Green Supply Chain Network Design with Emission Sensitive Demand

by

Cynthia Waltho

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Examining Committee Membership

The following served on the Examining Committee for this thesis. The decision of the Examining Committee is by majority vote.

External Examiner	Dr. Michael Haughton Professor, CN Fellow in Supply Chain Management, Wilfrid Laurier University
Supervisors	Dr. Samir Elhedhli Professor, Management Sciences, University of Waterloo
	Dr. Fatma Gzara Associate professor, Management Sciences, University of Waterloo
Internal Members	Dr. James Bookbinder Professor, Management Sciences, University of Waterloo
	Dr. Stanko Dimitrov Associate professor, Management Sciences, University of Waterloo
Internal-external Member	Dr. Ali Elkamel Professor, Chemical Engineering, University of Waterloo

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Over the last few decades, the argument for a link between greenhouse gas emissions and global warming has become stronger. In response, there has been a global shift. Politicians are implementing carbon policies while consumers are becoming more aware of their own impact on the environment. This thesis explores how environmental policies and consumer awareness impact supply chain network design and provides a new modelling framework in which demand is dependent on carbon footprint.

In the first part of the thesis, a comprehensive literature review on green supply chain network design between 2010 and mid 2017 is presented. The review focuses on models and methodologies that explicitly include carbon emissions and environmental policies. It is evident that incorporating carbon policy is popular, particularly carbon cap, carbon offset, cap-and-trade, and carbon tax. By reconfiguring the supply chain and investing in lower-emitting resources, each policy is able to achieve significant emission reduction with marginal increase in total cost. This is achieved by reconfiguring the supply chain and investing in lower-emitting resources. The review finds that there is a lack of models that consider the complex nature of emissions. Other complexities, such as multivariate emissions and uncertainty, are considered in only a few papers. Most importantly, however, it is clear that demand as a function of supply chain emissions is rarely accounted for in supply chain network design literature.

In the second part, a two echelon supply chain with emission sensitive demand is considered. A new model is provided that determines at which points investments in lower emitting technologies at the warehouses is necessary. Being nonlinear due to the complex carbon footprint constraint, the resulting model is first reformulated as a second-order cone program, and is tested on a hypothetical e-commerce supply chain. The results illustrate

that without proper response to consumer preferences, companies will lose out on revenue. It also illustrates investments are made at clear points as consumer sensitivity to emissions increases, rather than continuously. This work is important for e-commerce companies who wish to set themselves apart from competitors by catering to environmentally conscious consumers.

The third part of the thesis presents a new model for green supply chain network design with emission sensitive demand. The supply chain is composed of one plant and multiple warehouses that serve multiple customer zones. Decisions pertaining to the technology type used at the plant, the location and technology of the warehouses, the assignment of customer zones to warehouses, and the flow between the different echelons are modelled. In addition, demand is modelled as a function of carbon footprint. The resulting model is nonlinear due to the carbon footprint constraint. To be able to solve it, we reformulate the problem as a second-order cone program. To test the model and draw insights from it, we build a hypothetical, but realistic potato chip supply chain located in the province of Ontario, Canada. The testing confirms the ability of the model to trade-off between demand and emissions for environmentally conscious customers and provides insight into to how companies could advertise carbon footprint information to capture demand, and their potential impact on the supply chain.

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Chapter 1

Introduction[1]

With the pressing need for environmental conservation, the increase in customer awareness and expectations, and the introduction of stringent carbon policies, carbon emission reduction has become one of the primary goals in supply chain design and operation. Supply chain network design (SCND) that traditionally focused on cost minimization and demand responsiveness is slowly shifting towards minimizing environmental impact. As consumer behaviour is increasingly shaped by environmental consciousness, government agencies are educating the public on climate change due to global warming, and technology is becoming available to track carbon footprint, supply chains are under constant pressure to respond to this major shift.

GHG emissions have increased at an alarming rate since the industrial revolution. Global emissions in 2011 were 150 times greater than those in 1850 (Friedrich and Damassa, 2014). Logistics and supply chain operations have been identified as one of the major con-

[1]Parts of this introduction have been published in the International Journal of Production Economics. Waltho, C., Elhedhli, S, and Gzara, F., 2019. "Green supply chain network design: A review focused on policy adoption and emission quantification," International Journal of Production Economics, Elsevier, vol. 208, pages 305-318.

tributors to GHG emissions. In fact, 13% of all global GHG emissions are due to the logistics industry (World Economic Forum, 2016). In the retail industry, for example, emissions attributed to manufacturing, packaging, transportation, and other sourcing activities are estimated to account for 80 to 90% of the total carbon footprint (SCMA, 2016). For most manufacturing companies, the supply chain accounts for between 50 and 70% of total costs and emissions (Hanifan et al., 2012), with transportation being a significant contributor. In Canada, for example, transportation accounts for 23% of GHG emissions and almost half is caused by industrial transportation vehicles. In order to see any real reduction in emissions, transportation related emission have to be addressed (Neufeld and Massicotte, 2017).

Global warming occurs when certain gases in the earth's atmosphere are more prevalent than others, causing increased levels of infrared radiation to be trapped near the earth's surface. The seven GHGs covered by the United Nations Framework Convention on Climate Change (UNFCCC) and its Kyoto Protocol are: carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulphur hexafluoride (SF_6), and nitrogen trifluoride (NF_3). The Global Warming Potential (GWP) of a GHG is measured against CO_2, which has a GWP=1. For example, CH_4, N_2O, and HFC-134a (CH_2FCF_3) have GWPs of 25, 298, and 1430, respectively (United Nations, 1998a). The World Resources Institute/World Business Council for Sustainable Development (WRI/WBCSD) GHG Protocol defines three "scopes" for GHG emissions. Scope 1 emissions are direct GHG emissions from combustion fuels in stationary and mobile sources that are owned or controlled by the focal company within the supply chain, and from hydrofluorocarbon emissions during the focal company's use of refrigeration and air conditioning equipment. Scope 2 emissions are GHG emissions due to the generation of electricity purchased and consumed by the focal company. Scope 3 emissions are indirect

GHG emissions resulting from the the activities of the focal company attributed to sources not owned or controlled by it (WRI/WBCSD, 2014).

Accounting for emissions in the supply chain is important should a company wish to use that information to improve their processes, whether that be driven by environmental legislation or public image. Recently, consumers are becoming concerned with how their purchasing habits impact the environment. A product's carbon footprint accounts for the amount of carbon emissions emitted during the production and delivery of the single product to the customer.

Supply chain network design (SCND) plays a fundamental role in influencing the environmental impact of supply chains. With the increase in environmental awareness, 87% of company executives indicate that reputation risk is of greater concern than any other strategic risk (Deloitte, 2014). A company's reputation is linked to its environmental stewardship and social responsibility, among other key factors. In addition, a sustainable supply chain is no longer a luxury, but is now imperative to the success of an organization (Hanifan et al., 2012). In designing a supply chain, strategic decisions on the location of facilities (plants, distribution centers, warehouses and customer access points), capacity, production and inventory capabilities, and supply and delivery channels are made. As SCND models incorporate more elements, such as multiple periods, inventory decisions, transportation modes, and specific operation-related practices to better reflect reality, they inevitably become more complicated. Accounting for GHG emissions is no exception. While some activities have a linear impact on emissions, others are more complex to model, especially if combined with an environmental policy.

A report by the European Commission released in November 2017, highlights in one of their surveys that 94% of respondents in the European Union feel that protecting the environment is personally very important (European Commission, 2017). Additionally, the report finds that 87% of respondents agree that they as individuals play a part in protecting the environment in their own country (European Commission, 2017). The report also highlights the fact that 79% of respondents feel that big companies are not doing enough to protect the environment, and 43% have made the effort to buy local products (European Commission, 2017). The report indicates eco-labelling is becoming a more common method for consumers to distinguish between products. In fact, Sweden has the highest level of respondents (70%) stating that ecolabels play an important role in their product selection (European Commission, 2017). It should be noted, however, that environmental consideration is not unique to the European Union, as evidenced by reports like Abacus Data (2018) which evaluate similar trends in Canada. It is for these reasons that it is of utmost importance to consider consumer demand as variable, impacted by the carbon footprint of the individual item. Eco-labels are becoming more widely used as a method to promote environmentally responsible products, however no research has been done in designing the supply chain with these labels as a motivator. As consumers become more aware of their own carbon footprint, it is inevitable that companies will need to utilize their environmental acumen as tool for marketing. In this thesis, a green supply chain network design (GSCND) model is presented that models demand as a function of carbon footprint, something that has not yet been presented in the literature.

Supply chain network design problems consider strategic and tactical decisions, related to the location of facilities, the flow of commodities, and the allocation of demand. The objective is often the minimization of production, inventory, and transportation costs, while the constraints ensure demand is satisfied and flow through the system is maintained. As the model incorporates more elements to better reflect real supply chains, it inevitably becomes more complicated. With the added consideration of GHG emissions, some SCND models aim to simultaneously optimize the financial, environmental, and social objectives, or what is known as the triple-bottom-line (Kannegiesser and Günther, 2013). The difficulty with such trade-offs lies in the choice of common units of measure that truly reflect the importance of each objective.

Supply chains are major contributors to global warming due to the high levels of transportation and manufacturing activities, with industry contributing to 22% of total GHG emissions (United States Environmental Protection Agency, 2017). In fact, according to Bové and Swartz (2016) the supply chain accounts for more than 80% of a company's total greenhouse gas emissions.

Chapters 3 and 4 present models for an increasingly prevalent trend in consumer behaviour where purchasing decisions are based on a product's footprint alongside its price. In fact, an article from The Nielson Company highlights that companies that care about environmental issues are more sought out by consumers (The Nielsen Company, 2018). Further, 81% of global respondents "feel strongly that companies should help improve the environment", with this sentiment shared across all age groups and genders (The Nielsen Company, 2018).

1.1 Scope of this Research

Given the pressing need for environmental conservation, emission reduction has become one of the primary objectives in logistics and supply chain design and operation. Carbon policies, regulations, and environmentally conscious customers are changing the structure of the supply chain network. In the past two years there has been a steady increase in GSCND, predominantly focusing on closed-loop, reverse logistics, and the application of carbon policies: cap-and-trade, tax, cap, and offset. In spite of the increase in research, there has been little work focusing on how SCND is impacted by consumer awareness of the product's carbon footprint. Nouira et al. (2016) and Altmann (2015) are the only articles that include emission sensitive demand, though they only consider total emissions in the SC. It should be noted that there is research in the field of operations management that does consider emission sensitive demand, however these papers do not fall under SCND and are therefore outside of the scope of this thesis.

The goal of this thesis is to thoroughly explore previous research published in this area and include zone specific emission dependent demand functions based on each delivered item's carbon footprint (per item emissions). This is a beneficial vantage point to take since most companies distribute to a variety of consumer markets, each with differing behaviours. By constructing a nonlinear model, facility throughput is accurately presented, distributing total emissions correctly. The models presented in Chapters 3 and 4 are unique because the demand is a function of per item emissions. This allows the company to design a supply chain that can better cater to zone specific consumer beliefs.

In the proposed models, demand is linearly dependent on carbon footprint through an emission elasticity coefficient, which captures consumer sensitivity to a product's carbon footprint. Unlike carbon policies, this new way of looking at demand in the supply chain is advantageous since many people often voice concerns with carbon pricing schemes. A common concern is impact of consumer's wallets and where the money will be distributed. By placing the decision at the hand of consumers, policy makers can simply certify a company's footprint calculations and leave the rest to the free market.

1.2 Thesis Structure

This thesis is organized as follows. Chapter 2 provides a comprehensive review of supply chain network design literature that focuses on policy adoption and emission quantification.

Chapter 3 analyzes a two-echelon supply chain with technology selection and emission sensitive demand, presents a test case, and provides analysis. Chapter 4 introduces a three echelon green supply chain network design model with emission sensitive demand, along with a test case and numerical results and analysis. Finally, Chapter 5 concludes and provides directions for future research.

Chapter 2

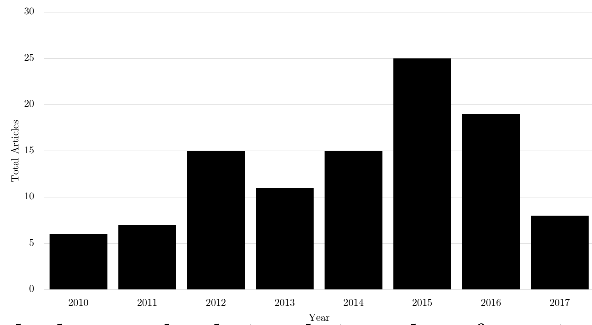
Literature Review[1]

To understand how emissions are accounted for, the carbon policies that are modeled, and their potential financial and structural impact on the supply chain, we review the recent literature on green supply chain network design, with the goal of providing answers to the challenges faced by policy makers and supply chain designers. Policy makers in different jurisdictions are tasked with designing effective carbon policies, tightening green-house gas (GHG) safety and emission standards of facilities and equipment, and establishing efficient procedures for their auditing and certification. Supply chain designers and managers in different industrial sectors are interested in determining the financial impact of policies and the possible tactics to react to them. Carbon policies will induce companies to reoptimize the supply chain network, to invest in low carbon emitting technologies, and to implement energy efficient practices.

