c	Emis_c	Total_e	Prod_e	Trans_e	Inv_e
98	1250.53	5859.70	5859.52	0.003%	80%	2152.00	2940.35	246.10	521.25	2051.59	610.21	1400.36	41.02
122	33.51	5948.67	5948.67	0%	100%	2107.60	3025.85	302.50	512.73	2017.89	610.16	1357.32	50.42
147	25.26	6013.96	6013.96	0%	100%	2080.00	3077.76	342.43	513.78	2022.98	610.12	1355.79	57.07

Case	Percentage of scenarios		Decision variables								
	with s2 buy	with s2 sell	s1 buy	s2 buy	s2 sell	Setup	Prod	Vehi light	Vehi heavy	Inv fact	Inv ware
98	49.2%	48.8%	2043.22	124.46	116.09	10.76	30376.25	10.01	9.65	16.76	729.00
122	49.2%	48.8%	2007.01	123.92	113.04	10.54	30376.25	2.90	13.16	0.18	916.47
147	49.0%	49.0%	2009.19	124.66	110.86	10.40	30376.25	2.34	13.46	1.80	1035.85

At first, it is observed that the model's computational time has been tremendously increased to 1250 seconds (more than 37 times longer) when the fixed cost of our 15t trucks is reduced by 20%.

This reduction also generates an average MIP gap of 0.003% between the value of the objective function and the lower bound, as only 80% of instances are solved to optimality, meaning that the model cannot find an optimal solution within the time limit in 2 out of 10 instances. A possible explanation for this phenomenon is the consideration between the use of two different truck types. When pfc_0 is reduced to 98, there are several circumstances in which dispatching two medium trucks (a cost of \$196 for a cumulative capacity of 1800 units) is cheaper than using one heavy truck that costs \$203 for a capacity of 2500 units, e.g., when the delivery quantity is more than 900 units but fewer than 1800 units, using two medium trucks is obviously a more cost-effective option. This is reflected in the significantly higher utilization rate of 15t trucks. Almost 3.5 times more medium trucks are used while the usage of heavy trucks declines by 27%, resulting in a higher overall number of vehicles used for the shipping activities, as shown in Figure 4.4-3.

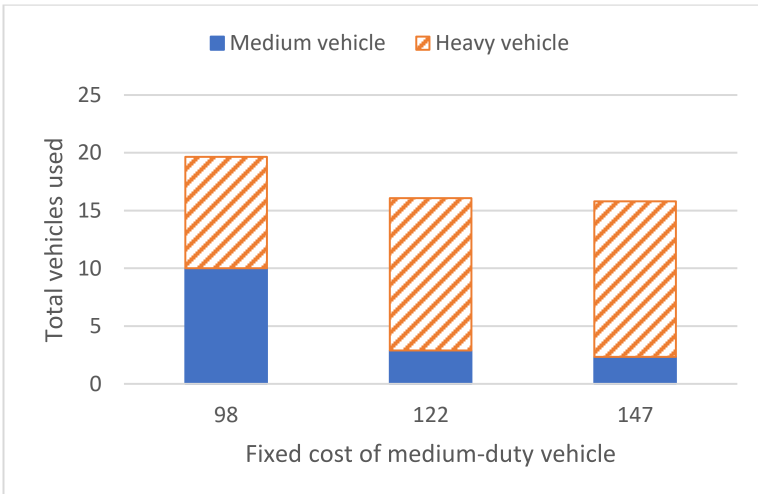

Figure 4.4-3: Effect of medium-vehicle fixed cost on total vehicle usage and total cost

Figure 4.4-4 illustrates a positive correlation between the medium-duty vehicle cost and total cost. When fixed cost of medium trucks rises to 147, a 1.7% increase is seen in the transportation cost which leads to an increase of 1.1% in the total cost. As fewer delivery trips are made due to the higher transporting rate, production setups take place less frequently (dropped from an average of 10.54 to 10.4 times), leading to moderately more products are kept in inventory. This also explains the slightly higher total emissions level under the higher medium-vehicle transporting rate. On the contrary, the lower transportation fixed cost has triggered more frequent machine setups with smaller production lot-sizes. It can reduce total cost by around 1.5%, but it raises the total emissions level to 1.16 times higher. This is mostly due to the rise in emissions from transportation as more vehicles are used. As a result, more allowances (an increase of 1.6%) are purchased by the firm to cover its higher carbon footprint.

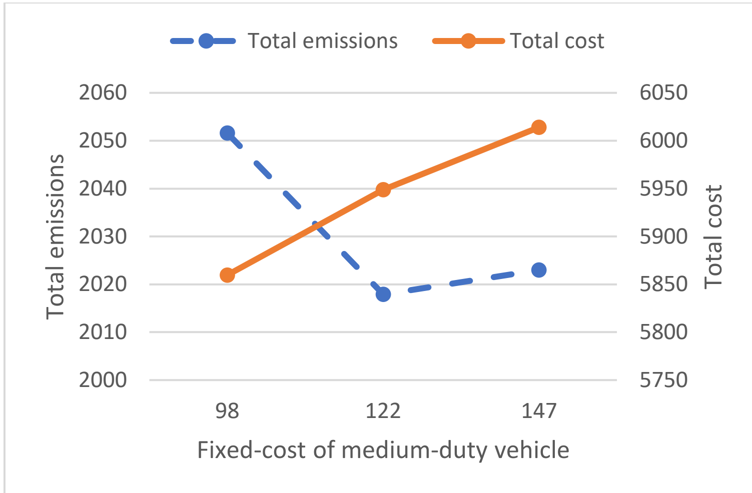

Figure 4.4-4: Effect of medium-vehicle fixed cost on total cost and total emissions

4.4.3 Inventory holding cost

Next, we vary the inventory holding cost at one of our storage spaces, i.e., the affiliated warehouse in the factory, as the cost of holding goods in inventory at different storage facilities also influences their relative utilization rates. This time, we impose a 30% decrease and a 30% increase in the holding cost of the factory warehouse, $hc_0 \in \{0.23, 0.33, 0.43\}$ where 0.33 is the holding cost of the base case. The average results are presented in Table 4.4-3.

Table 4.4-3: Average results under variations of the inventory holding cost

Case	Computational status					Costs				Emissions			
	MIP time	Upper bound	Lower bound	MIP gap	% Optimality	Prod_c	Trans_c	Inv_c	Emis_c	Total_e	Prod_e	Trans_e	Inv_e
0.23	47.97	5943.10	5943.10	0%	100%	2078.00	3032.55	318.37	514.18	2025.79	610.12	1359.30	56.37
0.33	33.51	5948.67	5948.67	0%	100%	2107.60	3025.85	302.50	512.73	2017.89	610.16	1357.32	50.42
0.43	31.89	5948.67	5948.67	0%	100%	2107.60	3025.85	302.50	512.73	2017.89	610.16	1357.32	50.42

Case	Percentage of scenarios		Decision variables								
	with s2 buy	with s2 sell	s1 buy	s2 buy	s2 sell	Setup	Prod	Vehi light	Vehi heavy	Inv fact	Inv ware
0.23	48.6%	49.4%	2010.34	124.36	108.91	10.39	30376.25	3.11	13.07	198.25	826.60
0.33	49.2%	48.8%	2007.01	123.92	113.04	10.54	30376.25	2.90	13.16	0.18	916.47
0.43	48.6%	49.4%	2008.72	123.07	113.89	10.54	30376.25	2.90	13.16	0.00	916.66

Under different holding costs, all instances are again solved to optimality within a short period of time (on average less than 50 seconds). These variations in inventory holding cost did not create considerable changes in the MIP solving time. In the base case (when holding costs at both warehouses are 0.33), the storeroom of the factory is hardly used to store products – only an average of less than 1 unit of product is held. Therefore, a 30% addition to its holding cost only further discourages its utilization (inventory level at factory becomes 0). This also explains why the results of the case with higher factory holding cost are almost identical to those of the base case. Most of their performance indicators (related to cost and emissions) as well as decision variables are remained unchanged. Only subtle differences are seen in the allowances trading and inventory decisions. This is possibly because for each solving cycle, various nodes are explored by the model, there exists alternative solutions which lead to the same outcome. In other words, the model has multiple optimal solutions, especially for the case where the holding cost at both warehouses are identical, such equivalent optimal solutions might exist.

On the other hand, when this cost drops to 0.23, the total inventory per planning horizon at the factory warehouse has jumped to almost 200 units on average, resulting in the firm's higher overall inventory level, with an increase of around 12% compared to the other cases, as shown in Figure 4.4-5. The impact of variations in the holding cost the factory affiliated warehouse is illustrated in Figure 4.4-6. When the inventory holding cost at this storage facility decreases by 30%, total cost declines slightly despite the higher inventory level. This can be explained by the lower production cost as fewer machine setups are made. However, total emissions increase marginally as there is more carbon emitted from inventory holding, requiring a slightly higher number of emission allowances to be purchased.

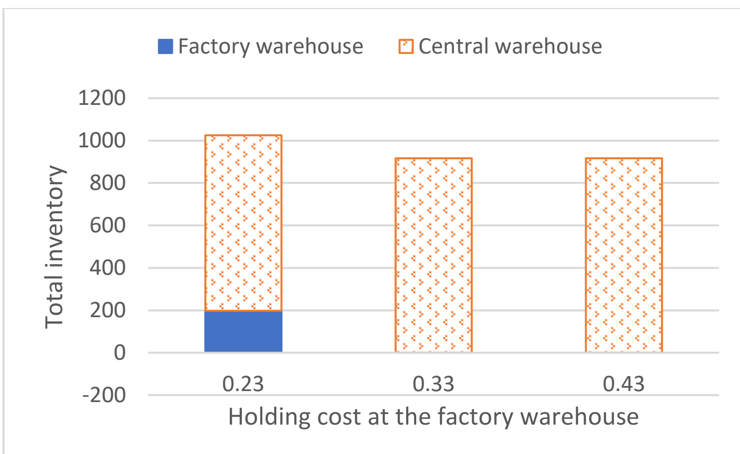

Figure 4.4-5: Effect of inventory holding cost on total inventory

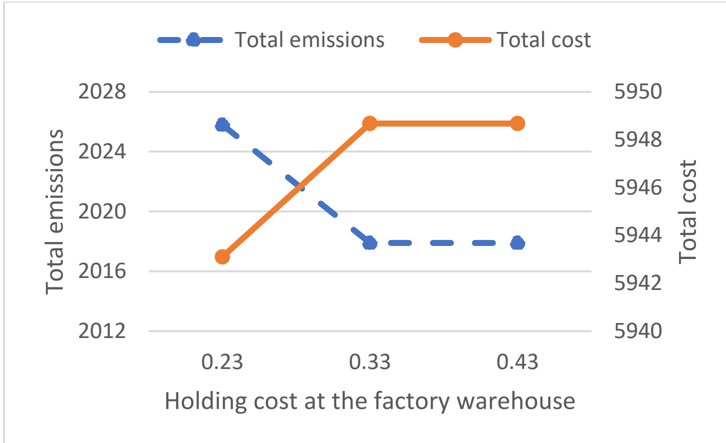

Figure 4.4-6: Effect of inventory holding cost on total cost and total emissions

4.4.4 Production emissions

After examining the impact of production fixed cost in section 4.4.1, we now vary both the fixed and variable emission factors in the production process under two settings: emission rates are 10 times lower and 10 times higher. The corresponding values of our variated production fixed emissions *pfe* and variable emissions *pve* are [0.025, 0.002] and [2.5, 0.2] respectively, while [0.25, 0.02] are their base case values. The computation results under different carbon intensity of the production line are presented in Table 4.4-4.

Table 4.4-4: Average results under variations of the production emissions

Case	Computational status					Costs				Emissions			
	MIP time	Upper bound	Lower bound	MIP gap	% Optimality	Prod_c	Trans_c	Inv_c	Emis_c	Total_e	Prod_e	Trans_e	Inv_e
[0.025, 0.002]	34.57	5808.01	5808.01	0%	100%	2108.00	3026.09	301.86	372.06	1468.72	61.02	1357.40	50.31
[0.25, 0.02]	33.51	5948.67	5948.67	0%	100%	2107.60	3025.85	302.50	512.73	2017.89	610.16	1357.32	50.42
[2.5, 0.2]	26.50	7356.03	7356.03	0%	100%	2107.20	3025.77	302.97	1920.10	7509.38	6101.59	1357.29	50.49

Case	Percentage of scenarios		Decision variables								
	with s2 buy	with s2 sell	s1 buy	s2 buy	s2 sell	Setup	Prod	Vehi light	Vehi heavy	Inv fact	Inv ware
[0.025, 0.002]	48.2%	49.8%	1463.56	84.11	78.94	10.54	30376.25	2.90	13.16	2.55	912.17
[0.25, 0.02]	49.2%	48.8%	2007.01	123.92	113.04	10.54	30376.25	2.90	13.16	0.18	916.47
[2.5, 0.2]	49.8%	48.2%	7446.76	522.35	459.73	10.54	30376.25	2.89	13.17	1.80	916.28

Table 4.4-4 shows that alternating emission factors in production does not create remarkable changes in the model's solving time as well as the relative MIP gap since all instances are solved to optimality. When the emissions rate in production is 10 times lower, the average total cost is reduced by around 2.3%. This reduction is mostly due to the lower carbon related cost, as the firm

does not need as many emission rights as in the base case (a drop of 27.3% is seen in its total quantity of allowances purchased). Correspondingly, a sharp decline (by 10 times) in the production emissions has majorly contributed to the firm's lower overall carbon footprint.

Figure 4.4-7 has shown a positive relation between the emission rates in production and the firm's total operational cost as well as the total emission rights needed. Particularly, when the production line is 10 times more carbon intensive, there is an increase of 26% in the total cost compared to the base case level, and as many as 3.7 times more permits have been purchased. This also indicates a surge in the total amount of GHGs being emitted into the environment. It is worth to mention that under such variations of emission factors in the production process, not many changes are seen in the firm's pivotal operational decisions except for those related to the buying and selling of emission rights. This is totally understandable as the firm needs to produce to satisfy market demand no matter how carbon intensive its production line is, and it is apparent that when the production generates more emissions, the firm needs to purchase more allowances.

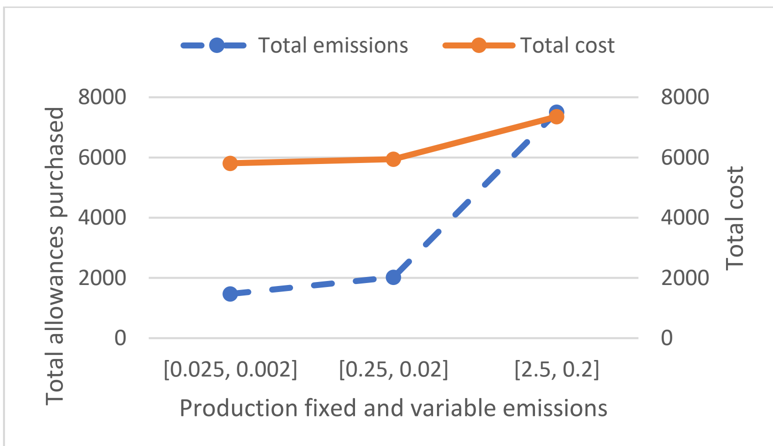

Figure 4.4-7: Effect of production emissions on total cost and total emissions

These variations have taken into account different levels of carbon intensity in a firm's production line. When a firm is subject to at least one emission regulation, or in other words, when a firm has to pay for the emissions it has generated, if its manufacturing process (or any other operational activities in general) is carbon intensive, emission cost can take up a large proportion in its overall operating cost. Therefore, it is essential for carbon-intensive firms to enhance their production lines or invest in green technology to reduce their carbon levels in the long term.

4.4.5 Holding emissions

In this section, we want to test if alternating another emission indicator, i.e., inventory holding emissions, would bring about similar impacts as in the previous experiment. We vary the inventory holding emissions by considering two alternative product sizes: half or double of the size that is applied in the base case. In the benchmark case, we assumed that a square meter of both warehouses could contain a maximum of 50 product units. By employing the emission feature of 33 kg CO_2e per m^2 per year provided by the literature, we come up with a holding emission rate of 0.055 kg CO_2e per unit item per month (or per planning period). If the product size is halved or doubled, it means that there is a maximum of 100 or 25 units of product that can be stored per m^2, resulting in a unit holding emissions of 0.0275 or 0.11 kg, respectively. Our experimental setting thus becomes $he_0 = he_1$ and $he_0, he_1 \in \{0.0275, 0.055, 0.11\}$. The average optimal results are presented in Table 4.4-5.

Table 4.4-5: Average results under variations of the inventory holding emissions

Case	Computational status					Costs				Emissions			
	MIP time	Upper bound	Lower bound	MIP gap	% Optimality	Prod_c	Trans_c	Inv_c	Emis_c	Total_e	Prod_e	Trans_e	Inv_e
0.0275	29.10	5943.16	5943.16	0%	100%	2102.40	3021.54	312.09	507.13	1992.06	610.15	1355.90	26.01
0.055	33.51	5948.67	5948.67	0%	100%	2107.60	3025.85	302.50	512.73	2017.89	610.16	1357.32	50.42
0.11	26.20	5959.24	5959.24	0%	100%	2117.20	3034.55	284.66	522.83	2065.22	610.17	1360.16	94.89

Case	Percentage of scenarios		Decision variables								
	with s2 buy	with s2 sell	s1 buy	s2 buy	s2 sell	Setup	Prod	Vehi light	Vehi heavy	Inv fact	Inv ware
0.0275	48.4%	49.6%	1979.48	127.29	114.70	10.51	30376.25	2.87	13.16	1.67	944.06
0.055	49.2%	48.8%	2007.01	123.92	113.04	10.54	30376.25	2.90	13.16	0.18	916.47
0.11	49.2%	48.8%	2055.16	118.26	108.20	10.59	30376.25	2.97	13.17	1.67	860.93

With these alterations in holding emissions, the model is still capable of finding an optimal solution in a short period of time. Again, the emissions index in inventory holding and the model's performance indicators (total cost and total emissions) are positively correlated, as illustrated in Figure 4.4-8. At a lower holding emission rate, the overall emissions level is obviously lower and the total cost is also slightly reduced despite the rise in inventory cost. This can be explained by the fact that under such circumstances, the firm has an incentive to keep more products in inventory, leading to a lower production setup and transporting frequency since fewer delivery trips are needed to transport finished goods to the warehouse. Therefore, the costs due to production, transportation, and allowances trading activities decrease, inducing an overall reduction in the value of the objective function. The same logic can be applied when holding emissions are two times higher.

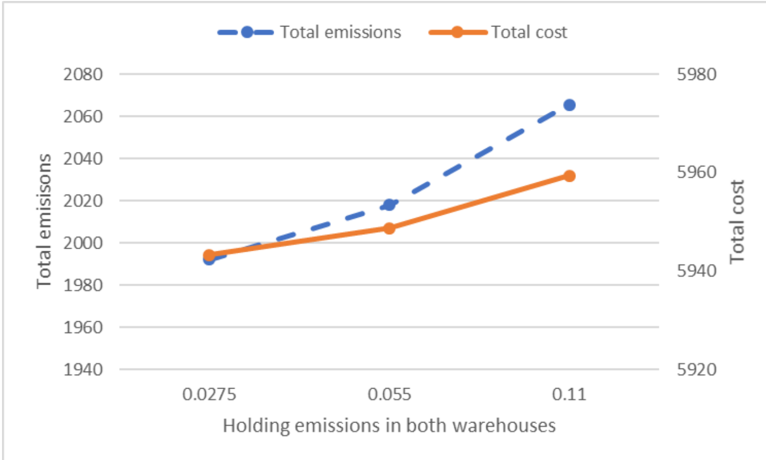

Figure 4.4-8: Effect of inventory holding emissions on total cost and total emissions

4.4.6 Vehicle capacity

To examine the influence of transportation capacity on decision making, we alter the capacity of our transporting vehicles by considering a product that weighs two times less or two times more compared to the initial case where the item weight is assumed to be 10 kg. As our medium- and heavy-duty trucks have a load capacity of 9 tons and 25 tons respectively, their vehicle capacity $Vcap_0$ and $Vcap_1$ will correspond to 1800 and 5000 units respectively when a unit of product weighs 5 kg. Similarly, the maximum number of units that those trucks can carry will have the values of 450 and 1250 respectively when the product weight is 20 kg per item. Table 4.4-6 presents the average results under different conditions of vehicle capacity.