The current review focuses on green SCND where carbon footprint is accounted for. As

[1]This chapter has been published in the International Journal of Production Economics. Waltho, C., Elhedhli, S, and Gzara, F., 2019. "Green supply chain network design: A review focused on policy adoption and emission quantification," International Journal of Production Economics, Elsevier, vol. 208, pages 305-318.

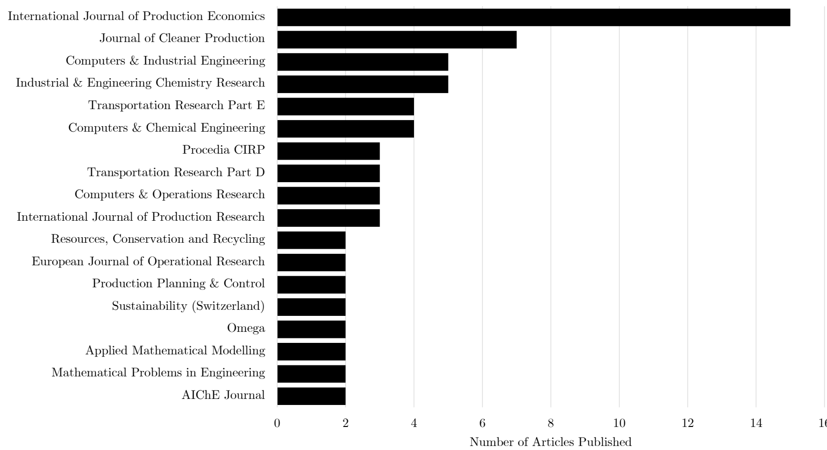
Figure 2.1: Distribution of articles per publication source (2+ articles).



products move through the supply chain, their carbon footprint increases. Raw material sourcing, manufacturing, handling, transportation, and storage contribute to the emissions a product directly or indirectly is responsible for. Over 100 related papers have been published since the first review by Seuring and Müller (2008), which is the main reason for the current review to only include articles published between January 2010 and July 2017. A total of 105 articles were reviewed, about 15% of which were published in the International Journal of Production Economics (see Figure 2.1). One of the first articles to consider carbon emissions in supply chain network design was published by Common and Salma (1992). They account for emissions based on the choice of technology and the fuel mixture. It was not until around 2007 that SCND models with emission accountability really took off. Figure 2.2 illustrates the distribution of published articles from 2010 to mid 2017. There is a peak in 2015, however, the trend still appears to be increasing. The suggested models are often referred to as Green SCND or Sustainable SCND, though the latter do not always refer to GHG emissions.

Based on the review, we find that carbon taxes implemented in literature are usually a linear function of emissions and that a high tax rate is necessary to see any real changes. Surprisingly, substantial emission reductions are achieved at a slight increase in total cost. We also find that a carbon cap can be an effective tool in forcing the supply chain to

Figure 2.2: Number of journal articles published per year from 2010 to mid 2017.



optimally reconfigure. As determining the proper cap is difficult, it is often set as a percentage of baseline emissions. Carbon offset may also be effective for similar reasons to carbon tax and cap. The selection of the carbon cap is important, and the credit price must be set high enough to discourage purchasing. As with the other policies, cap-and-trade is also found to be an effective tool if the cap and the price are selected carefully. Price seems to have a greater impact than the cap at controlling emissions.

The review is structured as follows. Section 2.1 starts by discussing the adoption and impact of carbon policies on supply chain network design. Carbon tax, carbon cap, cap-and-trade, and carbon offset are discussed in detail. Section 2.2 discusses the sources of emissions, their measurement and the related challenges faced. Finally, Section 2.3 gives conclusions and discusses future research.

2.1 Policy adoption in SCND

Carbon regulations were first introduced in the 1970's as a mechanism to mitigate emissions under the Clean Air Act in the United States (Calel, 2013). Today, 25 sub-national and 42 national jurisdictions have a carbon policy in place or scheduled to be implemented, accounting for around a quarter of all global GHG emissions (World Bank Group, 2017). Currently, there are four main policies in use: carbon tax, carbon cap, cap-and-trade, and carbon offset. We focus on the literature that explicitly accounts for carbon policies in the design of supply chains. Articles that provide models, carry out numerical analysis based on a case study, and compare multiple policies and their impact on the supply chain are of particular interest. Table 2.1 gives a detailed account of 41 research articles and the carbon policy they account for.

According to the table, few articles consider carbon offset, and most of the early work published between 2010 and 2012 focuses on cap-and-trade. From 2014 onward, carbon tax clearly becomes more dominant. This may be attributed to the increased adoption of carbon tax globally around that time. We also note that with the exception of 2015, which has 12 articles, there is almost steady state of 4 to 5 articles from 2012 onward.

Carbon policies are used to control emissions within a region by accounting for each unit of CO_2e emitted throughout the supply chain, then imposing either a price, a limit, and/or a tax to them. Carbon policies are often criticized for forcing companies to relocate to geographical regions that are less restrictive. This is referred to as "carbon leakage". One way regions are circumventing this problem is by placing a price/limit on the carbon footprint of a product, i.e. emissions throughout its entire life cycle.

Table 2.1: Summary of policies included in reviewed articles.

Citation	Cap	Carbon Offset	Tax	Cap-and-trade
Abdallah et al. (2010)				✓
Paksoy (2010)				✓
Chaabane et al. (2011)				✓
Paksoy et al. (2011b)			✓	
Abdallah et al. (2012)				✓
Akgul et al. (2012)			✓	
Chaabane et al. (2012)				✓
Giarola et al. (2012a)				✓
Kannan et al. (2012)				✓
Abdallah et al. (2013)				✓
Diabat et al. (2013)				✓
Kannegiesser and Günther (2013)	✓			
Mirzapour Al-e-hashem et al. (2013)	✓			
Baud-Lavigne et al. (2014)	✓			
Marufuzzaman et al. (2014)	✓	✓	✓	✓
Oh and Jeong (2014)	✓			
Paksoy and Özceylan (2014)			✓	
Zeballos et al. (2014)			✓	
Altmann (2015)		✓		
Choudhary et al. (2015)	✓		✓	✓
Fahimnia et al. (2015a)			✓	
Fahimnia et al. (2015b)			✓	
Fahimnia et al. (2015c)	✓			
Fareeduddin et al. (2015)	✓		✓	✓
Hammami et al. (2015)				
Liotta et al. (2015)			✓	
Martí et al. (2015)	✓		✓	
Niakan et al. (2015)			✓	
Rezaee et al. (2015)	✓			✓
Zakeri et al. (2015)			✓	✓
Alhaj et al. (2016)			✓	
Liotta et al. (2016)			✓	
Peng et al. (2016)	✓		✓	
Shaw et al. (2016)				✓
Xu et al. (2017)	✓		✓	✓
Yang et al. (2016)			✓	
Arampantzi and Minis (2017)				✓
Golpîra et al. (2017)				
Mohammed et al. (2017)	✓	✓	✓	✓
Soleimani et al. (2017)	✓			
Zhou et al. (2017)	✓		✓	

2.1.1 Carbon tax

Carbon tax, imposed by a regulating body, is a charge applied to each unit of CO_2e emitted. It aims to induce companies to decrease emissions through green practices and/or the adoption of green technology. The benefit of carbon tax is that it is relatively easy to implement as it can be incorporated within existing taxation systems and offers price stability, though emission level uncertainty remains (Almutairi and Elhedhli, 2014). The main difficulty with implementing a carbon tax is setting the correct rate. The policy maker will attempt to set the tax high enough so emissions are decreased, but low enough so that economic development is not hindered. Two of the earliest adopters of carbon tax are Finland and the Netherlands, who first implemented a carbon tax in 1990 (World Bank Group, 2017). Norway, Sweden, and Denmark followed in 1991, 1991 and 1992, respectively (Sumner et al., 2009). These countries also participate in the European Trading System. It took ten years for other countries to adopt a carbon tax policy.

To set a carbon tax, a marginal abatement cost curve is often utilized. It shows the relationship between emission reduction and the corresponding cost to a firm (Martí et al., 2015). Martí et al. (2015) use a marginal abatement cost curve to determine the tax required to achieve carbon reduction targets. The authors note that with multiple product types (functional versus innovative), different tax rates are needed to achieve the same emission reduction levels. This indicates that a tax will unfairly target one group (in this case innovative) over the other.

Carbon tax in SCND

Carbon tax is adapted in 20 of the 41 articles surveyed that consider a carbon policy, all of which linearly relate the carbon cost to total emissions. Each of these articles applies the tax to transportation emissions, most often in conjunction with other emission sources like production, raw materials, and storage.

A number of articles account only for emissions due to transportation activities (Paksoy et al., 2011b; Paksoy and Özceylan, 2014; Zeballos et al., 2014; Niakan et al., 2015; Liotta et al., 2015). Liotta et al. (2015) assume that transportation emissions are linearly proportional the number of items transported over an arc, which means that the model is taxing based on emission intensity. Niakan et al. (2015) apply a "carbon emission cost" instead of an explicit tax in the objective function, for which the total emission cost is influenced by energy consumption, road conditions, weight, and surface and air friction.

Electricity production accounts for 29% of global GHG emissions, of which burning natural gas, coal, and fossil fuels contribute around 67% of electricity emissions (United States Environmental Protection Agency, 2016). For this reason emissions due to manufacturing (mainly run by electricity) cannot be ignored. Twelve of the articles reviewed consider a carbon tax on the manufacturing or processing activities of a product. Out of the 12, three do not consider any additional emission sources other than transportation. The most comprehensive accounting of emissions at a macro level is presented in Mohammed et al. (2017). They include emissions due to manufacturing, storage at distribution centres, disposal, handling, and recycling. Closed loop supply chains also include all or part of the emissions due to incineration, recycling, and disposal (Choudhary et al., 2015; Fareeduddin et al., 2015; Xu et al., 2017; Mohammed et al., 2017).

Different approaches are used when applying carbon tax. Fareeduddin et al. (2015), Liotta et al. (2015), and Fahimnia et al. (2015b) among others apply the same tax rate to all emissions. A single tax rate will likely not reflect actual taxation in a supply chain, since policy makers often give leniency to more economically sensitive emitters (e.g. farmers). Xu et al. (2017) observe that by applying a uniform carbon tax, the costs at different echelons do not increase equally, highlighting how this imbalance could be problematic. Addressing this need, Martí et al. (2015) and Zhou et al. (2017) use different tax rates at different echelons of the supply chain. This is advantageous since it does not only address the aforementioned sensitive emitters, but also applies to global supply chains.

Zhou et al. (2017) investigate international carbon tariffs as a means to prevent carbon leakage. The authors observe that as carbon tariffs are introduced, countries that do not adopt a carbon policy will only interact with one another. In contrast, the adopters of carbon policy will reduce emissions in addition to increasing trade and competition with one another. This is no doubt a key driver in the creation of current global environmental agreements. Other authors do not explicitly include a carbon tax but aggregate it with other costs, which limits the exploration of its impact (Kannegiesser and Günther, 2013).

Setting the carbon tax rate

The carbon tax used for testing varies from study to study and depends on the county, year, and the analysis conducted. Some articles use the carbon tax of the region that the supply chain is being designed for. One example is Fahimnia et al. (2015a) who explore how the current Australian tax rate of 25.40 AUD/ton of CO_2 impacts the SCND. The authors find that a tax rate of 30-40 AUD/ton is necessary for noteworthy change and that the tax rate must match variations in fuel price. Both Zakeri et al. (2015) and Fahimnia et al. (2015b) use a tax rate of 23 AUD/ton of CO_2, also based on Australian environmental legislation at the time.

Others use projected or potential tax rates, such as Akgul et al. (2012), who apply a tax rate of £15/tonne CO_2 for a bioethanol production case study based in the UK. The £15 tax rate is based on an article from the BBC (BBC, 2010). Liotta et al. (2015)

consider varying scenarios (single vs. multi-modal and capacity limitation) with a tax rate of 11.24 €/tonne CO_2. This value is converted from a projected 2012 carbon tax rate of 15 CAD/tCO_2, which was taken from a GHG emissions report by Government Canada (2008). The report projects a tax rate of 15 CAD/tCO_2 from 2010 to 2012, and 20 CAD/tCO_2 in 2013.

Other articles base the tax rate on global trends, like Xu et al. (2017) who chose to test the tax range of 0 to 85 USD/ton, a range that includes the majority of carbon taxes used globally. Peng et al. (2016) evaluate carbon taxes from 0-4 CNY/kg CO_2 on transportation and warehousing emissions, however the authors do not state the foundation for which this range is selected. Fareeduddin et al. (2015) do not state the country in which the case study takes place, nor the source of the \$0.6/kg CO_2 tax.

Not all articles explicitly state that a monetary cost per unit of emissions is a tax. For example, Paksoy and Özceylan (2014) apply a cost of \$1.11/kg of CO_2 emitted by transportation and refer to it as a "social" cost. The cost for each kg of CO_2 is calculated based on 2.32 kg CO_2/litre of gasoline, and an average cost per litre of fuel equal to \$2.58/litre across Turkey (OPET, 2017; Bektaş and Laporte, 2011). Taxes are also applied to emission intensity. For example, Zeballos et al. (2014) use a carbon cost of 0.77, 0.86, and 0.95 cents per unit, for three different truck options.