Table 4.4-6: Average results under variations of the vehicle capacity

Case	Computational status					Costs				Emissions			
	MIP time	Upper bound	Lower bound	MIP gap	% Optimality	Prod_c	Trans_c	Inv_c	Emis_c	Total_e	Prod_e	Trans_e	Inv_e
1800-5000	2.49	4637.59	4637.59	0%	100%	2087.60	1868.14	272.30	409.55	1621.77	610.13	966.25	45.38
900-2500	33.51	5948.67	5948.67	0%	100%	2107.60	3025.85	302.50	512.73	2017.89	610.16	1357.32	50.42
450-1250	3297.35	8542.18	8537.76	0.05%	10%	2119.60	5367.74	336.66	718.18	2815.64	610.17	2149.36	56.11

Case	Percentage of scenarios		Decision variables								
	with s2 buy	with s2 sell	s1 buy	s2 buy	s2 sell	Setup	Prod	Vehi light	Vehi heavy	Inv fact	Inv ware
1800-5000	49.2%	48.8%	1623.21	83.99	85.43	10.44	30376.25	3.10	7.34	0.00	825.14
900-2500	49.2%	48.8%	2007.01	123.92	113.04	10.54	30376.25	2.90	13.16	0.18	916.47
450-1250	49.2%	48.8%	2810.18	179.49	174.03	10.60	30376.25	2.93	24.68	42.37	977.82

Given a stationary total demand level, it is apparent that fewer delivery trips are needed when more items can be loaded per trip, and in the opposite case, it will require more vehicle shipments. This is reflected in the 35% lower vehicle usage when both truck types can carry a doubled quantity of items, or in the 70% increase in the total number of shipments conducted when these vehicle capacities are halved. It is noted that heavy trucks account for most of the incremental delivery, as demonstrated in Figure 4.4-9. A rationale for this behavior lies in the fixed-cost structure of our vehicles: dispatching a 1250-unit capacity large truck which costs $203 is more cost-effective than dispatching multiple 450-unit trucks that costs $122. Therefore, heavy trucks are preferable in this circumstance.

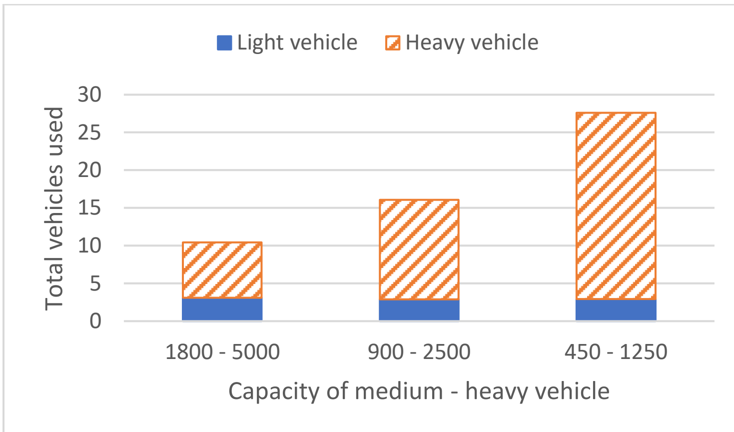

Figure 4.4-9: Effect of vehicle capacity on its utilization

From these vehicle capacity ranges, whenever the vehicle capacity is halved, more vehicles are used to transport products, leading to a tremendous increase in both the total emissions and the total cost. They are increased by 24% and 28% respectively when vehicle capacity diminishes from [1800, 5000] to [900, 2500] units, or increased by 39% and 43% when capacity shrinks to only [450, 1250] units, as shown in Figure 4.4-10. The increase in emissions means significant more carbon permits are bought by the company at both stages of its planning horizon to cover its surging carbon footprint. The reason why variations in vehicle capacity have such a strong impact on the firm's decisions is the critical role of the transportation activity in the firm's cost structure and carbon footprint – in the base case, transportation accounts for more than 50% of the firm's total cost and up to 67% of its total carbon footprint.

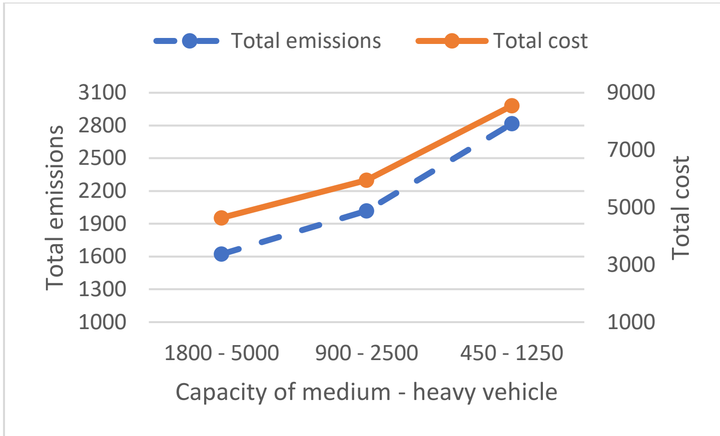

Figure 4.4-10: Effect of vehicle capacity on total cost and total emissions

Another downside of the lower fleet capacity is the vast increase in the MIP computing time. In this experiment, only in one out of the ten instances we are able to find an optimal solution within the time limit, creating a 0.05% gap between the average value of the upper bound and lower bound of the objective function. One possible explanation why the problem has become so hard to solve to optimality is the trade-offs it has to consider between transportation scheduling and the other operational decisions in order to satisfy the objective of minimizing total cost. As more frequent delivery corresponds to higher cost and emissions, the model thus needs to explore more possibilities to find out a solution that finds the best trade-off between these performance indicators.

4.4.7 Length of the planning horizon

In the base case, we set the number of periods *m* to 12 periods. In this section, we decrease the length of our planning horizon to comprise only 6 periods or extend it to 24 periods, with an aim to test if there is any impact of the horizon length on the model's performance. The results of these alternative settings along with those of the base case are presented in Table 4.4-7.

Table 4.4-7: Average results under variations of the length of the planning horizon

Case	Computational status					Costs				Emissions			
	MIP time	Upper bound	Lower bound	MIP gap	% Optimality	Prod_c	Trans_c	Inv_c	Emis_c	Total_e	Prod_e	Trans_e	Inv_e
6	9.30	2990.91	2990.91	0%	100%	1064.80	1524.52	138.03	263.56	1010.73	305.22	682.50	23.01
12	33.51	5948.67	5948.67	0%	100%	2107.60	3025.85	302.50	512.73	2017.89	610.16	1357.32	50.42
24	902.27	11848.42	11848.42	0%	100%	4184.40	6019.50	639.18	1005.34	4031.72	1220.86	2704.34	106.53

Case	Percentage of scenarios		Decision variables								
	with s2 buy	with s2 sell	s1 buy	s2 buy	s2 sell	Setup	Prod	Vehi light	Vehi heavy	Inv fact	Inv ware
6	49.2%	48.8%	1009.16	88.23	86.66	5.32	15194.64	1.55	6.58	1.16	417.12
12	49.2%	48.8%	2007.01	123.92	113.04	10.54	30376.25	2.90	13.16	0.18	916.47
24	49.6%	48.4%	4017.99	164.04	150.31	20.92	60781.34	5.61	26.28	6.77	1930.13

As the total demand level is positively correlated to the length of the planning horizon, our total cost value follows an increasing trend when there are more periods being included. All instances are again solved to optimality even though the computational time has been tremendously extended to 27 times longer when the number of periods doubled (m is equal to 24). This is intuitively reasonable as the problem size gets larger, the model takes longer time to explore more potential solutions before reaching the optimal one.

We also observe that whenever the number of periods is doubled, either from 6 periods to 12 periods or from 12 periods to 24 periods, the longer planning horizon experiences an approximate 2 times increase in all of its cost and emissions indicators as well as in its optimal decisions.

4.5 Analyzing the effect of allowance prices

Our study considers a firm that is subject to the carbon cap-and-trade system, carbon trading prices thus play a crucial role in its decision making. In section 4.3, we have presented the influence of emissions prices on the effectiveness of approximating the stochastic model using the deterministic mean model. In this section, we will provide a more comprehensive analysis into the interaction between these allowance prices and the firm's decision making.

4.5.1 Allowance prices vary simultaneously

As in section 4.3, we first examine the model when all of its allowance trading prices (first-stage buying price, second-stage buying price, and second-stage selling price) are altered collectively, keeping other parameters unchanged. In detail, case C4, C5, C6 and C7 are considered as discussed in Section 4.3, in which permit prices are respectively 10 times lower, halved, doubled, or 5 times higher than those of the base case C0. The results of these alternative settings are then compared with those of the C0 which are set to 1.0000, their relative values are presented in Table 4.5-1.

Table 4.5-1: Summary of the relative performance of different cases compared to C0

Case	Cost					Emissions				Decisions			
	Total_c	Prod_c	Trans_c	Inv_c	Emis_c	Total_e	Prod_e	Trans_e	Inv_e	Setup	Total allowances	Total vehicles	Total inventory
C4	0.9224	0.9985	1.0016	0.9944	0.1001	1.0007	1.0000	1.0012	0.9944	0.9985	1.0007	1.0010	0.9944
C5	0.9569	1.0000	1.0008	0.9919	0.5001	1.0002	1.0000	1.0006	0.9919	1.0000	1.0002	1.0006	0.9919
C0	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
C6	1.0862	1.0021	0.9994	0.9926	1.9990	0.9995	1.0000	0.9995	0.9926	1.0021	0.9995	1.0000	0.9926
C7	1.3444	1.0055	0.9967	1.0037	4.9910	0.9984	1.0000	0.9974	1.0037	1.0055	0.9984	0.9989	1.0037

It is observed that the firm tries to lower its carbon footprints when emission permits become more expensive by diminishing its number of vehicles used in transporting the finished products, as transportation accounts for the largest part of its emissions inventory (more than 67% of the total emissions). This is an effective practice as the total emissions level has actually decreased under higher allowance prices, despite resulting in a marginal increase in the inventory level and setup frequency. Table 4.5-1 also shows that total cost can increase by almost 35% when emission prices are five times higher (in case 7), but it can only decrease by around 8% when these prices are 10 times lower (in case 4). This can be explained as we look at the structure of the total cost function, in the latter case, emission cost makes up less than 1% of the total cost whereas it constitutes up to 32% in the former case. Therefore, it can be concluded that increasing allowance trading prices could only impact the amount of carbon emitted to a small extent but exacerbate the overall cost level, and the extent this cost-expanding effect will have depends on the proportion of the emission cost in the total cost function.

It is also worth to mention that there are no recognizable changes in the total emissions level among these different cases. This is intuitively logical as we enforce that demand needs to be satisfied, therefore, the firm needs to implement its operational practices to meet all the demand no matter how expensive the emissions allowances become. We observe indeed that the total emissions vary by less than 1% when increasing or decreasing the allowance prices within the indicated ranges. Therefore, it seems that operational decisions only have a minor impact on the overall emissions level for this case.