Impact of carbon tax on SCND

A few common conclusions are found throughout the articles examined. First, the total cost of the system does not increase dramatically with the introduction of a carbon tax, especially if the supply chain is flexible enough to compensate and adapt. Second, the tax must be much higher than what is currently set in most jurisdictions in order to prevent supply chains from paying the tax over actually reducing emissions. Third, the range in which the tax is effective is relatively small, and must therefore be considered carefully before enactment.

As mentioned, the articles reveal that the portion of the overall supply chain costs attributed to carbon tax is relatively small. Zakeri et al. (2015) and Fahimnia et al. (2015b) are among the articles that make note of this. Fahimnia et al. (2015b) find that the total supply chain cost only increased by 1.4% after resolving with a 23 AUD/ton CO_2 tax, as compared to the tax-free scenario. The authors mention that carbon tax is more beneficial in an uncertain market since it allows companies to make informed environmental investment decisions. Hammami et al. (2015) observe that significant carbon footprint reductions occur for the small increases in carbon tax. Zeballos et al. (2014) observe that after resolving with a 60% tax rate increase, the objective value only deteriorates by 2.7%. The storage and purchasing costs compensate for the increase in costs. The opposite is seen when emission costs are decreased by 60%, but more importantly the network structure (the selection of facilities and transportation routes) remains unchanged in each scenario. Paksoy et al. (2011a) observe the impact of varying the intensity of the emission rate, fluctuating between a 100% to 400% increase. Resolving with a 400% increase, the authors observe a maximum increase of 4.7% in total costs.

In Fahimnia et al. (2015a), it is observed that a high tax rate is necessary for noteworthy change, and it must match variations in fuel price. The authors solve the model with tax rates up to 50 AUD per ton, also noting that the cost attributed to carbon tax remains a minor portion of overall supply chain costs. Zakeri et al. (2015) reveal that a 23 AUD/ton tax rate does not lead a lower emitting system as compared to 5 AUD/ton. In fact, emission reductions do not become significant until the tax rate is greater than 50 AUD/ton, which may be specific to this case, but does provide insight into the importance of setting the right rate. The results in Akgul et al. (2012) demonstrate that the carbon tax rate of £15 per tonne of CO_2 is not nearly high enough to impact supply chain emissions due to the inflexibility of the supply chain. This illustrates how a carbon tax can only be effective in decreasing overall emissions, if the supply chain has the flexibility to easily switch to an alternative low emitting technology or method. Marufuzzaman et al. (2014) also observe that the supply chain is only slightly modified even when the tax rate is pushed to its maximum (3.5 USD/kg in their case) and the pipelines, being the lowest emitting mode of transportation, is still not selected. It is only when the tax reached 5.5 USD/kg (5500 USD/ton) that pipelines are opted for. It is not fair to compare carbon taxes globally since they depend on the price technology, services and goods, however, a price of 5500 USD/tCO_2e far exceeds the maximum rates currently in place. The Netherlands, for example, is at 55 €/t CO_2 (Evans, 2016). These observations echo that countries, effectively implementing a carbon tax policy, have to set a high rate. This is the only means by which companies will be induced to switch to lower emitting options, as opposed to just paying the tax.

To find the tax rate that will force the supply chain to invest in carbon efficient technologies, authors vary the tax within a preselected range, solving each case separately. Peng et al. (2016) gradually increase the carbon tax from 0-4 CNY/kg CO_2, observing a linear relationship between the total cost and emission tax rate. The authors notice that the incentive for emission reduction only occurs within a specific range of 0.5-2.5 CNY/kg CO_2. Peng et al. (2016) observe that emissions plateau after 2.5 CNY/kg CO_2, despite an increasing tax rate, due to limitations in technology.

2.1.2 Carbon cap

A carbon cap is an emission allowance allotted to a company by a regulating authority. Carbon capping is an effective way to ensure that carbon emissions are met, so long as the penalty for overage is high enough to deter companies from opting to pay. The main difficulty, much like carbon tax, is in the selection of the carbon cap so that economic development is not hindered. For this reason the policy is not in wide use in practice, though it does appear in journal articles. Within this review, we see that a carbon cap is applied in 13 out of the 41 articles that consider a carbon policy. It is often in comparison to other policies as discussed by Marufuzzaman et al. (2014) and Mohammed et al. (2017). Choosing a carbon cap can be difficult due to future uncertainty, however it is most likely selected as a function of current or past emission levels. The first account of a carbon cap was in the original 1970 US Clean Air Act, which limits the emissions at the federal and state levels (United States Environmental Protection Agency, 2007). We note that a company may wish to set an internal cap as sign of environmental commitment.

Carbon cap in SCND

A carbon cap is generally modeled by enforcing an upper bound on emissions. All articles account for emissions from transportation/shipping. Mirzapour Al-e-hashem et al. (2013) and Soleimani et al. (2017) choose to only measure transportation emissions. Mirzapour Al-e-hashem et al. (2013) measure emissions per unit-distance traveled, and a maximum allowance is set per period. In addition there is an amount of waste allowed each period from each factory, and a percentage of waste produced by each product type. The waste may represent other forms of pollution caused by the product, e.g. water pollution. In either case, a cap on the amount of pollution per period is set. In contrast, Soleimani et al.

(2017) set a limit on the CO_2 emissions per produced or recycled unit due to transportation, effectively capping emissions from the transportation carbon footprint.

All the other papers include emissions from at least one source other than transportation. Oh and Jeong (2014) account for emissions due to production and transportation, linearly relating them to production quantity and imposing a cap at each manufacturer. Peng et al. (2016) apply a cap to warehousing and transportation in proportion to inventory levels and weight and distance traveled, respectively. On the other hand, Martí et al. (2015) introduce carbon footprint, taking into account emissions from raw materials, warehousing, manufacturing, and transportation. The warehousing emissions are a function of emission intensity, mean value of the demand function, order quantity, reorder point, and total lead time. As a variation of the traditional strict carbon cap, Kannegiesser and Günther (2013) minimize time-to-sustainability by setting emission bounds that are a percentage of a baseline emission level. The authors model the supply chain as a multi-period system to illustrate change over time, and account for raw material, transportation, warehousing, and/or disposal emissions.

Carbon caps can be set internationally, domestically or internally. An international cap applies to global companies, and a domestic cap to a country or sub-region. An internal cap is imposed by a company on its own supply chain. Since a single supply chain is complex enough as is, all articles reviewed apply an internal cap, though enforcement may be at a higher level such as a government agency or a parent company. Zhou et al. (2017) apply a carbon cap to a multinational computer company, capping transportation, product assembly based on technology, and supplier (cradle-to-gate and future usage). Emissions are measured on a per unit basis (carbon footprint). Similarly, Baud-Lavigne et al. (2014) account for emissions per unit in component selection, production, and transportation.

We also see emission accounting in reverse supply chains, which includes recycling, collection, and disposal, among other activities. This would be another example of an internal carbon cap. In addition to forward logistics activities, Choudhary et al. (2015) and Mohammed et al. (2017) account for emissions from product recovery, collection, and disposal centres. Fareeduddin et al. (2015) include emissions from recycling activities.

Selecting the carbon cap in SCND

Few articles use real data to set a carbon cap. Most vary the cap to better understand its impact. Peng et al. (2016) arbitrarily vary the cap from 0 to 3000 kg CO_2. Peng et al. (2016) point out that the emission levels are based on information from the Intergovernmental Panel on Climate Change (2006) and the United States Environmental Protection Agency (2013). Xu et al. (2017) investigate the impact of a carbon cap policy on hybrid as well as dedicated closed-loop supply chains. They consider emissions from product transportation, handling, and manufacturing and vary the cap between 15,000 and 19,500 tons of CO_2 for a supply chain involving two different plastic products. Marufuzzaman et al. (2014) vary the cap from 1,200 to 2,000 tons CO_2/year and test on a waste water sludge biomass supply chain based in Mississippi and use a planning horizon of 10-years (2012 to 2022). The carbon cap range (and other policies in the article) is said to be motivated by the Chicago Climate Exchange, European Carbon Exchange market, and Hoen et al. (2014), though the exact source or method is not specified. Also based on a real case study, Rezaee et al. (2015) apply their stochastic model to a furniture company in Australia, which distributes to five different states. The carbon cap in 2015 is set to 90% of 2013 levels, which is based on current legislature in Australia.

To better understand the impact of a carbon cap on the supply chain, a number of articles choose a cap or a range arbitrarily. For example, in Mirzapour Al-e-hashem et al. (2013) a reduction in the GHG cap from 16,648 to 4,150, resulted in a gradual decrease in transportation cost and profit, which is due to unfulfilled demand. Mohammed et al. (2017) use a hypothetical automotive products company and vary the carbon cap from 50 to 53 tons CO_2 while Hammami et al. (2015) set the caps as a percentage of emissions from a policy-free supply chain network and consider 95%, 90%, 80%, 70%, 60%, and 50%. They try a global cap as well as local caps where the global cap is split equally among the facilities. Similarly, Baud-Lavigne et al. (2014) uses a carbon cap as a multiple of the supply chain's minimum carbon emissions and Zhou et al. (2017) set the carbon cap as a percentage of a cap-free scenario. Martí et al. (2015) use generated data that is inspired by the apparel industry. The authors compare a cap on the carbon footprint of the entire supply chain to that of units sold in a market (market cap). Oh and Jeong (2014) impose different emission caps on each manufacturer, for each period, for example caps used in four fabric manufacturers are 2200, 2350, 2090, and 2430 tCO_2.

Slightly higher level sub-caps are seen in Choudhary et al. (2015), who place separate caps on the forward (600 then 700 tCO_2) and reverse (100 then 200 tCO_2) portions of the supply chain. The authors use partial data from Benjaafar et al. (2013) and Pishvaee et al. (2009).

Impact of carbon cap on SCND

As expected, a stricter carbon cap has a huge effect on the supply chain (Baud-Lavigne et al., 2014). Choudhary et al. (2015) observe that the lowest emissions and the highest cost occur when a strict carbon cap is used as compared to carbon tax or cap-and-trade. This is due to the inflexibility of the cap policy, which forces expensive options. Mirzapour Al-e-hashem et al. (2013) also observe that as the cap became stricter, profits decrease and transportation costs increase. With a looser cap, the supply chain takes advantage of larger vehicles, saving on transportation and shortage costs by combining customer demands. The optimal solution requires transportation and inventory costs to be balanced with lost sales and shortage costs. It highlights the necessity of cost-emission trade-offs to create an economically viable solution. Similarly, Hammami et al. (2015) notice that total emissions decrease as the cap is tightened, however, per item emissions can increase as fewer products are produced. Fareeduddin et al. (2015) also observe high supply chain costs under a carbon cap scheme (at $11.91 million for a single period).

It is not uncommon to find that a large decrease in the carbon cap leads only to a small increase in total costs. For example, Choudhary et al. (2015) illustrate that if the carbon cap decreases from 1904 to 1525 tons, emissions decrease by 31.19% while the cost only increases by 1.79%. The same is observed in Mirzapour Al-e-hashem et al. (2013), Kannegiesser et al. (2014), Rezaee et al. (2015), Peng et al. (2016) and Mohammed et al. (2017). The latter observe that the cost curve is concave decreasing as the cap increases. In contrast, Marufuzzaman et al. (2014) and Peng et al. (2016) find the relationship between cost and emission to resemble a step function.

It is obvious that the low increase in cost is due to the optimal redesign of the supply chain network; for example, switching to low emitting technology and greener modes of transportation. A strict cap can cause a supply chain to reconfigure completely, whether it be a forward, reverse, or a closed loop supply chain. This observation is confirmed in Xu et al. (2017). As the cap becomes excessively restrictive, the supply chain has no choice but to choose the lowest emitting options regardless of cost. The authors observe that the carbon cap policy effectively limits total emissions, however, the impact is not equally distributed among participants. Careful consideration should be made in implementing a high level carbon cap, in order to ensure each party is impacted fairly.

In a global economy, a cap on a supply chain that spans multiple geographical regions may be an effective motivator for countries to participate in emission reduction. For example, Zhou et al. (2017) find that the cap must be reduced to 76.2% of its original level for China to invest in low emitting technology, and to 68.5% for Taiwan.

2.1.3 Cap-and-trade

Cap-and-trade is a policy in which a finite number of carbon credits are bought and sold in a market that is regulated by a third party. The basic design of cap-and-trade scheme involves giving a number of free credits to each market member, indicating their cap over a given time frame. If the member emits less than the cap, the remaining credits are sold in a market, creating additional profit. If the member wishes to emit more than their cap, they will have to purchase more credits from the market at the seller's price. "Grandfathering" occurs when the number of credits distributed are based on the members' past emissions. A drawback of grandfathering is that it can lead to a "waterfall", which is when a member has far more credits then they need and therefore sells the credits at a very high price allowing them to make considerable profit.

A variation of cap-and-trade involves auctioning a finite number of credits. Auctioning takes place before each time period, allowing members to buy the number of credits they require at a price dependent on credit demand. In order to regulate the price of credits, the regulator can set a price floor and ceiling, and restrict the percentage of credits a single member can buy. One problem with cap-and-trade is the uncertainty and lack of control over carbon credit price during an auctioning phase. Larger players can drive up the credit cost considerably, which can deter new players from entering the market. This is a case in which price regulation can help. In addition, the administrative burden required to successfully run a cap-and-trade system can introduce further difficulties (Environmental Commissioner of Ontario, 2016).