4.5.2 Allowance prices vary separately (with a fixed first stage buying price)

In this section, we further investigate the impact of allowance trading prices on the firm's trading decisions as well as its performance in terms of total cost and total emissions, by varying the second-stage buying and selling prices, with the first-stage buying price being fixed (*s1b* is always equal to 0.24). We first determine four cases of the second-stage selling price that will be considered, *s2s* ϵ {0.096, 0.12, 0.18, 0.24}, these values correspond to the cases when *s2s* is 20% lower, equals to the base case, 50% higher, or the case when it equals to *s1b*. We do not consider the case when *s2s* is larger than *s1b*, as the firm will earn profit from merely trading emission allowances. Under each case of *s2s*, four cases of second-stage buying price are examined, *s2b* ϵ {0.24, 0.36, 0.468, 0.72}, conforming to the circumstances when it equals to *s1b*, equals to the base case, 30% higher, or two times higher. The experimental setting for the variations in allowances trading prices is briefly presented in Table 4.5-2.

Table 4.5-2: Variations in the second stage selling price and buying price

Variation	*20% lower*	*Base case*	*50% higher*	*Equal to s1b*
s2s value	0.096	0.12	0.18	0.24

Variation	*Equal to s1b*	*Base case*	*30% higher*	*200% higher*
s2b value	0.24	0.36	0.468	0.72

With each pair of the second-stage selling and buying prices, we solve the model for 10 different demand instances and their average results are presented in Table 4.5-3. First of all, we notice that unlike the sensitivity analysis conducted in Section 4.4 where the firm generally needs to purchase extra allowances in around 50% of the scenarios and it also has excessive allowances to sell in roughly the other half of all scenarios, these relative variations in emission prices have entirely changed the firm's emission rights trading strategy.

Table 4.5-3: Experimental average results under variations of the second-stage trading prices with the fixed first-stage buying price

s2 sell price	s2 buy price	s1 buy allowances	s2 buy allowances	s2 sell allowances	% with s2 buy	% with s2 sell	Total emissions	Total cost	VSS	% of SP solution
0.096	0.240	1347.790	669.888	0	98%	0%	2017.677	5920.204	0	0%
	0.360	1968.414	144.075	94.625	54%	44%	2017.865	5951.158	1.210	0.0203%
	0.468	2096.357	83.898	162.313	38%	60%	2017.942	5962.765	9.181	0.1540%
	0.720	2238.833	40.116	260.709	22%	76%	2018.240	5977.100	40.431	0.6764%
0.120	0.240	1347.790	669.888	0	98%	0%	2017.677	5920.204	0	0%
	0.360	2007.146	123.853	113.105	49.2%	48.8%	2017.893	5948.674	1.969	0.0331%
	0.468	2136.109	69.242	187.351	34%	64%	2018.000	5958.532	11.688	0.1962%
	0.720	2277.455	31.770	291.028	18.8%	79.2%	2018.197	5970.444	45.363	0.7598%
0.180	0.240	1347.790	669.888	0	98%	0%	2017.677	5920.204	0	0%.
	0.360	2150.506	64.445	197.117	32%	66%	2017.833	5939.785	6.541	0.1101%
	0.468	2271.932	32.910	286.941	20%	78%	2017.901	5944.953	20.950	0.3524%
	0.720	2400.242	13.840	396.145	10%	88%	2017.938	5950.641	60.848	1.0225%
0.240	0.240	0	2017.677	0	100%	0%	2017.677	5920.204	0	0%
	0.360	2680.804	0	663.127	0%	98%	2017.677	5920.204	21.792	0.3681%
	0.468	2680.804	0	663.127	0%	98%	2017.677	5920.204	41.369	0.6988%
	0.720	2680.804	0	663.127	0%	98%	2017.677	5920.204	86.956	1.4688%

For a given value of *s2s*, both the number of carbon permits to buy at the first stage and the total cost increase in *s2b*, with fewer permits to be bought yet more are sold at the second stage. When buying emission allowances become more expensive in the second stage, the firm would rather purchase more upfront to avoid the additional cost incurred when it needs to buy later in the spot market, even facing the potential loss of selling unused permits in the end. When *s2b* is equal to *s1b* (*s2b* = *s1b* = 0.24), buying at the first or the second stage will not entail any differences, and there exist alternative optimal solutions.

When *s2s* is equal to *s1b*, depending on the correlation between the second-stage buying and selling prices, there are two possible scenarios: (1) if *s2b* is equal to *s2s*, meaning that *s1b* = *s2b* = *s2s* = 0.24, there is only one transaction conducted at the second stage, i.e., the firm buys an exact amount of the allowances needed; (2) if *s2b* is higher than *s2s*, the firm only buys allowances at the first stage and those excessive allowances will be sold in the second stage. Apparently, there is no incentive for the firm to buy at the second stage when it can buy as much as possible at the first stage without facing the loss in reselling in the future.

Likewise, for a given *s2b*, the number of permits being bought at the first stage and being sold at the second stage increase in *s2s*, while the quantity to be bought at the second stage decreases in *s2s*. In this case, a decline in total cost can be observed as the firm can get more revenue by selling its excessive allowances when the selling price goes up.

In terms of total emissions, again, no noticeable difference can be seen. This can be explained as no backlog is allowed. The firm needs to satisfy demand regardless of the emission prices, therefore, emission levels from those operation activities remain relatively constant. This indicates again that in this case the operational decisions have only a minor impact on the total emission level.

In Table 4.5-3, we also include the Value of the Stochastic Solution for each case of the second stage selling price and buying price. When *s2b* = *s1b*, buying emission rights at the first or the second stage will not generate any impacts on the total cost value between the EEV and the SP model as long as the total allowances being purchased remains constant. Therefore, the VSS is zero. When *s2b* > *s1b*, the VSS increases in *s2b*, indicating that the mean value problem is a less accurate approximation of the stochastic model when the second-stage allowance buying price is higher. Particularly, a 33-time increase in the VSS is seen when s2b is 200% higher (from 0.36 to 0.72) under a second-stage selling price of 0.096. However, its value is increased by only 4 times when s2s = 0.24. Therefore, it is observed that, for a given s2b, the VSS also has the tendency to increase in s2s. This implies that the mean value problem becomes less accurate not only when the buying price is higher but also when the selling price grows.

The results of this experiment imply that the firm's emission rights trading policy is versatile and contingent on the market trading prices. Any variations in these prices could considerably influence the firm's decisions as well as its total cost. Therefore, we suggest that decision makers in the reality should collect sufficient data on the carbon allowances trading market, including fluctuations in prices, developing trends, historical trading quantities, etc. in order to make well-informed decisions.

Chapter 5. Analysis of different demand patterns

In this chapter, we conduct a further experiment which involves several different patterns of demand, with an aim to cover several different business settings as different product types exhibit different demand patterns. The various demand patterns that are studied include stationary (STAT), random (RAND), sinusoidal (SIN1 and SIN2), life cycle (LCY1 and LCY2) patterns. These patterns were also used in Purohit *et al.* (2016) for a stochastic lot-sizing problem.

5.1 Demand generation for different demand patterns

The patterns that are considered will determine the average demand in each period over the planning horizon. In our study, these patterns are defined as follows:

- STAT pattern means that the average demand per period remains constant throughout the planning horizon. In this experiment, we assume a theoretical average demand of 2500 units for all 12 periods.

- RAND pattern represents the average demand values of all periods in the planning horizon which do not follow a particular pattern but take random values within a specific interval. We generate 12 theoretical random demand values for the 12 periods of the planning horizon, each of which has a value within [0, 5000] using a uniform distribution.

- Sinusoidal pattern comprises demand values that follow the sine equation: $y = a \sin b(x - c) + d$, where a is the amplitude of the sine function (the reflection over the x-axis), b determines the period of the function (with period = $\frac{2\pi}{b}$), c is the horizontal displacement, and d is the vertical displacement of the equation. In our experiment, we consider two sinusoidal patterns, SIN1 and SIN2, which are differentiated by the lower and higher levels of the amplitude of the sine function. For the numerical study, SIN1 and SIN2 functions are set to $y = 2000 \sin (\frac{\pi}{6} x) + 2500$ and $y = 1000 \sin (\frac{\pi}{6} x) + 2500$, respectively. For each function, we generate 12 demand values with $x \in \{1, 2, \ldots, 12\}$ for each of the 12 periods.

- Life cycle pattern resembles the curve of the product life cycle concept which goes through the introduction, growth, maturity, and decline stages. For simplification purposes, we linearize our life cycle pattern that only includes three stages – developing, maturity, and decline. Similarly, we also consider two life cycle patterns LCY1 and LCY2 which are also differentiated in their levels of demand variability (lower and higher) over the x-axis. In our experiment, for LCY1, we assume demand follows the equation $y = \frac{2500}{3} x + 278$ from period 1 to period 4 of the developing phase, $x \in \{1, 2, 3, 4\}$. Starting from period 4, demand remains constant until the end of the maturity phase, $x \in \{5, 6, 7, 8\}$, and it follows the equation $y = -\frac{2500}{3} x + 10278$ during the decline phase, $x \in \{9, 10, 11, 12\}$. Similarly, for

LCY2, the demand function is y = $\frac{2500}{8}x$ + 1667 in the developing phase and it is y = -$\frac{2500}{8}x$ + 5417 in the decline phase.

The resulting theoretical mean demand for each of the demand patterns are then presented in Table 5.1-1. It is noticeable that in our experiment, demand patterns are designed so that each of them has a similar level of average total demand, i.e., the theoretical total mean demand over a span of 12 periods is set to be 30000 for each demand pattern, with an aim to avoid any effect incurred due to the variation in total demand. Figure 5.1-1 shows all the demand patterns, where each point represents the theoretical mean demand of a period, for which the actual demand may have a different value.