The cap in the cap-and-trade system is selected such that environmental objectives are met. For example, in Ontario, Canada, the carbon cap from 2017 to 2020 will be reduced gradually by approximately 4% per annum (Environmental Commissioner of Ontario, 2016). By 2020, these caps are set to cut emissions by 15% as compared to 1990 levels (Cassese, 2016). The slow decrease is purposefully done so that industry has time to make the necessary adjustments and investments to meet these goals. That being said, since Ontario has joined the Western Climate Initiative with California and Quebec, additional credits will be available for purchase if necessary, while the collective cap will still be met (Environmental Commissioner of Ontario, 2016). At this point, 36 national and 25 sub-national jurisdictions have implemented or scheduled cap-and-trade or emission trading programs (World Bank Group, 2017). The first account of a cap-and-trade was in the Acid Rain Program of the 1990 Clean Air Act, which was introduced to trade sulfur dioxide credits in the United States (United States Environmental Protection Agency, 1990).

Within the literature, cap-and-trade is used almost as much as carbon tax. The reason is probably its popularity in practice. Though it is complex to implement in practice, it is easy to incorporate in supply chain network design models. It amounts to adding the profit of selling unused credits or the cost for the purchase of additional emission credits to the objective function.

Cap-and-trade in SCND

As with the previous policies, there is a focus on transportation and manufacturing emissions because they are easy to measure. In fact, all 20 articles that use cap-and-trade (out of the 41 that use a policy) include transportation emissions. Paksoy (2010), Chaabane et al. (2011), and Rezaee et al. (2015) linearly relate emissions from manufacturing and transportation to production volume. All articles but 4 include emissions from manufacturing/production. Abdallah et al. (2010) cap emissions due to raw material, product delivery, electricity consumption at plants, and distribution centres. All emissions are linearly proportional to either the quantity of goods or distance travelled. Similarly, Diabat et al. (2013) include emissions from power consumption of plants, distribution centres, collection centres, and remanufacturing centres, as well as emissions due to materials from the supplier and transportation. We distinguish between emissions due to electricity/power consumption and production/manufacturing since production can have its own emissions. Kannan et al. (2012) accounts for emissions from open facilities and transportation. The same is done in Choudhary et al. (2015) and Shaw et al. (2016) where fixed emissions due to open facilities are included. As it is easier to calculate the carbon footprint when emissions are a function of flow. Fareeduddin et al. (2015), Zakeri et al. (2015), Arampantzi and Minis (2017) and Xu et al. (2017) use the per unit emission intensity. Similarly, Abdallah et al. (2013) include emissions due to raw material and Giarola et al. (2012a) consider emissions at all stages of the production of biofuel. Raw material can be a large source of GHG emissions. In some cases the product is recyclable while in others, it must be harvested or mined. Abdallah et al. (2013) for example account for raw material emissions during the lifecycle of a product. It is clear that, regardless of the policy, a comprehensive understanding of the emissions in one's supply chain is imperative to the effectiveness of any policy. Once the sources are accounted for in an explicit manner, the selection of policy parameters is far less daunting.

Setting the cap and the credit price

The selection of the carbon cap and the credit price is imperative to the success of both the policy and the supply chain. Too stringent and the supply chain will be over burdened with carbon costs, too loose and there will be little to no reduction in emissions. In this section we discuss the different parameters used in articles that employ a cap-and-trade policy.

Some articles only consider a single cap and credit price. An example would be Chaabane et al. (2011), who consider a bi-objective model. The first objective minimizes total costs, which includes cap-and-trade (applies only to the transportation and manufacturing emissions), while the second objective minimizes the remaining emissions. The credit cost is set at 15 CAD/tCO_2 and the carbon cap is set at 60,000 tCO_2. Both parameters are based on the Regulatory Framework for Industrial Greenhouse Gas Emissions (Government Canada, 2008), which targets an emission reduction of 25%. We also see a single set of parameters in Fareeduddin et al. (2015), who consider closed-loop SCND model that incorporates carbon tax, cap-and-trade, and a hard cap, separately. The cap-and-trade model uses a carbon credit price of \$0.3/kg to sell and \$0.5/kg to buy, with a cap of 16.16 tCO_2. Similarly, Paksoy (2010) uses a single cap and price and tests on a hypothetical example with "realistic" parameters.

Exploring the impact of the policy a bit further, other research chooses to vary the credit price while holding the cap constant. In Rezaee et al. (2015) who apply a cap-and-trade system to a furniture supply chain in Australia, the cap is set at 90% of 2013 levels, the credit price is varied between 0 and 110 AUD/ton CO_2, and demand is stochastic following a finite set of scenarios. Another example of a single cap and varying credit price is by Abdallah et al. (2013). The authors evaluate carbon credit prices that range from 0 to 200 USD/tCO_2, with the carbon cap set at 100,000 tCO_2. Mohammed et al. (2017) on the other hand, clearly state that the selected carbon cap of 30 tCO_2, with carbon credits at \$5, \$10, and \$15/tCO_2 were selected for numerical testing. Similarly, Shaw et al. (2016) and Diabat et al. (2013) use hypothetical parameters to better understand how the supply chain network is impacted.

A unique instance by Choudhary et al. (2015) explores a variety of carbon caps while maintaining a single credit price. They base their 3 models on those proposed by Benjaafar et al. (2013) and Pishvaee et al. (2009). The third model incorporates cap and trade, setting a different cap on the forward (600 and 700 tCO_2) and reverse (100 and 200 tCO_2) supply chain processes, with the carbon credit price (buy or sell) set at \$50/tCO_2.

A more comprehensive exploration of cap-and-trade involves varying both the cap and the credit price, allowing for a better understanding of their individual impact. Similar to Rezaee et al. (2015), Zakeri et al. (2015) test their model using a case study based on a company in Australia that produces outdoor furniture, with distribution to 5 different customer zones. The authors base the policy parameters on current Australian carbon prices and the limits are based on a grandfathering system (percent reduction). As mentioned in Section 2.1.2, Marufuzzaman et al. (2014) consider a 10 year period using data from the state of Mississippi, with policy values based on information from the Chicago Climate Exchange, European Carbon Exchange market, and Hoen et al. (2014). They evaluate the model with caps ranging from 1200-2000 tCO_2/year, and credit prices 30, 50, and 80 USD/tCO_2. Another article which uses real data to select the policy parameters is Xu et al. (2017), who vary the carbon price from 5 to 40 USD/tCO_2 and the carbon cap from 10 to 20 tCO_2. The prices are based on The European Climate Exchange data, and information from Wacket (2015).

Again, we encounter articles, in which the source of the policy parameters is not clear. Chaabane et al. (2012) compare two carbon caps: 25,000 tCO_2e and 5000 tCO_2e, illustrating that as the cap becomes more stringent, the amount of material recycled increases. In addition, the cost of carbon credits increases from approximately \$3 to \$20/tCO_2e as the periods progress. The authors do not specify the location or currency of the problem. The model by Giarola et al. (2012a) uses cap-and-trade to control carbon emissions, with the objective of maximizing profit. This model considers feed-stock and carbon cost uncertainty using a scenario based approach. The authors consider four different cases: no carbon trading (base case), and trading with 35%, 50%, and 60% emission reduction caps. The baseline is set according to threshold levels of the European Union (European Commission, 2009). The credit price is a stochastic parameter assumed to grow over time, with the maximum value starts at 0.025 €/kgCO_2e per year, increases to 0.1 €/kgCO_2e per year; while the minimum increases from 0.015 to 0.03 €/kgCO_2e per year.

Impact of cap-and-trade on SCND

The cap-and-trade policy does succeed in reducing emissions under the correct parameter selection. Abdallah et al. (2010) observe that emissions are significantly reduced with the introduction of a carbon price. These reductions are due to multi-sourcing and decentralizing the supply chain. Giarola et al. (2012a) note that the most cost effective way to see significant emission savings may be by applying cap-and-trade to the transportation sector.

Similar to carbon cap, the higher the cap in cap-and-trade, the lower the supply chain cost. For example, Chaabane et al. (2011) observe that as the emission cap is raised, costs decrease since the model may choose cheaper, higher emitting alternatives. When the credit price increases, companies may opt to sell credits and limit production (Shaw et al., 2016; Marufuzzaman et al., 2014). Mohammed et al. (2017) observe that for a fixed carbon credit price, the increase in cap leads to lower overall cost. This is because lower cost technologies can be used if they have high emissions, and less credits need to be purchased. As the cap increases further, the company can begin selling off unused credits, decreasing the overall cost even more. The authors observe that with a fixed credit price, the emissions and the SCND remain the same despite the cap level chosen. This is due to the fact that even if the cap is set at a higher level, a firm would wish to minimize total cost further by selling off the remaining credits. The important step is selecting the correct cap in order to minimize the increase in cost. This is in contrast to carbon offset (Section 2.1.4), in which there is no incentive to emit less than the cap.

The carbon credit price has a bigger effect on the configuration of the supply chain than the cap (Choudhary et al., 2015; Rezaee et al., 2015; Xu et al., 2017; Shaw et al., 2016). In Chaabane et al. (2012), as the credit price increases from \$3 to \$20/tCO_2e, both the number of products recycled and credits purchased decreases, indicating that if recycling is a goal, then credit price should be carefully chosen since recycling activities are most likely a source of GHG emissions. Diabat et al. (2013) demonstrate that when the procurement activities are carbon intensive, remanufacturing is an attractive strategy. They also note that some companies can opt to not invest in reverse logistics under circumstances with high carbon prices, which indicates that policy makers should provide a recovery credit to enhance the incentive of product remanufacturing.

While some articles look into how different prices impact a variety of selected caps, Zakeri et al. (2015) attempt to find the carbon price necessary to ensure the carbon cap is met. The authors observe the change in carbon credits bought/sold at different carbon caps, highlighting that at times when many credits are sold, the supply chain has decreased transportation emissions due to investments in green modes. It is also observed that if emissions are reduced by more than 22%, the company must choose to either sacrifice service level or invest in improving service. This is where conflict arises between policy makers and industry partners.

2.1.4 Carbon offset

Carbon offset is a policy in which a cap is placed on emissions from a company or supply chain, with a penalty (offset cost) on additional emissions. Unlike cap-and-trade, carbon offset does not allow a company to sell off unused carbon credits. Only 3 of the 41 articles that consider a carbon policy include carbon offset, which is likely attributed to the lack of incentive to reduce emissions below the cap. In principle, the carbon offset policy is a self-imposed, voluntary, carbon tax with the rate being set based on the offset activity. As it leads to similar models, no new insights would be expected. This and its voluntary nature are reasons behind the low number of GSCND articles considering this policy. We also see the cap as a goal for long term objectives, such as the minimum 5% emission reduction target (with respect to 1990 levels) agreed upon by countries participating in the Kyoto Protocol (United Nations, 1998b). The Kyoto protocol does allow for the purchase of carbon credits, should a country not meet the set limit. The Kyoto protocol also uses "naming and shaming" to apply social pressure for the enforcement of the carbon limits (Poplawski-Stephens, 2014).

In the following subsections, we will discuss which emission sources are most often included with the policy, how the policy parameters are selected in literature, and the impact carbon offset has on the SCND.

Carbon offset in SCND

Marufuzzaman et al. (2014) use carbon policies (including offset) to control shipping, production, and inventory related emissions from a biodiesel supply chain. In contrast, Altmann (2015) only account for emissions from transportation and production. Although the authors do not explicitly state that an offset policy is in place, the model punitively fines emissions over a legal limit. A unique feature found in Altmann (2015) is the exploration of SCND with emission sensitive customers. This is note-worthy because almost every other article considers demand that is independent of emissions.

The most comprehensive account for emissions is found in Mohammed et al. (2017), who utilize the carbon offset policy to investigate how costs and emissions are impacted by varying the cap and the offset price. As mentioned in previous sections, the authors account for emissions from production, storage, collection, recycling, disposal, and shipping.

Setting the cap and the credit price

All three articles that use a carbon offset policy use hypothetical values within a range to asses the impact of the policy on the supply chain. Marufuzzaman et al. (2014) vary the offset price in the range of 5 to 20 USD/ton, while Mohammed et al. (2017) vary the carbon cap from 30 to 55 tCO_2 with offset prices set to \$5, \$10, and \$15/$kgCO_2$. Altmann (2015) do not consider a real case, and do not explicitly state the limits or credit price chosen for testing. Their focus is on customer sensitivity to emissions as opposed to the offset policy.

Impact of carbon offset in SCND

In Marufuzzaman et al. (2014), the lowest emitting transportation method is by pipeline. But to make it a viable option, the policy must be highly restrictive with levels set at 1200 tCO_2/450 USD, 1300 tCO_2/600 USD, and 1350 tCO_2/900 USD (cap per year/offset prices per tCO_2). As the cap becomes stricter, the total cost of the supply chain and the number of credits purchased increases in an approximately linear fashion, regardless of offset price. The only exception to this trend, is between the cap of 1800 and 2000

tCO_2/year, where the number of credits purchased remains close to zero. This is due to the fact that the supply chain can be reconfigured to meet emission requirements without heavily impacting costs or sacrificing production levels in this range. Conversely, the production level with respect to carbon cap follows a step-wise function, where the increasing offset price shifts the curve over towards the higher cap. This indicates that as the cap increases, achieving the high production levels becomes easier. When the offset price is 5 USD/ton CO_2, the production level decreases if the cap is set to less than 1400 tons CO_2/year. When the offset price is 20 USD/ton CO_2, production levels decrease if the carbon cap is less then 1700 tons CO_2/year. The authors suggest that unless restrictions are tight, companies will pay the penalty rather than make operational changes necessary to reduce emissions. With a low carbon cap, Mohammed et al. (2017) observe that as the offset price increases, so does the total supply chain cost, and lower emissions are achieved with a lower cap and a higher offset price.