Table 5.1-1: Theoretical mean demands for different patterns

Pattern/ Period	1	2	3	4	5	6	7	8	9	10	11	12	Sum
STAT	2500	2500	2500	2500	2500	2500	2500	2500	2500	2500	2500	2500	30000
RAND	2031	4726	2564	866	2976	1048	4026	1364	1191	1271	3568	4369	30000
SIN1	3500	4232	4500	4232	3500	2500	1500	768	500	768	1500	2500	30000
SIN2	3000	3366	3500	3366	3000	2500	2000	1634	1500	1634	2000	2500	30000
LCY1	1111	1945	2778	3611	3611	3611	3611	3611	2778	1945	1111	277	30000
LCY2	1979	2292	2605	2917	2917	2917	2917	2917	2605	2292	1979	1663	30000

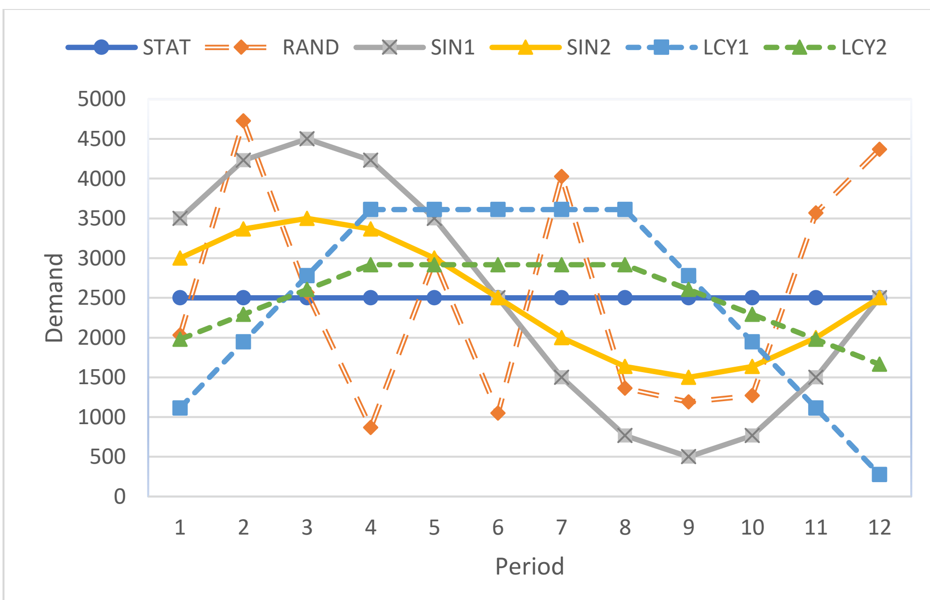

Figure 5.1-1: Demand patterns

Each pattern hence consists of a mean demand μ_t for every period t. From these theoretical mean demands, for each pattern, we generate 50 random demand scenarios by assuming that demands in each period are normally distributed with mean μ_t and standard deviation σ, under a coefficient of variation CV = 0.1. The coefficient of variation is defined as the ratio of the standard deviation to the average demand per period, $CV = \frac{\sigma}{\mu}$ (Purohit *et al*., 2016). Table 5.1-2 shows the theoretical mean demand and the standard deviation by period of the SIN1 pattern based on which the 50 demand scenarios for SIN1 are generated.

Table 5.1-2: Demand data for the SIN1 pattern (with CV = 0.1)

Period	1	2	3	4	5	6	7	8	9	10	11	12
μ	3500	4232	4500	4232	3500	2500	1500	768	500	768	1500	2500
σ *(CV=0.1)*	350	423.2	450	423.2	350	250	150	76.8	50	76.8	150	250

We then replicate this scenario demand generation method to create 10 different demand instances for each pattern, and each of these instances comprises 50 demand scenarios. The average demand per period over 10 instances for each pattern type is shown in Table 5.1-3. We can observe that in each period, the average of its normally distributed demands is close to the theoretical mean demand as mentioned in Table 5.1-1, leading to the equivalent average total demands among these demand patterns, with a value of around 29965 units.

More information on the demand generation can be found in Appendix 4.

Table 5.1-3: Average demand per period over the 10 instances of different demand patterns

Pattern/ Period	1	2	3	4	5	6	7	8	9	10	11	12	Sum
STAT	2497.14	2497.14	2497.14	2497.14	2497.14	2497.14	2497.14	2497.14	2497.14	2497.14	2497.14	2497.14	29965.73
RAND	2028.63	4720.55	2561.04	865.01	2972.53	1046.80	4021.36	1362.41	1189.65	1269.54	3563.89	4363.94	29965.36
SIN1	3495.98	4227.11	4494.83	4227.11	3495.98	2497.14	1498.27	767.12	499.44	767.12	1498.27	2497.14	29965.51
SIN2	2996.55	3362.13	3495.98	3362.13	2996.55	2497.14	1997.69	1632.11	1498.27	1632.11	1997.69	2497.14	29965.51
LCY1	1109.70	1942.75	2774.80	3606.84	3606.84	3606.84	3606.84	3606.84	2774.80	1942.75	1109.70	276.68	29965.38
LCY2	1976.71	2289.38	2602.00	2913.66	2913.66	2913.66	2913.66	2913.66	2602.00	2289.38	1976.71	1661.09	29965.56

5.2 Computational results

With more fluctuations in the demand values, random demand can take a value as high as 5684 units as in period 3 of instance 6 of the SIN1 pattern, or in another case, there are three consecutive periods with a demand value over 5000 units. To avoid infeasibility in the computation process, we enhance both the periodical production capacity *Pcap* and the storage capacity of the factory warehouse $Icap_0$ to 6000 units.

We then solve the two-stage stochastic model with these demand patterns, each with 10 different demand instances. The results are presented in Table 5.2-1.

Table 5.2-1: Average results over 10 instances of different demand patterns

Pattern	Computational status					Costs				Emissions			
	MIP time	Upper bound	Lower bound	MIP gap	% Optimality	Prod_c	Trans_c	Inv_c	Emis_c	Total_e	Prod_e	Trans_e	Inv_e
STAT	3347.13	5804.51	5797.92	0.11%	10%	2400.00	2773.70	151.37	479.44	1894.76	602.31	1267.22	25.23
RAND	175.57	6157.51	6157.51	0%	100%	2298.00	3094.49	264.40	500.63	2021.11	602.18	1374.86	44.07
SIN1	3642.81	6009.76	6005.13	0.08%	0%	2151.20	3045.57	314.91	498.09	2014.59	602.00	1360.11	52.48
SIN2	92.87	6075.20	6075.20	0%	100%	2393.20	3103.18	84.15	494.67	1993.90	602.30	1377.57	14.03
LCY1	3645.08	6053.13	6035.94	0.28%	0%	2196.80	3140.23	210.80	505.30	2028.87	602.05	1391.69	35.13
LCY2	93.31	5961.98	5961.98	0%	100%	2399.60	2948.05	128.92	485.41	1948.41	602.31	1324.61	21.49

Pattern	Percentage of scenarios		Decision variables								
	with s2 buy	with s2 sell	s1 buy	s2 buy	s2 sell	Setup	Prod	Vehi light	Vehi heavy	Inv fact	Inv ware
STAT	48.8%	48.8%	1796.15	152.23	53.62	12.00	29965.73	2.77	12.00	0.00	458.69
RAND	49.2%	48.8%	1999.05	75.89	53.83	11.49	29965.36	3.83	12.94	0.00	801.20
SIN1	49.2%	48.8%	2001.12	67.51	54.04	10.76	29965.51	2.42	13.55	0.00	954.26
SIN2	49.2%	48.8%	1964.03	82.15	52.28	11.97	29965.51	3.86	12.97	0.00	255.00
LCY1	48.8%	49.2%	2042.87	69.54	83.53	10.98	29965.38	2.77	13.80	0.00	638.78
LCY2	48.0%	50.0%	1953.92	71.37	76.89	12.00	29965.56	4.06	12.08	0.00	390.66

It is observed that demand pattern has a strong impact on the computational time. Of the six different patterns that are considered, the model can be solved to optimality in less than 3 minutes on average when demands follow the SIN2, LCY2, or RAND pattern, while with the STAT pattern, only 1 out of 10 instances is solved to optimality within a one-hour (or 3600 seconds) time limit, leading to an average MIP time of around 3347 seconds and a relative gap of 0.11%. A possible explanation for the difficulty in solving the STAT patterned model is that, in lot-sizing, if a parameter is stationary over time (i.e., demand is exactly the same over periods in our case), it is often more challenging for the model to find the optimal result as there might be several potential near optimal solutions. However, the same logic cannot be applied to explain why the model has become so hard to solve when demand follow the SIN1 and or the LCY1 pattern, which in fact have a greater degree of demand fluctuations. For these two patterns, no optimal solution has been found within one hour of computation for all the instances, resulting in a respective MIP gap of 0.08% and 0.28%, whereas the flatter SIN2 and LCY2 patterns are much easier to solve. To the best of our knowledge, there is no explanation in the literature and we are not able to provide an appropriate explanation for this phenomenon.

We hereby conduct performance comparisons among these patterns based on the solutions obtained within the time limitation. Figure 5.2-1 and Figure 5.2-2 present the total costs and total emissions of the model solved under different demand patterns. The stationary pattern has resulted in the lowest value for both cost ($5804.51) and emissions (1894.76 kg CO_2e) while randomly fluctuated demand induces the highest level of cost ($6157.51) and a relatively high emissions level (2021.11 kg CO_2e). This is intuitively reasonable as when demand is constant throughout the planning horizon, there are fewer variations in the operational decisions, generating lower transportation and inventory costs. Emissions cost in this case is also the lowest as the firm can estimate the number of allowances to trade based on the preceding periods. On the other hand, when demand does not follow any specific trend, it is more challenging for the firm to conduct operational planning, which can lead to higher operational costs. A relative high level of carbon footprint is also captured as more vehicles are used and more products are stored in inventory to anticipate the unpredictability in demand.

When looking at one type of pattern separately, either the sinusoidal or the life cycle pattern, the degree of variability in the average demand also has certain effects on the firm's performance. As discussed before, SIN2 (LCY2) shows less variation in the average demand levels compared to SIN1 (LCY1). Compared to the less variable SIN2 pattern, SIN1 has lower total cost but it leads to more emissions. This can be explained by looking at the average value of those operational decision variables. Under SIN1, fewer production setups and deliveries are conducted (10% less). As the firm experiences considerably high and low demands, it can always produce in bigger batches to cover those extremely low demand periods, thus fewer setups and delivery trips are needed. This brings about significantly lower costs in production and transportation. Under this circumstance, although the surge in inventory leads to an increase of 3.7 times in inventory cost, it has been offset by the significantly lower production and transportation costs. Meanwhile, within the life cycle patterns, LCY1 generates higher total cost and also a higher carbon footprint. Although there are also fewer production setups as in SIN1, more vehicles (particularly more heavy-duty vehicles) are necessary to transport goods in those consecutive high-demand periods in the maturity phase of the life cycle. Therefore, the cumulative increase in inventory, emissions, and transportation costs has led to an overall higher total cost. The increase in total emissions level can also be justified with the same logic.

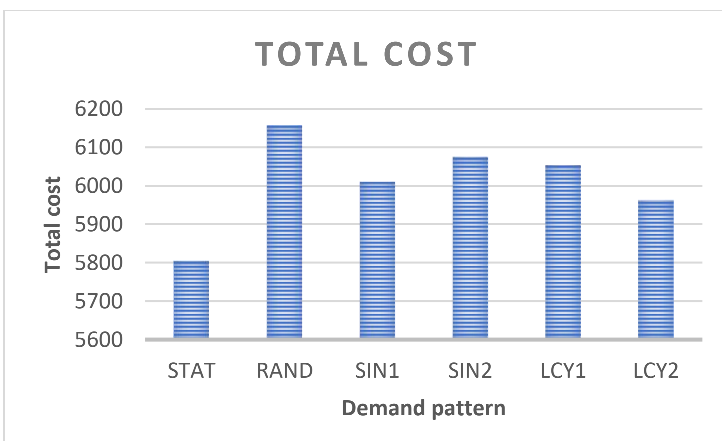

Figure 5.2-1: Total cost of different demand patterns

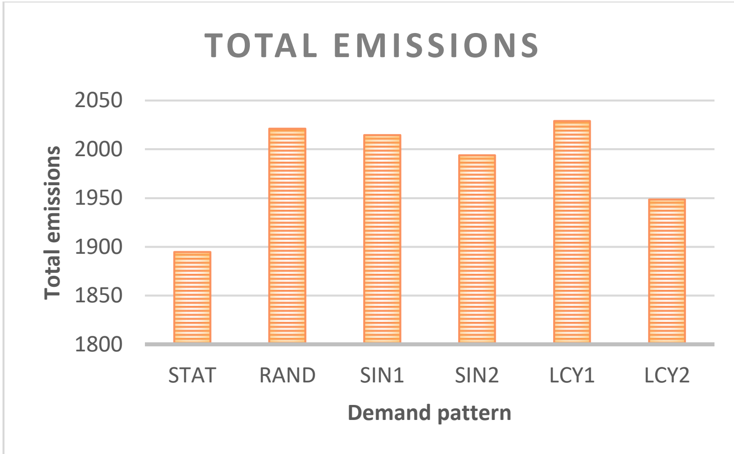

Figure 5.2-2: Total emissions of different demand patterns

We also include the Value of Stochastic Solution for the different demand patterns in Table 5.2-2, in which negative values are possible for those cases that cannot reach optimality within the computing time limit. Of those cases where an optimal solution is obtained (RAND, SIN2, and LCY2), the VSS is pretty small, equivalent to only 0.0009% to 0.0013% of the optimal value of the objective function. This implies that using the deterministic mean model to approximate the stochastic problem is a suitable and effective approach in the setting of this problem. This finding also aligns with what we have seen in the previous experiments.

Table 5.2-2: Value of Stochastic Solution of different patterns

Pattern/ Instance	1	2	3	4	5	6	7	8	9	10	Average	% of SP solution
STAT	0.110	-0.114	0.028	-0.451	-0.181	-0.014	-0.087	-0.280	-1.092	-0.833	-0.291	-
RAND	0.190	0.010	0.037	0.011	0.150	0.019	0.000	0.000	0.132	0.004	0.055	0.0009%
SIN1	-0.135	-0.093	-0.073	0.014	-0.014	-0.005	-0.190	-0.088	0.074	-0.050	-0.056	-
SIN2	0.158	0.008	0.027	0.016	0.399	0.026	0.000	0.000	0.305	0.005	0.094	0.0015%
LCY1	-0.500	-5.909	-2.508	-0.894	-5.217	-2.045	-3.167	-2.440	-3.928	-1.609	-2.822	-
LCY2	0.449	0.010	0.044	0.011	0.138	0.018	0.000	0.000	0.122	0.003	0.080	0.0013%

Chapter 6. Conclusion, limitations, and future research

6.1 Conclusion

With the rising concern over the impact of greenhouse gas emissions from industrial activities on the environment, research on supply chain activities with emissions factors are expected to continue growing for the foreseeable future. This thesis contributes to the current body of the literature firstly by integrating the element of carbon emissions into a two-stage stochastic planning model. A two-stage MILP model has been built to assist a manufacturing firm facing stochastic market demand in making operational decisions under the carbon cap-and-trade regulation. The first stage decision includes the initial quantity of emission rights to purchase to cover its overall emissions level, while the second stage comprises recourse decisions on emissions rights trading as well as operational planning decisions after uncertain demands are realized. Secondly, this model has involved both the cost and emission features of the firm's most essential operational activities – production, inventory control, and transportation planning. Thirdly, heterogeneous truck types, i.e., medium-duty and heavy-duty trucks, each with an associated carbon emission standard and a full truckload cost rate, have been considered in the study.

To model the uncertainty in market demand, we have generated different demand instances, each comprises multiple scenarios of randomly distributed demands. A set of base case parameters is generated with some values taken from the literature while others are based on preliminary tests.

In the numerical analysis, we have applied the concepts of Value of Stochastic Solution and the Expected Value of Perfect Information to evaluate the effectiveness of using the approximating method when the stochastic model is too hard to solve. In our experiments, both the VSS and EVPI are relatively small under all of the parameter cases that have been studied. This implies that with the problem being considered, using the deterministic model to approximate the performance of the stochastic model is an effective approach. This effectiveness level will depend heavily on the emissions trading prices as well as the importance of emissions cost in the firm's total cost.

In order to observe the impact of the model parameters on the firm's performance, we have conducted a sensitivity analysis by separately varying some key parameters, including the cost and emission factors in production, transportation, and inventory management, the results of which are compared to those of the base case. We found that these major operational decisions are closely correlated to one another and that there is an apparent negative correlation between the machine setup frequency and the inventory level. The relative utilization rate between different vehicle types or warehouses is highly contingent on their cost indicators as well as their capacity (in the case of vehicle utilization rate). Additionally, when an emission factor is varied, either in the production, transportation, or the inventory holding activity, not only the total emissions but also the total cost will be accordingly influenced. In a later part of the numerical analysis, we also vary the emission permit buying and selling prices to take into consideration the potential impact of fluctuations in emission allowances prices on the firm's carbon trading scheme. The experimental results have shown that increasing the emission prices only induces a slight reduction in the total carbon being emitted as the firm needs to operate to satisfy demand anyway, while it can trigger a significant increase in the total cost index. The decisions between buying or selling are also proved to experience considerable fluctuations when these market prices change.

Further in the experiment, we have extended the stochastic demand problem by considering various types of possible demand pattern, i.e., stationary, random, sinusoidal, and life cycle patterns, in order to model different product types. Solving the MILP model under these demand patterns provides us a closer look into how the distribution of the uncertain demand can influence its overall performance. The model seems very hard to solve to optimality when demand follows the stationary, highly variated sinusoidal or the highly variated life cycle pattern.

In general, the numerical experiments presented in this thesis have provided managerial insights for decision makers in planning operational activities, as well as the main trade-offs that it needs to make between the total cost and the total emissions, under the presence of stochastic market demand along with the restriction on carbon emissions.

6.2 Limitations

Although we have tried to provide an effective decision-making model that could better reflect the real-life problem by involving the stochasticity in market demand and the variations in cost and emissions factors, there are still limitations as we have made several assumptions to narrow the scope of the study.

First of all, regarding the general setting of the problem, we only consider one single product while a manufacturing company in reality often produces more than one product type. Each type is associated with specific characteristics and may require different levels of resources resulting in a more complex production planning schedule. With regard to transportation, it is not practical for the firm to own an unlimited transporting fleet as there are apparent issues on costs and utilization rate. In reality, the firm may own a fleet of limited size and if its transport capacity is insufficient, it usually needs to contract external carriers on the spot market with a higher shipping rate. It is also a common practice for firms to outsource their transportation sector to third-party service providers if transportation is not their core activity, under which case the cost and emissions factors would be quantified in a different way. In terms of inventory control, the holding costs at different storage facilities can be different as these costs are determined by multiple factors, e.g., geographic, labor cost, electricity rate, capital investment, etc. Lead times related to the machine setup, production process, and transportation are also ignored.

This thesis is also limited by the lack of a full set of real data on costs as well as on emissions. As it is hard to obtain the actual features for all the parameters, we have applied a mix of real data from the literature and the data from preliminary tests when assigning values to the parameters for our model. In measuring the emissions from transportation, we have also ignored the speed of transportation which can change according to the traffic flow and the road condition.

While expanding our problem to involve different demand patterns in the experiment of Chapter 5, we have not successfully implemented a totally random sampling technique. The demand generation method we employed has synchronously created a temporal dependence among different time periods within a planning horizon as well as a positive correlation among different demand patterns. In practice, an identical standardized normal variable is often used to generate random demand for all patterns.

Regarding the carbon cap-and-trade system, unlike what we have assumed, there is a limitation on the number of emissions permits that firms can trade in the real-life carbon market. As the primary objective of the cap-and-trade regulation is to technically reduce emissions, the carbon cap is designed to be tightened over time. This also implies that there could be a case where no permits are available for firms to purchase to cover their extra emissions. Under this case, firms might either turn to other carbon offset projects or invest in green technology.

6.3 Future research

It would be interesting to consider the case where the firm's transportation activity is outsourced to third-party logistics provider. When outsourcing to a 3PL, the shipper no longer has control over the actual shipping situation, and this corresponds to the situation where less-than-truckload shipments are employed. Under this case, unit transportation cost and unit emissions rate will be applied as opposed to the fixed cost and fixed emissions rates per shipment employed in this study, which means that the total transportation cost and total emissions will depend on the total shipping weight and/or volume. It is also noticeable that when the firm no longer owns transportation fleet, the emissions resulted from their transporting activities may be considered as indirect emissions, which is reported as scope 3 emissions (according to the GHG Protocol) and will not be counted in its emission quota. Another possibility is that instead of considering a constant fixed transportation cost, the firm can apply flexible freight rates, i.e., freight rates decrease as shipping weights and/or volumes increase.

The problem can also be developed further by considering a company that manufactures multiple products with a common finite production capacity, or products that require specific storing conditions (e.g., temperature-controlled storage units). In addition, with the current setting, the firm could possibly include one or more green production technologies in dealing with emissions related problems since it is acknowledged that green technology combined with emissions trading system could work effectively in the effort of emissions abatement.