2.1.5 Comparing policies

We briefly summarize observations made in articles that compared two or more policies. First, we start with comparing carbon tax and carbon cap policies. As mentioned in Section 2.1.1, Martí et al. (2015) use the marginal abatement cost curve to determine the tax level that will induce an equivalent carbon cap. The authors note that although the network remains similar, under a carbon tax scheme, total costs are higher. Similarly, Peng et al. (2016) observe that modifying the carbon cap within a specified range leads to emission reduction without significant increases in cost. They do note, however, that carbon tax provides incentives to reduce emissions in order to save costs.

The only article to compare carbon cap and cap-and-trade is Rezaee et al. (2015). The authors observe that a cap system is more expensive, but achieves the lowest emissions. That being said, in order to achieve the same emission levels using a cap-and-trade system, the credit price would have to be high. This indicates that carbon capping can be a successful mechanism for emission reduction, though it comes at a high financial cost.

Comparing the two most popular carbon policies carbon tax and cap-and-trade, Zakeri et al. (2015) observe that although cap-and-trade is more flexible, carbon tax is preferable in an uncertain environment due to the fixed price. Despite the reliability of a fixed carbon price, there is a risk of setting the tax too high or too low, imposing too much or not enough pressure. The authors note, cap-and-trade is a more effective policy to reduce emissions. That being said, uncertainty is an important aspect of SCND, and should be carefully considered when designing a policy.

Fareeduddin et al. (2015) and Choudhary et al. (2015) are two of the articles that compare carbon cap, tax, and cap-and-trade. Fareeduddin et al. (2015) observe that carbon tax leads to the highest cost and second highest/lowest emission supply chain. Carbon cap has the lowest emissions and the second highest/lowest cost. Cap-and-trade has the lowest cost and the highest emissions. Choudhary et al. (2015) also observe that the lowest cost, highest emitting configuration occurs with cap-and-trade, while the highest cost, lowest emitting occurs with a strict carbon cap. This seems, however, to depend on the particular data used.

Only Marufuzzaman et al. (2014) and Mohammed et al. (2017) compare all four policies. Marufuzzaman et al. (2014) observe that the carbon cap policy imposes the most change in the SCND. The authors also note that cap-and-trade is a more efficient method for reduce carbon footprint than tax or offset, because a switch to the lowest emitting alternative (pipeline) is seen at lower carbon prices, and this is caused by the incentive to sell unused credits. Mohammed et al. (2017) observe that after testing all four policies, the most cost effective and lowest emission solutions were achieved under the cap-and-trade policy. The reason for this is that the cap-and-trade policy is more flexible than the others, optimizing expenditures, while presenting financial incentives for emitting below the set cap. The authors do note that this conclusion is particular to the data set used.

In summary, it appears that carbon cap is the most effective in reducing emissions but comes at a high cost, particularly if the supply chain can not be reconfigured to compensate for low production output. Carbon Tax would achieve the same objective at a high cost, but provides the extra incentive to invest in green technology. Likewise, carbon offset can be viewed as a self-imposed carbon tax, that would lead to the same benefits as carbon tax provided that the offset rate is set at the proper level. Cap-and-trade is the most flexible with a desirable balance between cost and emissions, but lacks the robustness that would be achieved under a carbon cap or a carbon tax.

The majority of the reviewed articles focus on modelling carbon policies at the design stage of the supply chain, but do not discuss implementation details. Two important elements should be considered before proceeding to implementation. The first concerns the perspective of the decision maker. While policy makers and supply chain owners share the common objective of reducing environmental impact, the objectives may not be well aligned, especially in the presence of multiple players and competition. The scope, configuration, and the position of the supply chain within its industrial sector play an important role in adopting a certain carbon policy. The second is the type of carbon disclosure regime adopted. Mandatory and voluntary disclosure regimes have different impact and require different mechanisms. Mandatory carbon disclosure regimes such as the EU emissions trading scheme, the US environmental protection agency, the California-Quebec cap and trade, the Australian emissions trading scheme, and South African carbon tax, force companies to report their GHG emissions in a standard format such as that of the WRI/WBCSD GHG Protocol (WRI/WBCSD, 2014). Voluntary carbon disclosure regimes, such as the Carbon Disclosure Project (CDP, 2018) and the Global Reporting Initiative (GRI, 2018) provide investors and the public with standardized data that enables comparisons across companies and industrial sectors. Strong performers are rewarded with reputational benefits while non-disclosers and poor performers are subject to social pressure through "naming and shaming".

2.2 Emissions in SCND

In this section, we explore the sources of emission in SCND, discuss life cycle analysis, and review articles that account for uncertainty and nonlinearity in carbon emissions.

2.2.1 Sources of Emissions

In green SCND, emissions are either considered partially or for the entire life cycle of a product. Partial consideration of emissions is popular in SCND as it is primarily a strategic model and the greatest sources of emissions have high capital and operating costs. Tables 2.2 to 2.3 outline the emission sources included in the articles. We will now further explain the sources of emissions encountered in the reviewed papers.

Transportation: Transportation contributes to 31% of global CO_2 emissions, which is second only to electricity (37%) (United States Environmental Protection Agency, 2016). It is for this reason that 103 of the 105 (98%) articles reviewed explicitly include emissions from transportation. Transportation types include air, train, and water channels, though motor vehicles are most considered. Light-weight and heavy-weight truck transportation are the most commonly selected mode of motor transportation due to their ability to carry large quantities at a low cost. Road transportation has the highest emission rate, after air transportation.

When multiple modes of transportation are considered, different emissions intensities are used. Unit, weight and volume based intensities are used in Nurjanni et al. (2016), Akgul et al. (2012), and Boukherroub et al. (2013, 2015), respectively. Inter-modal transportation is even less common. Only Arampantzi and Minis (2017) consider global inter-modal transportation in SCND.

Transportation emissions are most often measured as a function of distance travelled. This is a great simplification of transportation emission rates, since they do not account for travel speed (impacting fuel consumption) and vehicle idling. That being said, transportation emissions are calculated as a function of speed in Paksoy and Özceylan (2014), using empirical values based on data from Hickman et al. (1999). Fuel consumption is calculated in a similar fashion using data from Bektaş and Laporte (2011). In order to factor in road roughness, an empirical multiplier is used, which is found using data from Sinha and Labi (2007). These additional factors could significantly impact the calculated vehicle emissions (thus better representing reality), which possibly illustrate greater disparity between two paths. Danloup et al. (2015) include very specific vehicle emission sources, such as, starting and running the engine, evaporation of fuel, distance travelled, full and empty loads, and per pallet addition to a vehicle. Marufuzzaman et al. (2014) provide detailed equations for calculating the fixed truck and pipeline emissions. The truck emission parameters are a function of the pumps used to load/unload the trucks and the fuel consumption for full (delivery) and empty (backhaul) transportation. Pipeline emissions are only a function of the electric pumps used to boost flow. In Niakan et al. (2015), CO_2 emission costs are a function of road condition, air friction, velocity, weight of vehicle, and energy consumed.

The emission parameters are not explicitly provided, they are instead calculated within the model, requiring the use of cosine and sine functions over an arc, incorporating road condition. Refrigerated vehicles (or "reefers") introduce even more pollutant sources, such as the evaporation of fluorocarbons due to the refrigerated portion of the vehicle (Ameknassi et al., 2016). Ameknassi et al. (2016) include the fixed annual evaporative fluorocarbon emissions from a refrigeration truck and variable emissions due to fuel combustion. Similarly, Saif and Elhedhli (2016) include CO_2 emissions and refrigerant leakage due to the transportation of refrigerated goods.

As we can see, transportation is integral to the function of the supply chain, and therefore it is important to consider when accounting for emissions. Authors choose a wide variety of methods to account for transportation emissions, and there is no hard and fast rule for how all SCND decision makers should do so. That being said, it should be noted that the more explicit the calculations, the better the SCND will reflect reality.

Manufacturing: Within this category we include the emissions due to plants, manufacturing, technology selection, and remanufacturing. Manufacturing within a plant is a significant source of emissions in the supply chain due to the level of activity taking place within, which is often impacted by the choice of technology used. Much like transportation, the choice of plant location or technology used can have conflicting attributes. Older technology or facilities may not meet current environmental guidelines, making them high emitters but less costly to operate. Of course the opposite is often true, that newer lower emitting technologies or facilities will cost more. For this reason it is important that the selection of plants or technology are carefully made in conjunction with the other supply chain decisions, balancing cost and emissions throughout. 66 of the 105 articles reviewed explicitly incorporate manufacturing (or plant) emissions. The methods used to calculate the plant emissions are either a fixed total, a per unit of product, or proportional to the size of the facility.

Raw Material: Raw material emissions are incorporated in 32 out of the 105 articles reviewed. The selection of suppliers may depend on its emission levels, especially when considering international versus domestic sourcing. For example, Baud-Lavigne et al. (2014) include emissions due to components/parts, which is based on the raw materials and the energy consumed during production, recycling, and use. Similarly, Mari et al. (2014) minimize the total carbon footprint of the procured material. With respect to biomass supply chains, Kanzian et al. (2013) include emissions due to the volume of wood harvested, which differs based on the its source.

Storage and Warehousing: Storage and warehousing emissions are included in 24 of the 105 articles reviewed. Accounting for emissions due to storage is often related to the number of units stored or proportional to the size of the facility. The simplest way to account for fixed emissions at distribution centres is based on an estimate from past data (Saif and Elhedhli, 2016). Should the emission level be impacted by the product throughput, possibly due to frequent handling, emissions can be linked linearly to flow (Fahimnia et al., 2015c; Brandenburg, 2017). Fixed emissions can also be calculated proportionately with respect to the building size or area (Abdallah et al., 2010, 2013). Saif and Elhedhli (2016) use a more complex method to measure emissions, by using a concave function of a volumetric capacity. This is suited for a refrigerated warehouse, since the power required to cool is a function of volume.

Facility Construction and Operation: Facility construction is a significant source of CO_2 emissions due to the carbon footprint of materials used and the operation of heavy machinery. Eight articles include emissions due to installation, opening, or construction of a facility. They all use a fixed value, except Nagurney and Nagurney (2010) who relate emissions to facility capacity. Seven articles incorporate operation-related emissions, either as a fixed value or as a function of facility area (Abdallah et al., 2012; Kannan et al., 2012). Finally, idling is a large source of emissions when a facility experiences frequent loading/unloading of trucks or vehicle congestion (Guyon et al., 2012; Mohammadi et al., 2014). Nagurney and Nagurney (2010) and Nagurney (2015) account for emissions as a convex and continuously differentiable function of flow, with bounded second-order partial derivatives.

Disposal, Customer Use and Handling: Emissions due to disposal and customer use are included in 8 of the 105 articles reviewed. A common method of disposal by companies and customers is by sending a product to landfill, however, some products may need to be incinerated for safe disposal. In other cases, the end use of a product may not include disposal, but involve its extended use. Disposal can be measured per unit or by product weight (Choudhary et al., 2015; Ameknassi et al., 2016). Product handling may refer to assembly or packaging, but can also include the movement of product within a facility using heavyweight machinery. We note that in some processes, a distinction between assembly and packing is necessary (Das and Rao Posinasetti, 2015). Eight of the 105 articles consider product handling emissions independent of warehousing operations and relate it to the number of units handled.

Recycling: The recycling of a product begins with its collection. Recycling may include disassembly, inspection, and the disposal of a portion of the collected product. It may even be necessary to include emissions specifically attributed to the disassembly and remanufacturing of the collected products (Nurjanni et al., 2016). Eight of the 105 articles reviewed explicitly include recycling emissions. Though recycling is used to limit waste and emissions, the process is rarely carbon neutral. In all of the articles reviewed that include recycling emissions, the emissions are a function of the number of units processed.

2.2.2 Life Cycle Assessment

Life cycle assessment is a technique used to comprehensively account for a product's environmental impact, starting from its raw materials to its final disposal (cradle-to-grave) (ISO, 1997). The Society for Environmental Toxicology and Chemistry (SETAC) code of practice divides life cycle assessment into four stages: scoping, inventory, eco-profile analysis, and improvement assessment (Ayres, 1995). Scoping involves defining the bounds of the product or service's environmental impact (e.g. cradle-to-grave). The inventory phase (life cycle inventory) involves gathering the data regarding direct and indirect flow of material and energy in, through, and out of the product system (Reap et al., 2008). Eco-profile analysis involves conducting an impact assessment, which determines the environmental effects through classification and characterization (Reap et al., 2008). Finally, the improvement assessment draws conclusions and provides recommendations based on the inventory and eco-profile analysis phases. Within this review, 18 articles use life cycle assessment to quantify and evaluate the environmental impact of the supply chain network. The low proportion of articles using life cycle assessment is in large part due to the amount of information required to conduct the analysis.

Table 2.2: Emissions in SCND (part 1 of 2).