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Appendix

Appendix 1: Random demands over 50 scenarios of instance 1

Scenario/ Period	1	2	3	4	5	6	7	8	9	10	11	12	Sum
S1	1200	4762	616	2189	1065	4158	3782	3968	3209	1819	868	4096	**31732**
S2	332	3293	3645	117	3748	2281	1974	4942	937	2700	350	282	**24601**
S3	308	4535	175	3222	1874	3557	337	4422	1916	3687	4161	4629	**32823**
S4	2009	2931	1991	1892	3865	2473	276	3509	4658	919	1622	2528	**28673**
S5	1090	2825	4202	3557	4259	1655	2585	2427	4913	4190	4239	3322	**39264**
S6	4925	382	4034	2088	3411	3494	1517	3107	4595	3169	808	3695	**35225**
S7	4265	984	1441	4367	3321	3135	4111	342	3944	456	2627	4959	**33952**
S8	4836	3324	1495	1481	4214	1959	200	1734	4520	4591	2001	3413	**33768**
S9	4308	2916	4833	2994	3861	2305	4589	146	3243	4298	1158	4349	**39000**
S10	4698	1783	3590	559	4041	3087	4769	4641	1737	4234	3486	4072	**40697**
S11	3022	3494	2935	112	4511	4524	2812	3853	329	1980	1551	4611	**33734**
S12	4887	1580	850	4614	2191	365	677	781	236	3810	219	2403	**22613**
S13	2144	2300	996	1612	2921	2478	669	1471	1407	2190	4420	1477	**24085**
S14	2335	2512	3824	2737	4167	3981	1035	293	2655	3266	2912	3548	**33265**
S15	1640	2216	990	2176	4278	1812	3636	270	1946	246	3354	1299	**23863**
S16	389	1412	3750	4247	3595	4562	1907	4331	3793	1928	4391	351	**34656**
S17	3335	4817	2731	3592	581	2546	1129	1837	488	2609	679	726	**25070**
S18	2642	2540	1396	3509	4727	2167	1168	169	4693	410	4938	1882	**30241**
S19	4771	3875	1505	4268	406	3196	1741	2942	911	1785	4797	3646	**33843**
S20	4944	1690	4133	955	3295	2525	4229	4194	240	2765	3395	2404	**34769**
S21	248	1385	1745	2784	4714	1207	2877	3616	1845	2283	889	3206	**26799**
S22	4586	2916	4477	4069	4462	2022	635	430	793	1189	1490	1464	**28533**
S23	4509	1844	2295	2821	4244	2191	3115	2875	2887	1033	2485	2026	**32325**
S24	4104	1208	4851	4615	954	2727	420	3430	699	3214	1306	1124	**28652**
S25	2892	1039	4912	3196	727	4775	4607	1932	4736	769	2285	3089	**34959**
S26	2521	4723	4476	1036	3850	2370	982	474	2522	201	219	851	**24225**
S27	3487	1042	427	1639	2063	4907	3548	1427	1046	3793	1471	2077	**26927**
S28	1402	942	3664	3198	4547	2508	4607	2175	4007	2676	920	1800	**32446**
S29	2700	424	323	186	2521	4987	2723	3785	3305	2666	3364	615	**27599**
S30	625	2699	3834	1012	2148	1862	4547	3941	3014	2222	1600	4536	**32040**
S31	1802	2617	1731	2118	3052	766	2400	832	3769	841	4805	2876	**27609**
S32	1963	3298	2613	436	2780	1630	2694	4843	2580	2113	2838	926	**28714**
S33	4558	4843	4982	854	2107	1903	266	2096	3391	692	2295	4615	**32602**
S34	680	715	276	181	2482	3042	4140	3940	1363	926	4207	2787	**24739**
S35	731	4271	1519	1571	1325	1259	2719	2603	975	4313	2504	1134	**24924**
S36	1793	1260	4568	360	2689	4629	1782	1559	2548	3644	4503	1393	**30728**
S37	497	2125	2169	627	3759	3623	4599	2149	4534	3699	4507	3813	**36101**
S38	189	3341	2874	1505	2213	4079	299	3513	4774	254	610	3007	**26658**
S39	4851	1232	4962	1125	1234	2222	2368	3358	4720	3385	1510	831	**31798**
S40	2013	4081	161	1554	4431	2698	4203	3690	1949	2052	2663	4155	**33650**
S41	4022	1943	3477	2860	4690	2354	1897	494	686	4291	3120	1406	**31240**
S42	4291	1769	2654	2547	2554	4624	3144	1453	3907	4970	796	1109	**33818**
S43	4310	4779	3190	1544	1376	2152	3595	1882	4765	527	4155	3324	**35599**
S44	2950	3245	4319	1450	4558	433	4394	840	2190	927	2291	785	**28382**
S45	1239	771	3745	2074	3232	3646	3354	1449	2766	3689	1134	4097	**31196**
S46	1836	1076	3632	4474	3444	1067	2520	2374	2133	3203	4682	132	**30573**
S47	1655	4428	3694	4843	272	352	2084	2233	1792	1516	2432	1315	**26616**
S48	4542	1742	2338	2648	4898	2155	3756	1476	4567	3024	4120	3540	**38806**
S49	1097	1811	4773	3239	1777	2426	985	297	1067	4763	208	4566	**27009**
S50	2528	1218	715	4199	3161	4790	2649	3681	4220	3023	4428	2751	**37363**

Appendix 2: Total demand per scenario over 10 different demand instances

Scenario/ Instance	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
S1	31732	23650	39429	26500	23857	28679	28627	25130	31573	31835
S2	24601	35966	31573	25900	22952	35673	26595	36356	24363	32220
S3	32823	29030	27054	28609	40401	26153	31701	28751	27754	30125
S4	28673	43099	29564	32527	35556	37968	36305	28840	22548	33235
S5	39264	39960	26223	26904	36929	30505	35157	38540	24078	29725
S6	35225	41473	25717	34572	28388	28016	36822	30719	34187	28386
S7	33952	41880	20640	30958	32626	34775	32088	33188	25268	32361
S8	33768	26142	34109	25656	35516	35242	37632	26955	33532	29656
S9	39000	24760	26785	26872	30234	29184	28526	25334	30874	29234
S10	40697	16705	24730	27124	27861	35886	28443	30202	28394	38938
S11	33734	23338	30735	27412	31654	39966	35871	27121	32577	42279
S12	22613	27593	28396	28701	37019	32669	26449	30818	27807	20402
S13	24085	29605	26323	33555	34222	27254	31714	24641	20300	39975
S14	33265	32853	35737	27914	24347	29682	33075	33476	28305	32077
S15	23863	20644	20354	31739	35232	22357	23630	29323	38028	30536
S16	34656	31879	33615	33152	23539	28180	24578	31172	18524	31692
S17	25070	20024	26783	30389	36826	32500	32025	30441	43442	36989
S18	30241	29410	24658	30207	23164	31154	29293	32399	40018	24721
S19	33843	38574	32871	23487	30182	23748	35736	41101	30204	39367
S20	34769	26868	27755	35825	31788	28501	29869	32847	31546	41116
S21	26799	27557	29005	23803	19845	33558	28505	31424	19545	32755
S22	28533	23716	31815	29975	29187	32913	29009	34732	27916	29464
S23	32325	28890	33577	34918	28046	37202	25687	21505	33317	37115
S24	28652	28441	23792	25762	36478	16359	30312	25715	17002	33712
S25	34959	38972	33677	35043	30871	33588	30842	25211	26543	28305
S26	24225	36604	30713	33688	29913	20611	38672	27782	24530	35893
S27	26927	23655	22225	29836	26817	31776	25427	23875	23479	32192
S28	32446	34006	27303	30375	28648	32182	36814	29233	36388	28489
S29	27599	34255	36067	25844	30891	22525	27724	32140	32981	30655
S30	32040	35438	32015	30752	27345	30334	42189	38398	27876	30412
S31	27609	33991	28345	40399	42368	35214	32136	43332	34648	29969
S32	28714	30630	28468	35542	31732	28623	22055	25309	20797	32349
S33	32602	35205	37510	29463	33172	37933	34759	33851	37073	36756
S34	24739	33950	41561	29260	30349	26629	32640	30645	30047	23340
S35	24924	29435	38841	18658	20880	30715	21112	27502	33712	30835
S36	30728	28496	31955	28837	28619	30971	35420	34811	27793	18339
S37	36101	38015	34897	30826	28406	24839	17666	35211	32397	31862
S38	26658	30879	28699	28458	29507	29778	27507	43431	34982	27181
S39	31798	34735	21321	24662	20721	21592	29425	25960	33785	24226
S40	33650	26829	37831	34577	35426	26717	24912	19264	29488	27724
S41	31240	34536	35980	32713	23602	26852	37233	20579	29519	26017
S42	33818	24522	20606	31382	26094	34915	22101	33069	33682	30482
S43	35599	43578	29854	26394	33675	40040	25446	28119	32497	36092
S44	28382	30734	26554	21059	31642	22171	29369	27440	29003	32745
S45	31196	24908	30437	35145	37666	29824	27409	33318	23832	24969
S46	30573	36942	30967	30583	27984	33366	24705	31748	26042	28984
S47	26616	24260	29006	27332	35021	34791	32185	35208	27608	39395
S48	38806	24410	29589	23774	31885	33820	35027	28991	40665	29293
S49	27009	34293	33543	32063	36732	22445	28735	31223	32838	29898
S50	37363	43131	23136	23546	28000	32220	28365	26491	31233	30480
Average	**30970.08**	**31169.32**	**29846.8**	**29453.44**	**30476.3**	**30251.9**	**30150.48**	**30457.42**	**29690.8**	**31295.94**

Appendix 3: Results of Wait-and-see, Stochastic, Expected value of Expected problem over 10 instances

Case	Instance 1					Instance 2				
	WS	SP	EEV	EVPI	VSS	WS	SP	EEV	EVPI	VSS
C0	5958.81	5984.59	5986.55	25.78	1.96	6008.87	6045.72	6045.72	36.85	0.0002
C1	7005.16	7030.65	7033.05	25.49	2.39	7046.90	7083.02	7083.07	36.13	0.0442
C4	6288.64	6332.04	6335.70	43.41	3.65	6342.75	6405.06	6405.12	62.31	0.0655
C3	7302.50	7409.29	7411.38	106.79	2.09	7361.16	7515.41	7515.82	154.25	0.4168
C0b3	5517.56	5520.15	5520.29	2.59	0.14	5562.89	5566.57	5566.57	3.68	0.0000
C0b4	5713.68	5726.58	5727.56	12.90	0.98	5761.16	5779.61	5779.61	18.45	0.0001
C0b5	6449.03	6500.56	6504.35	51.53	3.78	6504.13	6577.72	6577.72	73.59	0.0004
C0b6	7918.71	8047.31	8056.40	128.6	9.10	7989.16	8172.76	8172.76	183.60	0.0010