Author(s)	T	M	RM	P	S/DC	FC	FO	D/C	H	R	LCA
Abdallah et al. (2010)	✓		✓	✓	✓						
Abdallah et al. (2012)	✓		✓				✓				
Abdallah et al. (2013)	✓	✓	✓		✓						
Miranda-Ackerman et al. (2017)	✓	✓	✓	✓			✓				✓
Adenso-Díaz et al. (2016)	✓										
Akgul et al. (2012)	✓	✓	✓								
Alhaj et al. (2016)	✓				✓						
Altmann (2015)	✓	✓									✓
Ameknassi et al. (2016)	✓	✓			✓			✓			
Arampantzi and Minis (2017)	✓	✓	✓		✓	✓					
Azadeh et al. (2015)			✓								
Bairamzadeh et al. (2016)	✓	✓	✓								✓
Baud-Lavigne et al. (2014)	✓	✓	✓								
Bernardi et al. (2013)	✓	✓									
Boonsothonsatit et al. (2015)	✓		✓								✓
Boukherroub et al. (2013)	✓	✓									
Boukherroub et al. (2015)	✓	✓									
Brandenburg (2015)	✓	✓			✓						
Brandenburg (2017)	✓	✓			✓						
Cambero et al. (2016)	✓	✓	✓					✓			
Chaabane et al. (2011)	✓	✓									
Chaabane et al. (2012)	✓	✓						✓		✓	✓
Choudhary et al. (2015)	✓	✓				✓		✓			
Danloup et al. (2015)	✓										
Das and Rao Posinasetti (2015)	✓	✓						✓	✓		
Diabat et al. (2013)	✓		✓	✓	✓						
Duarte et al. (2016)	✓	✓	✓								✓
Elhedhli and Merrick (2012)	✓										
Fahimnia et al. (2015a)	✓	✓									
Fahimnia et al. (2015b)	✓	✓									
Fahimnia et al. (2015c)	✓	✓			✓						
Fareeduddin et al. (2015)	✓	✓						✓	✓	✓	
Giarola et al. (2011)	✓	✓	✓								✓
Giarola et al. (2012a)	✓	✓	✓								
Giarola et al. (2012b)	✓	✓	✓								
Golpîra et al. (2017)	✓	✓									
Govindan et al. (2014)	✓	✓				✓		✓	✓		
Govindan et al. (2015)	✓	✓	✓			✓					
Guillén-Gosálbez and Grossmann (2010)	✓	✓	✓								✓
Guillén-Gosálbez et al. (2010)	✓	✓			✓						✓
Guyon et al. (2012)	✓						✓				
Hammami et al. (2015)	✓	✓			✓			✓	✓		
Harris et al. (2014)	✓			✓							
Jamshidi et al. (2012)	✓	✓									
Jonker et al. (2016)	✓	✓	✓								
Kannan et al. (2012)	✓						✓				
Kannegiesser and Günther (2013)	✓		✓					✓			
Kanzian et al. (2013)	✓	✓	✓		✓						
Keramydas et al. (2017)	✓				✓						
Liotta et al. (2015)	✓										
Liotta et al. (2016)	✓										
Mallidis et al. (2012)	✓										

T: Transportation, M: Manufacturing, RM: Raw Materials, P: Power, S/DC: Storage/Distribution Centre, FC: Facility Construction, FO: Facility Operations, D/C: Disposal/Customer, H: Handling, R: Recycling, LCA: Life Cycle Assessment

Table 2.3: Emissions in SCND (part 2 of 2).

Author(s)	T	M	RM	P	S/DC	FC	FO	D/C	H	R	LCA
Mari et al. (2014)	✓	✓	✓								
Mari et al. (2016)	✓	✓	✓							✓	
Martí et al. (2015)	✓	✓	✓		✓						
Marufuzzaman et al. (2014)	✓	✓			✓						
Mele et al. (2011)	✓	✓									✓
Memari et al. (2015)	✓										
Mirzapour Al-e-hashem et al. (2013)	✓										
Mohammadi et al. (2014)	✓						✓				
Mohammed et al. (2017)	✓	✓			✓			✓	✓	✓	
Mota et al. (2015)	✓	✓				✓					
Nagurney and Nagurney (2010)	✓	✓			✓	✓	✓				✓
Nagurney (2015)	✓	✓			✓						
Nguyen and Olapiriyakul (2016)	✓										✓
Niakan et al. (2015)	✓										
Nouira et al. (2016)	✓	✓									
Nurjanni et al. (2016)	✓	✓						✓	✓	✓	
Oh and Jeong (2014)	✓	✓									
Paksoy (2010)	✓	✓									
Paksoy et al. (2011a)	✓										
Paksoy et al. (2011b)	✓										
Paksoy et al. (2012)	✓										
Paksoy and Özceylan (2014)	✓										
Peng et al. (2016)	✓				✓						
Pishvaee et al. (2012)	✓	✓									✓
Pishvaee and Razmi (2012)	✓	✓						✓	✓	✓	✓
Pishvaee et al. (2014)	✓	✓				✓		✓	✓	✓	
Rahmani and Mahoodian (2017)	✓	✓									
Rezaee et al. (2015)	✓	✓									
Ruiz-Femenia et al. (2013)	✓		✓	✓							✓
Sadrnia et al. (2013)	✓										
Saffar et al. (2014)	✓										
Saffar et al. (2015)		✓								✓	
Saif and Elhedhli (2016)	✓				✓						
Santibañez-Aguilar et al. (2014)	✓	✓	✓								✓
Shaw et al. (2012)	✓	✓	✓								
Shaw et al. (2016)	✓	✓			✓						
Soleimani et al. (2017)	✓										
Tajabadi and Kazemi (2016)	✓										
Talaei et al. (2016)	✓	✓				✓					
Tayyar et al. (2013)	✓						✓				✓
Validi et al. (2014)	✓										
Validi et al. (2015)	✓										
Wang et al. (2011)	✓	✓									
Xu et al. (2017)	✓	✓						✓	✓		
Yang et al. (2016)	✓	✓									
You and Wang (2011)	✓	✓	✓		✓						
You et al. (2012)	✓		✓	✓							
Yu et al. (2014)	✓										
Yue et al. (2013)	✓	✓	✓								✓
Yue et al. (2014)	✓	✓	✓		✓						
Zakeri et al. (2015)	✓	✓			✓						
Zeballos et al. (2014)	✓										
Zhou et al. (2017)	✓	✓	✓								

T: Transportation, M: Manufacturing, RM: Raw Materials, P: Power, S/DC: Storage/Distribution Centre, FC: Facility Construction, FO: Facility Operations, D/C: Disposal/Customer, H: Handling, R: Recycling, LCA: Life Cycle Assessment

Guillén-Gosálbez and Grossmann (2010), Guillén-Gosálbez et al. (2010), Pishvaee et al. (2012), Pishvaee and Razmi (2012), Tayyar et al. (2013), Santibañez-Aguilar et al. (2014), and Nguyen and Olapiriyakul (2016) all use the Eco-indicator 99 database, a life cycle assessment product developed by PRé-Consultants. Miranda-Ackerman et al. (2017) use SimaPro (PRé-Consultants, 2016), another tool from PRé-Consultants. Articles using Eco-indicator 99 will often measure emissions in disability-adjusted life years, in order to estimate the number of people affected by the supply chain (Nguyen and Olapiriyakul, 2016). Guillén-Gosálbez and Grossmann (2010) measure environmental performance of raw material production, energy consumption, transportation of materials, and product manufacturing with Eco-indicator 99. Similarly, Guillén-Gosálbez et al. (2010) use Eco-indicator 99 to measure environmental performance for transportation, manufacturing tasks, and storage. Some articles go as far as using the database to measure the environmental impact of handling, incinerating, and recycling the product after customer use. For example, Pishvaee and Razmi (2012) follow this approach for a medical needle and syringe non-closed-loop supply chain.

Measuring and quantifying emissions could be done using two approaches: energy-based and the activity-based. Energy-based approaches convert energy use to equivalent emissions while activity-based approaches relate emissions to specific activities. A combination of both approaches is often needed for a complete account of emissions and third party agencies, such as the Carbon Disclosure Project (CDP, 2018), would be used for validation and approval.

2.2.3 Uncertainty

One of the uncertain elements in SCND is emissions. To handle this, Pishvaee et al. (2012) use a chance-constrained model, while Saffar et al. (2014, 2015) and Bairamzadeh et al. (2016) use fuzzy uncertainty. Saffar et al. (2015) account for uncertain production and recovery emissions, while Saffar et al. (2014) only include uncertain transportation emissions. Bairamzadeh et al. (2016) incorporate uncertainty in the harvesting, conversion, and transportation of bioethanol products. Mirzapour Al-e-hashem et al. (2013), Ruiz-Femenia et al. (2013), Brandenburg (2015), Govindan et al. (2015), Alhaj et al. (2016), and Brandenburg (2017) use scenario-based stochastic programs. Guillén-Gosálbez and Grossmann (2010) use life cycle assessment to account for the environmental impact of various chemicals and use Gaussian probability functions to describe the uncertainty in the level of damage in each category. In contrast, Golpîra et al. (2017) use the uncertainty set approach to deal with environmental uncertainty and a scenario-based approach to handle demand uncertainty. The authors also allow for the selection of the level of environmental protection to invest in.

Uncertainty related to the future establishment of carbon policies and the difficulty in setting its parameters should be taken into account at the supply chain design stage, possibly using stochastic and robust models. Possible solutions to deal with uncertain parameters, especially for voluntary carbon disclosure, could be based on the social cost of carbon, which is a monetary quantification of the long term damage caused by a ton of CO_2, a carbon tax that ensures financial viability for green projects, or an emission trading scheme with a rate based on fuel prices to attain emission future targets.

2.2.4 Nonlinear emissions

Most of the articles reviewed relate emissions linearly to decision variables, however emissions do not always behave in this way. Elhedhli and Merrick (2012) use Mobile6, a vehicle emission modeling software (United States Environmental Protection Agency, 2006), to account for the long term emissions from transportation as a function of weight and vehicle speed, which is found to be concave. Paksoy and Özceylan (2014) use a different approach, by presenting CO_2 emissions, fuel consumption, and noise pollution as a nonlinear function of speed. The functions are created based on empirical data generated by Hendriks (1995), Sinha and Labi (2007), and Bektaş and Laporte (2011). Finally, Fahimnia et al. (2015a) use piecewise functions to find speed-dependent emission rates. It is clear that accounting for emissions in a nonlinear fashion is common, especially outside transportation. Future research can explore this aspect, especially if based on data and empirical functions.

2.2.5 Other sources

Although emissions are the main measure for the environmental impact of a supply chain, there are definitely others. In addition to tracking CO_2 emissions, Mirzapour Al-e-hashem et al. (2013) include a measure of waste produced at manufacturing and limit the total waste per period from each factory. Waste may include wastewater, noise pollution, waterway pollution, infrastructure deterioration, sewage, and material waste. Nagurney (2015) include general waste cost and environmental impact, allowing the model to apply in different settings. Therefore, a cap on waste generated from different processes in the supply chain may be needed (Fahimnia et al., 2015c). Finally we note that waste can be an input to the supply chain, as in Lam et al. (2013) who use waste motor oil and other industrial waste to produce energy. Similarly, Marufuzzaman et al. (2014) model a supply chain that uses sludge from wastewater treatment facilities to produce renewable energy (biodiesel). Although these additional sources of waste are important, this review focuses on GHG emissions due to the current focus on carbon policies.

Having identified the sources of emissions and their measurement, additional aspects related to the complexity of the supply chain (e.g. national versus global), the position of the supply chain within its industrial sector (e.g. leader versus follower), and the degree of influence of policy makers (e.g. ability to prevent carbon leakage) are very important factors in leading to sustainable green supply chains.

2.3 Conclusions and Future Research

We reviewed 105 articles from 2010 to mid 2017 that explicitly study green, environmentally friendly, and sustainable supply chain network design and that model the trade-offs between environmental impact and cost. The review is structured around carbon policies and quantifiable emission sources in supply chain network design. The four common policies, carbon cap, carbon offset, cap-and-trade and carbon tax are reviewed in detail with a focus on the specifics of their application and the observed impact on the supply chain. When selected carefully, carbon tax succeeds in reducing emissions without a significant increase in cost. Similarly, carbon cap, carbon offset and cap-and-trade policies can achieve desirable reductions at a slight increase in cost. Comparing the four policies, it is clear that cap-and-trade is the most favoured due to its flexibility. The ability to sell off unused credits provides further incentive to reduce emissions and invest in green technology.

In the second part of the review, we analyze the different sources of supply chain emissions and how they are captured in supply chain network design. Emissions are most often modeled as a linear function of a single variable, which is a simplistic assumption in practical settings. A more accurate representation of emissions, possibly nonlinear and multi-variate, is a better reflection of practice. The same applies to carbon policies. The cap, credit price and tax rate should not be applied uniformly but should, for example, depend on the source of emissions. Overall, research suggests that substantial reductions in emissions may be achieved with small increases in cost. This is mostly possible by optimizing the use of resources and the flow of materials within the supply chain.

Based on the review, there is a clear paradigm shift in supply chain network design in light of increasing environmental awareness both by consumers and supply chain decision makers. Carbon footprint, accumulated as products move through the supply chain, will play a role as important as cost and price in influencing market share and supply chain configuration. In addition, environmental policies and regulations are being introduced worldwide and will sure have an impact on sourcing, manufacturing, storage and disposal of products.

As consumers become more aware and concerned about climate change, it is necessary to consider emission-sensitive demand. Only Nouira et al. (2016) and Altmann (2015) relate customer demand to emissions. This is obviously a future research direction that is worth investigating. In addition, the review reveals a lack of consistency in setting the parameters of any adopted policy. Although this is a problem faced by policy makers, supply chain owners should be consulted in order to promote investment in green technology without hurting financial sustainability. The parameters are definitely dependent on the industry type, the market structure, and the geographical region and is more prevalent in global supply chains. A complete cradle-to-grave analysis is needed to avoid carbon leakage. Finally, there is a need for real-data and empirical work to accurately model emissions within the supply chain. Given the many avenues that still require exploration, research interest in green SCND will most likely continue to grow. It will be interesting to observe how industry and policy makers respond to it.

Chapter 3

Two Echelon Green Supply Chain Technology Selection

3.1 Introduction

As the public becomes more aware of climate change and how they contribute to it, consumer buying habits are changing. According to Statista (2018), worldwide e-retail sales reached over 1.3 trillion USD in 2014, increasing to over 2.8 trillion USD in 2018. This growth in online shopping means that consumers are able to compare and contrast products like never before. In order to become desirable, supply chains need to increasingly do more to set themselves apart from the competition. In this chapter, a two-echelon supply chain with emission sensitive demand is presented. We consider an e-commerce supply chain, in which a plant produces the product, which is then sold directly from the warehouses. Decisions on technology selection at the warehouses, product flow, and demand served are modelled.

Based on Waltho et al. (2019) (Chapter 2 of this thesis), most research on green supply chain design focuses on location and flow decisions. In this chapter, however, we focus on technology selection at existing facilities, in an effort to understand the trade off between cost and environment impact. Location decisions will be considered in a later chapter. We explicitly model demand as a function of emissions, as motivated by Klassen and McLaughlin (1996) and Kassinis and Soteriou (2003), who have established that there is a negative relationship between a company's impact on the environment and consumer demand.

The two echelon supply chain problem is outlined in Section 3.2, and the associated model is presented in Section 3.2.1. The following section (Section 3.3) formulates and presents the final mathematical model. Section 3.4 presents a test case which is then used to illustrate the strengths of the model. Finally, concluding statements are presented in Section 3.6, which will summarize the finding and present avenues for future research.

3.2 Problem description

The problem under consideration applies to an e-commerce supply with a single plant and multiple warehouses. Each warehouse has a choice to operate with one of multiple technologies that differ in cost and emissions. Based on the notation in Table 3.1, warehouses are denoted by index $j \in J$ and the technology options are denoted by index $q \in Q$. Among these technologies, at each location, there exists at least one low carbon alternative. M and V_{jq} represent the plant and warehouse capacities, respectively. There is also a fixed cost for operating the plant (g) or warehouse (f_{jq}), independent of flow volume. The emissions due to plant (e^w) and warehouse (e^z_{jq}) operations are also independent of flow volume. This assumption holds because it is assumed that the sizes of the facilities are fixed, therefore energy and resources required to operate the facility at a peak level will be proportionately higher than the variable flow. Products are transported from the plants to open warehouses using a single-type of vehicle, so the cost (and emissions) to transport a single item is only dependent on distance travelled. These costs (c_j) and emissions (e_j^x) implicitly take into account the distance between the locations of the plant and warehouse j. Should the decision maker wish to include variable costs and/or emissions at the facilities, the facility cost/emissions can be reduced to a minimal level and the variabilities can be incorporated in the "transportation" parameters (c_j and e_j^x). As a result, c_j and e_j^x will no longer strictly represent transportation, but the variable cost and emissions from plant, transportation, and warehousing activities combined.

Each warehouse serves a customer zone with demand $\boldsymbol{D}_j$ that depends on per unit carbon emissions tracked from plant to warehouse. For this reason, each warehouse is assigned a carbon emission elasticity (γ_j), which represents the warehouse's demand sensitivity to per unit emissions. Each warehouse does however have a maximum ($\overline{D}_j$) and minimum ($\underline{D}_j$) level of annual demand. It is assumed that flow through the plant and warehouses are strictly positive ($\underline{D}_j > 0,\ \forall j \in J$). It is also assumed that the manufacturer has already determined the price of the product at each warehouse, π_j. This problem is illustrated in Figure 3.1 and the complete set of nomenclature is presented in Table 3.1.

Figure 3.1: Schematic of the two-echelon GSCND with emission sensitive demand. Notation is defined in Table 3.1.

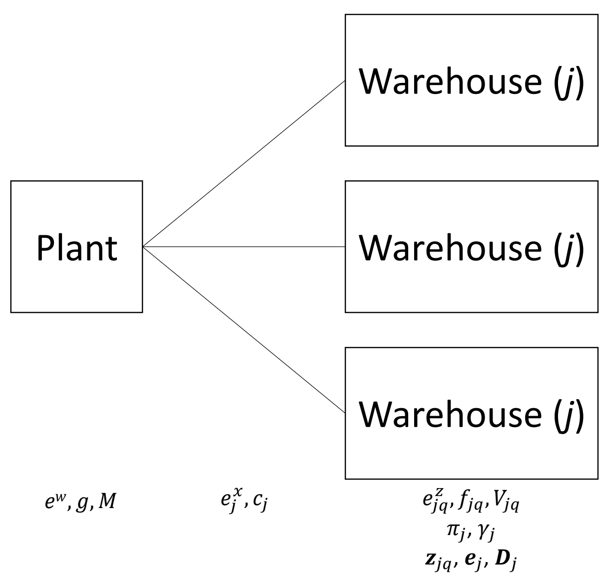


Table 3.1: Definitions of parameters and decision variables

Sets	
J	set of warehouse locations indexed by $j \in J$.
Q	set of warehouse technologies indexed by $q \in Q$.
Parameters	
π_j	market price of a single item at warehouse j.
g	annual cost to operate the plant.
f_{jq}	annual cost to operate warehouse j with technology q.
c_j	cost to transport a single unit of product from the plant to warehouse j.
e^w	annual emissions due to the operation of the plant.
e^z_{jq}	annual emissions due to the operation of warehouse j with technology q.
e^x_j	emissions due to the transportation of a single unit of product from the plant to warehouse j.
$\overline{D}_j$	maximum annual consumer demand at warehouse j.
$\underline{D}_j$	minimum annual consumer demand at warehouse j. $\underline{D}_j > 0$.
γ_j	demand sensitivity to per unit emissions at warehouse j (emission elasticity).
M	capacity of the plant.
V_{jq}	capacity of warehouse j using technology q.
Decision Variables	
$\boldsymbol{z}_{jq}$	equal to 1 if warehouse j uses technology q, 0 otherwise.
$\boldsymbol{D}_j$	demand at warehouse j.
$\boldsymbol{e}_j$	per unit product emissions out of warehouse j.

3.2.1 Nonlinear mathematical formulation

The mathematical formulation for the two-echelon supply chain with emission-sensitive demand is:

$$
\begin{aligned}
(\text{Loc}_{\text{2NLP}}):\ \max\quad & \sum_j \pi_j \boldsymbol{D}_j - \sum_j \sum_q f_{jq} \boldsymbol{z}_{jq} - \sum_j c_j \boldsymbol{D}_j && && (3.1)\\
\text{s.t.}\quad & \sum_j \boldsymbol{D}_j \le M, && && (3.2)\\
& \boldsymbol{D}_j \le \sum_q V_{jq} \boldsymbol{z}_{jq} && \forall j \in J, && (3.3)\\
& \sum_q \boldsymbol{z}_{jq} = 1 && \forall j \in J, && (3.4)\\
& \boldsymbol{D}_j = \overline{D}_j - \gamma_j \boldsymbol{e}_j && \forall j \in J, && (3.5)\\
& \boldsymbol{e}_j = \frac{e^w}{\sum_j \boldsymbol{D}_j} + e^x_j + \frac{\sum_q e^z_{jq} \boldsymbol{z}_{jq}}{\boldsymbol{D}_j} && \forall j \in J, && (3.6)\\
& \boldsymbol{e}_j \ge 0; \boldsymbol{D}_j \ge \underline{D}_j, && \forall j \in J && (3.7)\\
& \boldsymbol{z}_{jq} \in \{0,1\} && \forall j \in J, q \in Q && (3.8)
\end{aligned}
$$

(Loc_{2NLP}) is constructed with objective (3.1) maximizing profit. The profit is calculated by subtracting total costs from revenue. The total costs include the cost to operate the warehouses j using technology q and transportation from the plant to warehouse. The cost to operate the plant is not included because it is a constant. The revenue is simply the price of the product multiplied by the demand at warehouse j. The model ensures that facility capacities are not exceeded using constraints (3.2) and (3.3). The single technology selection constraint for the warehouse (constraint (3.4)) is set to equality since all warehouses are already operational, and therefore must be open. As mentioned, demand is negatively proportional to the product's carbon footprint, which is presented in constraint (3.5). This is a common demand function used for example in Yalabik and Fairchild (2011).

To calculate the carbon footprint for products at the warehouse, constraint (3.6) accounts for the average emissions at the plant and warehouse j plus the per unit emissions along the transportation path to warehouse j.

To construct the carbon footprint constraint (3.6), the emissions from the plant are first accounted for. Since the carbon footprint is of concern, total emissions from the plant are divided by the total flow through, which is equivalent to total demand, $\sum_j \boldsymbol{D}_j$. Then, the per item emissions due to transportation from plant to warehouse is added. Since this parameter is already per unit, this parameter need not be divided by flow. The emissions due to warehousing is then included. To ensure that only the emissions for the selected technology are taken into account, the warehouse emissions parameter e^z_{jq} is multiplied by the binary variable $\boldsymbol{z}_{jq}$. Again, since the carbon footprint is of concern, total emissions from the warehouse is divided by the total flow through, $\boldsymbol{D}_j$. In order to ensure a zero does not exist in a denominator of constraint (3.6), this model stipulates that $\underline{D}_j > 0$.

In order to solve the model without emission elasticity, (Loc_{2NLP}) reduces to the following model in which demand does not depend on emissions.

$$
\begin{aligned}
(\text{Loc}_{\text{2NoEm}})\text{:}\ \max \quad & \sum_j (\pi_j - c_j)\, \boldsymbol{D}_j - \sum_j \sum_q f_{jq} \boldsymbol{z}_{jq}, \\
\text{s.t.} \quad & (3.2), (3.3), (3.4) \\
& \boldsymbol{D}_j \geq \underline{D}_j, && \forall j \in J, \\
& \boldsymbol{z}_{jq} \in \{0, 1\} && \forall j \in J, q \in Q
\end{aligned}
$$

($\text{Loc}_{\text{2NoEm}}$) is a very simple model, assigning flow to the various warehouses. This problem is trivial if the plant and warehouse capacities are large enough to accommodate all demand, otherwise the model will strategically assign demand in order to maximize profit. In the following section, (Loc_{2NLP}) will be reformulated to address the nonlinear carbon footprint constraints.

3.3 A SOCP reformulation

In order to solve the (Loc_{2NLP}) using a commercial solver, the nonlinear constraint (3.6) must be reformulated. To begin linearizing constraint (3.6), variables $\boldsymbol{l}$, $\boldsymbol{r}_{jq}$, $\sum\limits_{j} \boldsymbol{D}_j = \boldsymbol{D}^T$, and $\boldsymbol{D}^T_{jq} = \boldsymbol{z}_{jq}\boldsymbol{D}_j$ are introduced such that

$$\boldsymbol{l} = \frac{1}{\boldsymbol{D}^T} \tag{3.9}$$

$$\boldsymbol{r}_{jq} = \begin{cases} \dfrac{\boldsymbol{z}_{jq}}{\boldsymbol{D}^T_{jq}} & \text{if } \boldsymbol{z}_{jq} = 1 \\ 0 & \text{if } \boldsymbol{z}_{jq} = 0 \end{cases} \qquad \forall j \in J, q \in Q \tag{3.10}$$

$$\boldsymbol{D}^T_{jq} \leq \overline{D}_j \boldsymbol{z}_{jq} \qquad \forall j \in J, q \in Q \tag{3.11}$$

$$\boldsymbol{D}^T_{jq} \leq \boldsymbol{D}_j \qquad \forall j \in J, q \in Q \tag{3.12}$$

$$\boldsymbol{D}^T_{jq} \geq \boldsymbol{D}_j - \overline{D}_j \left(1 - \boldsymbol{z}_{jq}\right) \qquad \forall j \in J, q \in Q \tag{3.13}$$

Equation (3.9) states lets $\boldsymbol{l}$ be equal to the inverse of total flow in the supply chain (and through the plant). Similarly, equation (3.10) states that when the warehouse is in operation, let $\boldsymbol{r}_{jq}$ be equal to the multiplicative inverse of the flow through warehouse j with technology q. If technology q is not selected, set $\boldsymbol{r}_{jq} = 0$. Constraints (3.11) to (3.13) are included to ensure that $\boldsymbol{D}^T_{jq} = \boldsymbol{D}_j \boldsymbol{z}_{jq}$. In order to introduce equations (3.9) and (3.10) to the new model, they must be reformulated.