Case	Instance 3					Instance 4				
	WS	SP	EEV	EVPI	VSS	WS	SP	EEV	EVPI	VSS
C0	5858.90	5887.28	5889.26	28.39	1.97	5805.82	5829.31	5833.80	23.49	4.49
C1	6877.56	6905.76	6908.66	28.20	2.90	6823.91	6847.86	6852.86	23.95	5.01
C4	6178.38	6227.11	6230.57	48.72	3.46	6121.15	6160.94	6169.44	39.79	8.50
C3	7153.92	7271.20	7271.36	117.28	0.16	7083.86	7180.41	7181.57	96.54	1.16
C0b3	5429.76	5432.59	5432.85	2.83	0.25	5382.47	5384.82	5385.28	2.36	0.45
C0b4	5620.50	5634.68	5635.72	14.17	1.04	5570.71	5582.48	5584.74	11.77	2.26
C0b5	6335.52	6392.43	6396.16	56.91	3.74	6275.75	6322.92	6331.81	47.17	8.89
C0b6	7763.98	7906.45	7915.73	142.46	9.29	7684.84	7802.14	7823.83	117.30	21.69

Case	Instance 5					Instance 6				
	WS	SP	EEV	EVPI	VSS	WS	SP	EEV	EVPI	VSS
C0	5925.14	5954.39	5956.12	29.24	1.73	5893.75	5920.75	5923.79	27.01	3.04
C1	6947.27	6976.07	6978.07	28.80	2.00	6916.21	6943.13	6946.57	26.93	3.43
C4	6251.28	6300.82	6303.18	49.54	2.36	6218.10	6264.61	6270.99	46.51	6.38
C3	7247.36	7366.20	7366.33	118.84	0.13	7206.31	7323.79	7325.36	117.48	1.57
C0b3	5487.40	5490.33	5490.51	2.93	0.18	5459.88	5462.59	5462.90	2.71	0.30
C0b4	5681.96	5696.59	5697.48	14.63	0.89	5652.74	5666.24	5667.76	13.50	1.52
C0b5	6411.22	6469.78	6473.09	58.56	3.31	6375.48	6429.78	6435.66	54.30	5.88
C0b6	7868.33	8014.73	8022.64	146.40	7.91	7819.57	7955.89	7970.15	136.32	14.26

Case	Instance 7					Instance 8				
	WS	SP	EEV	EVPI	VSS	WS	SP	EEV	EVPI	VSS
C0	5905.90	5934.08	5935.20	28.18	1.12	5962.60	5990.56	5993.29	27.96	2.73
C1	6935.47	6963.31	6965.07	27.84	1.75	6995.49	7023.18	7026.45	27.69	3.28
C4	6230.08	6276.67	6279.95	46.59	3.28	6288.51	6335.75	6340.41	47.25	4.66
C3	7214.16	7330.29	7330.72	116.13	0.43	7284.12	7400.06	7400.90	115.94	0.84
C0b3	5472.87	5475.70	5475.75	2.83	0.05	5525.11	5527.90	5528.18	2.80	0.27
C0b4	5665.35	5679.49	5680.06	14.14	0.56	5719.63	5733.58	5734.95	13.95	1.37

Case	Instance 7/8 (cont.)									
C0b5	6386.85	6443.13	6445.38	56.29	2.25	6448.24	6504.14	6509.51	55.89	5.37
C0b6	7829.17	7968.96	7976.79	139.80	7.83	7904.06	8043.41	8056.44	139.35	13.03

Case	Instance 9					Instance 10				
	WS	SP	EEV	EVPI	VSS	WS	SP	EEV	EVPI	VSS
C0	5831.50	5863.65	5865.63	32.14	1.98	6050.74	6076.40	6077.34	25.66	0.94
C1	6844.13	6875.81	6878.17	31.69	2.36	7084.37	7109.29	7111.13	24.92	1.83
C4	6149.52	6203.80	6210.68	54.28	6.88	6387.06	6430.53	6432.53	43.47	2.00
C3	7119.72	7250.30	7250.70	130.58	0.40	7408.43	7513.40	7513.97	104.97	0.57
C0b3	5404.02	5407.24	5407.41	3.22	0.17	5600.36	5602.93	5603.02	2.57	0.09
C0b4	5594.03	5610.11	5610.98	16.09	0.86	5800.58	5813.43	5813.90	12.86	0.47
C0b5	6306.22	6370.14	6375.04	63.93	4.89	6550.85	6602.11	6603.92	51.26	1.81
C0b6	7728.50	7887.50	7899.65	159.00	12.15	8048.61	8176.40	8180.59	127.78	4.19

Appendix 4: Demand generation for Chapter 5

In generating demands that follow a certain pattern, we have concurrently created the temporal dependency of demands among periods of a given scenario. This means, within one scenario, once the demand value of the first period is determined, demands of the other periods are respectively determined. More specifically, for a specific scenario, we generate a random variable from a standard normal distribution (i.e., with mean zero and a standard deviation of 1), and we determine the actual demand for each period by multiplying the same standard normal variable with the mean demand of that period. We further used the same set of 10 standard normal variables to generate the 10 instances for each pattern type. Hence, a positive correlation is seen in the average total demand by scenario over the 10 instances among different patterns, as presented in the table below, in which the lowest demand level is 27710.4 units while the highest has a value of 31930.8 units. We can observe that, for each scenario, the average total demands among patterns are approximately equal. This can be explained as we have applied the same seed numbers (from 1 to 10) to generate the different instances for these patterns, therefore, demands are always generated starting from the same point in the distribution.

Scenario/Pattern	STAT	RAND	SIN1	SIN2	LCY1	LCY2
S1	31887.6	31886.4	31887.4	31886.8	31886.9	31886.7
S2	30516.0	30515.6	30515.7	30515.4	30515.6	30516.2
S3	28352.4	28353.2	28353.1	28352.7	28352.9	28352.3
S4	29173.2	29173.8	29173.3	29173.2	29172.7	29173.4
S5	27945.6	27947.0	27946.6	27946.8	27946.3	27946.7
S6	29588.4	29587.2	29586.8	29587.7	29587.1	29587.6
S7	30663.6	30663.5	30663.3	30662.6	30663.4	30663.6
S8	28777.2	28778.0	28778.0	28779.1	28777.8	28778.1
S9	30886.8	30886.0	30886.6	30886.4	30885.1	30885.4
S10	29164.8	29163.5	29164.0	29163.8	29164.0	29163.8
S11	30607.2	30605.9	30605.5	30605.6	30604.7	30605.3
S12	31833.6	31834.0	31833.4	31834.6	31833.1	31833.9
S13	29710.8	29713.1	29713.8	29712.1	29712.7	29713.3
S14	30957.6	30957.3	30957.1	30957.4	30957.1	30957.4
S15	30133.2	30132.8	30132.9	30133.0	30132.8	30133.0
S16	28893.6	28892.8	28893.3	28893.5	28893.8	28893.0
S17	30512.4	30511.1	30511.5	30511.4	30510.8	30511.0
S18	30338.4	30338.2	30338.0	30338.3	30339.1	30338.4
S19	30506.4	30504.6	30503.9	30504.3	30502.7	30503.7
S20	29842.8	29842.7	29843.4	29842.9	29842.6	29842.8
S21	29078.4	29076.3	29077.2	29076.5	29077.1	29076.7
S22	29889.6	29887.9	29888.2	29888.6	29890.2	29887.7
S23	30360.0	30359.4	30360.2	30359.6	30359.9	30360.7
S24	30861.6	30861.8	30862.3	30861.6	30861.7	30862.7

S25	31059.6	31059.1	31059.8	31059.1	31059.7	31060.2
S26	29304.0	29304.0	29303.8	29303.7	29304.1	29304.4
S27	31086.0	31085.2	31086.3	31086.0	31085.8	31085.9
S28	29266.8	29267.2	29267.6	29267.5	29267.1	29267.1
S29	29832.0	29831.8	29832.2	29832.7	29832.6	29832.9
S30	28995.6	28993.4	28994.1	28994.4	28994.2	28994.9
S31	29905.2	29907.5	29906.8	29907.6	29906.8	29906.8
S32	31501.2	31499.2	31499.3	31499.1	31500.2	31498.2
S33	27710.4	27711.9	27711.6	27712.3	27712.3	27712.8
S34	28935.6	28935.4	28935.6	28935.9	28936.1	28935.9
S35	29042.4	29041.6	29041.3	29042.0	29042.0	29043.1
S36	29775.6	29776.0	29775.3	29776.7	29775.4	29776.6
S37	29826.0	29826.3	29826.2	29826.4	29825.5	29826.3
S38	30236.4	30235.1	30235.1	30234.8	30234.4	30235.0
S39	31735.2	31734.2	31734.4	31734.5	31734.4	31734.3
S40	31099.2	31098.4	31099.6	31098.8	31098.6	31097.9
S41	29314.8	29315.5	29315.2	29314.7	29315.7	29315.1
S42	29862.0	29862.1	29861.7	29861.9	29861.3	29863.2
S43	28281.6	28282.8	28282.4	28282.0	28280.7	28281.1
S44	30676.8	30675.4	30675.7	30675.4	30675.1	30675.8
S45	29366.4	29366.5	29366.6	29367.3	29366.6	29366.8
S46	29034.0	29032.8	29033.7	29032.3	29033.5	29033.1
S47	31695.6	31694.0	31694.6	31694.0	31694.3	31693.3
S48	31930.8	31929.8	31928.9	31929.4	31929.5	31929.8
S49	27902.4	27902.4	27902.3	27903.2	27902.7	27903.6
S50	30429.6	30428.4	30429.7	30429.8	30430.1	30430.3
Average	29965.73	29965.36	29965.51	29965.51	29965.38	29965.56

Appendix 5: Generation of the theoretical random mean demands for the RAND pattern in Chapter 5

```
def constrained_sum(n, total):
    value = [random.randint(0, 5000)]
    values = value + random.sample(range(1, total), n-3)
    values.sort()
    for i in range(1, n-2):
        while values[i] - values[i-1] > 5000:
            values.remove(values[i])
            values.append(random.randint(0,total))
            values.sort()
    values.append(random.randint(25000,total))
    values.sort()
    while values[n-2] - values[n-3] > 5000:
        values.remove(values[n-2])
        values.append(random.randint(25000,total))
        values.sort()
    return [a-b for a,b in zip(values + [total], [0] + values)]

demand = constrained_sum(nb_periods,30000)
print(demand)
```