In order to include equation (3.9) as a second order cone programming (SOCP) constraint (a form that is more easily handled by the solver), $\boldsymbol{D}^T$ is brought over and the equality is relaxed:

$$\boldsymbol{l}\boldsymbol{D}^T \geq 1 \tag{3.14}$$

The equality can be relaxed, because the carbon footprint constraint is actively being minimized when $\gamma_j > 0$. As a result, $\boldsymbol{l}$ is being minimized as $\boldsymbol{D}^T$ is being maximized to increase revenue, making the solution only optimal if the constraint is active. In order to ensure $\boldsymbol{l}$ and $\boldsymbol{D}^T$ maintain the correct values:

$$\boldsymbol{l} \leq 1 \tag{3.15}$$

$$\sum_j \boldsymbol{D}_j = \boldsymbol{D}^T \tag{3.16}$$

In a similar fashion, equation (3.10) is reformulated. Equation (3.10) presents two cases which are equivalent to:

$$\boldsymbol{r}_{jq}\boldsymbol{D}^T_{jq} = \boldsymbol{z}_{jq} \qquad \text{if } \boldsymbol{z}_{jq} = 1 \qquad \forall j \in J, q \in Q \tag{3.17}$$

$$\boldsymbol{r}_{jq} = 0 \qquad \text{if } \boldsymbol{z}_{jq} = 0 \qquad \forall j \in J, q \in Q \tag{3.18}$$

Like before, equation (3.17) can be reformulated as a SOCP constraint by relaxing the equality and squaring the binary variable z_{jq}. The new equivalent set of constraints are:

$$\boldsymbol{r}_{jq}\boldsymbol{D}_{jq}^{T} \geq \boldsymbol{z}_{jq}^{2} \qquad \forall j \in J, q \in Q, \tag{3.19}$$

$$\boldsymbol{r}_{jq} \leq \boldsymbol{z}_{jq} \qquad \forall j \in J, q \in Q, \tag{3.20}$$

Constraints (3.11) to (3.13) are needed for constraints (3.19) and (3.20) to hold. The use of $\boldsymbol{D}_{jq}^{T}$ in lieu of $\boldsymbol{D}_{j}$ is necessary because it provides a stronger formulation, ensuring that the flow is specified for each technology at the warehouse.

Two sets of SOCP constraints have now been introduced. For completeness, equation (3.19) is derived as follows:

$$\begin{aligned}
\boldsymbol{r}_{jq}\boldsymbol{D}_{jq}^{T} &\geq \boldsymbol{z}_{jq}^{2} \\
4\boldsymbol{r}_{jq}\boldsymbol{D}_{jq}^{T} &\geq 4\boldsymbol{z}_{jq}^{2} \\
\left(\boldsymbol{r}_{jq} + \boldsymbol{D}_{jq}^{T}\right)^{2} - \left(\boldsymbol{r}_{jq} - \boldsymbol{D}_{jq}^{T}\right)^{2} &\geq 4\boldsymbol{z}_{jq}^{2} \\
\left(\boldsymbol{r}_{jq} + \boldsymbol{D}_{jq}^{T}\right)^{2} &\geq 4\boldsymbol{z}_{jq}^{2} + \left(\boldsymbol{r}_{jq} - \boldsymbol{D}_{jq}^{T}\right)^{2} \\
\boldsymbol{r}_{jq} + \boldsymbol{D}_{jq}^{T} &\geq \sqrt{4\boldsymbol{z}_{jq}^{2} + \left(\boldsymbol{r}_{jq} - \boldsymbol{D}_{jq}^{T}\right)^{2}} \\
\boldsymbol{r}_{jq} + \boldsymbol{D}_{jq}^{T} &\geq \left\| \begin{bmatrix} 2\boldsymbol{z}_{jq} \\ \boldsymbol{r}_{jq} - \boldsymbol{D}_{jq}^{T} \end{bmatrix} \right\|
\end{aligned}$$

As mentioned before, introducing these SOCP constraints is possible because at optimality the demand will be maximized while the inverse variables are minimized, making these active constraints.

By introducing variables $\boldsymbol{l}$ and $\boldsymbol{r}_{jq}$ to the carbon footprint constraint, the variables in the denominator are eliminated. Adding equations (3.11)-(3.16) and (3.19)-(3.20) to the model, the carbon footprint constraint may now take the form:

$$\boldsymbol{e}_j = e^w \boldsymbol{l} + e_j^x + \sum_q e_{jq}^z \boldsymbol{r}_{jq} \quad \forall j \in J$$

To summarize, the variables indicating flow to the warehouses have been taken out of the denominator of carbon footprint equation (constraint (3.26)) and equations (3.11)-(3.16) and (3.19)-(3.20) have been introduced.

3.3.1 SOCP formulation

After making the necessary changes to the carbon footprint constraint, and introducing the additional constraints, the model is now in its final form:

$$
\begin{aligned}
(\text{Loc}_{2\text{SOCP}}):\ \max\quad & \sum_j (\pi_j - c_j)\, \boldsymbol{D}_j - \sum_j \sum_q f_{jq}\boldsymbol{z}_{jq} && && (3.21)\\
\text{s.t.}\quad & \sum_j \boldsymbol{D}_j \leq M, && && (3.22)\\
& \boldsymbol{D}_j \leq \sum_q V_{jq}\boldsymbol{z}_{jq} && \forall j \in J, && (3.23)\\
& \sum_q \boldsymbol{z}_{jq} = 1 && \forall j \in J, && (3.24)\\
& \boldsymbol{D}_j = \overline{D}_j - \gamma_j \boldsymbol{e}_j && \forall j \in J, && (3.25)\\
& \boldsymbol{e}_j = e^w \boldsymbol{l} + \sum_q e^z_{jq}\boldsymbol{r}_{jq} && \forall j \in J, && (3.26)\\
& \boldsymbol{l}\boldsymbol{D}^T \geq 1 && && (3.27)\\
& \boldsymbol{D}^T = \sum_j \boldsymbol{D}_j && && (3.28)\\
& \boldsymbol{r}_{jq}\boldsymbol{D}^T_{jq} \geq \boldsymbol{z}^2_{jq} && \forall j \in J, q \in Q, && (3.29)\\
& \boldsymbol{r}_{jq} \leq \boldsymbol{z}_{jq} && \forall j \in J, q \in Q, && (3.30)\\
& \boldsymbol{D}^T_{jq} \leq \overline{D}_j \boldsymbol{z}_{jq} && \forall j \in J, q \in Q && (3.31)\\
& \boldsymbol{D}^T_{jq} \leq \boldsymbol{D}_j && \forall j \in J, q \in Q && (3.32)\\
& \boldsymbol{D}^T_{jq} \geq \boldsymbol{D}_j - \overline{D}_j\,(1 - \boldsymbol{z}_{jq}) && \forall j \in J, q \in Q && (3.33)\\
& \boldsymbol{e}_j, \boldsymbol{D}^T, \boldsymbol{r}_{jq}, \boldsymbol{D}^T_{jq} \geq 0; \boldsymbol{D}_j \geq \underline{D}_j, 1 \leq \boldsymbol{l} \leq 0 && \forall j \in J && (3.34)\\
& \boldsymbol{z}_{jq} \in \{0,1\} && \forall j \in J, q \in Q && (3.35)
\end{aligned}
$$

Constraints (3.21) to (3.25) remain the same as in ($\text{Loc}_{2\text{NLP}}$). Constraint (3.26) is now linearised, and constraints (3.27) to (3.33) allow for this linearisation to hold. Constraint (3.28) makes handling the summation of total flow through the warehouse easier by setting it to a single variable. The SOCP constraints (3.27) and (3.29) are also included, as discussed above, along with constraints (3.30) to (3.33). Finally, constraints (3.34) and (3.35) set bounds on all variables in the model.

It should be noted that when $\gamma_j = 0$, the carbon footprint does not impact the demand at all. In this case, ($\mathrm{Loc}_{\mathrm{2NoEm}}$) is solved in lieu of ($\mathrm{Loc}_{\mathrm{2SOCP}}$).

3.4 Test case

The model is tested on a hypothetical e-commerce supply chain. The product is produced at a single plant with three choices in technology, each having a unique cost, emission level, and capacity. The plant parameters will be evaluated using parametric analysis. The emission, cost, and capacity parameters are presented in Table 3.4. In the second echelon, there are four warehouses each with three choices in technology. Each combination of warehouse location and technology has a unique cost, emission level, and capacity. Each warehouse acts as a demand point, serving customers in the immediate vicinity. The warehouse emission, cost, and capacity parameters are presented in Table 3.5. The emissions and costs at the warehouses are calculated such that the ratio between each value and volume is constant for all sites. These ratios are presented in Table 3.2. The distances between the plant and warehouses are also presented in Table 3.3, and the associated transportation cost and emissions are presented in Table 3.6.

All emissions are in kg of CO_2 per year, demand is per 1000 units, price per unit is (CAD/1000 units), and other costs are in CAD per year. Based on the units selected, the environmental sensitivity variable (γ_j) will have the units (1000 units less/kg CO_2). This means, for each kg of CO_2 increased per 1000 units of product, demand will decrease by 1000 units.

Table 3.2: Ratios between facility emissions and costs with respect to facility capacity.

Plant Paramter Ratios

Emission Level	**High**	**Med**	**Low**
ew/M	2500	1600	750
g/M	1500	1700	1900

Warehouse Parameter Ratios

Technology (q)	**1**	**2**	**3**
e^z_{jq}/V_{jq}	1125	750	650
f_{jq}/V_{jq}	750	850	950

Table 3.3: Distances between plant and warehouses.

Warehouse Index	**Dist. from Plant (km)**
1	447
2	97
3	346
4	100

Table 3.4: Parameter values for for e^w, g, M (instance J=4, Q=3)

Emission Level	High	Medium	Low
e^w (1000's)	10,025	6416	3007.5
g (1000's)	6015	6817	7619
M	4010	4010	4010

Table 3.5: Parameter values for e^z_{jq}, f_{jq}, V_{jq} (instance J=4, Q=3)

$j \setminus q$	1	2	3
$e^z_{1,q}$ (1000's)	135	90	78
$f_{1,q}$ (1000's)	90	102	114
$V_{1,q}$	120	120	120
$e^z_{2,q}$ (1000's)	2812.5	1875	1625
$f_{2,q}$ (1000's)	1875	2125	2375
$V_{2,q}$	2500	2500	2500
$e^z_{3,q}$ (1000's)	680.625	453.75	393.25
$f_{3,q}$ (1000's)	453.75	514.25	574.75
$V_{3,q}$	605	605	605
$e^z_{4,q}$ (1000's)	1125	750	650
$f_{4,q}$ (1000's)	750	850	950
$V_{4,q}$	1000	1000	1000

Table 3.6: Parameter values for for e^x_j, c_j, $\overline{D}_j$, $\underline{D}_j$, and

j	1	2	3	4
e^x_j	745	162	577	167
c_j	752	181	646	187
$\overline{D}_j$	115	2403	602	883
$\underline{D}_j$	10	10	10	10
π_j	2000	2000	2000	2000

3.5 Results and Analysis

Since each warehouse has a different capacity and demand, the sensitivity to emissions required to cause a switch in technology will have to differ as well. To do this, the emission elasticity (γ_j) is calculated for each warehouse as a function of percent change in demand (d) with respect to 1% decrease in maximum emissions at each warehouse j (e_j^0). The following equation is used to construct Table 3.7:

$$\gamma_j = \frac{d\overline{D}_j}{e_j^0 \times 0.99} \tag{3.36}$$

Each value of percent change in demand (d) used to calculate a set of emission elasticity values will be referred to as the "emission elasticity setting." In order to perform a balanced analysis, the emission elasticity values for all test cases will be calculated using the maximum supply chain emissions in the high emitting plant supply chain. The maximum emissions in the supply chain at each warehouse j is calculated based on the highest emitting configuration, paired with the maximum flow through each facility (reflective of a emission insensitive customer set):

$$e_j^0 = \frac{e^w}{\sum\limits_j \overline{D}_j} + e_j^x + \frac{\max\limits_j e_j^z}{\overline{D}_j}$$

An overview of the solutions for different levels of plant emissions (low, medium, and high) can be found in Tables 3.8, 3.9, and 3.10 (respectively). These tables present the objective value, total emissions, and total demand for each percentage demand reduction. The following three columns present the percentage decrease with respect to the no emissions case ($\gamma_j = 0$), followed by three more columns presenting the percentage decrease with respect to the no emissions case ($\gamma_j = 0$) if all warehouses are forced to take the highest emitting technology. These last three columns are designed to illustrate the case should the decision maker choose to make no changes to technology selection, but still operate with emission sensitive demand. In these tables, it should be noted the total profits do not include the cost of the plant (g) since it is a constant, however total emissions do include plant emissions (e^w) because flow through will impact the carbon footprint at each warehouse.

As the test case explains, there are three tiers of plant emission levels. These are discussed together in Section 3.5.1.

3.5.1 Results

As previously mentioned, Table 3.7 presents the emission elasticities at each warehouse for each selected emission elasticity setting. When discussing the "emission elasticity setting", these tables may be used to understand what the elasticity is at each warehouse, giving a complete picture of the system. The maximum emission elasticity settings are 62, 40, and 29 for low to high level plant emissions, respectively, because beyond this value the problem is either no longer feasible for the respective emission elasticity parameters.

Figure 3.2 visually illustrates the change in technology selection as the percent change in demand increases for all emission levels at the plant. The first change in technology for the low level emitting plant occurs when the emission elasticity setting reaches 34, with a switch to the medium level emission technology at warehouses 2 and 4 (see Figure 3.2a). The same switch in technologies occurs when the emission elasticity setting reaches 28 for the medium level emitting plant. In contrast, the first switch for the high emitting plant cases occur only at warehouse 2 when the emission elasticity setting reaches 23. It

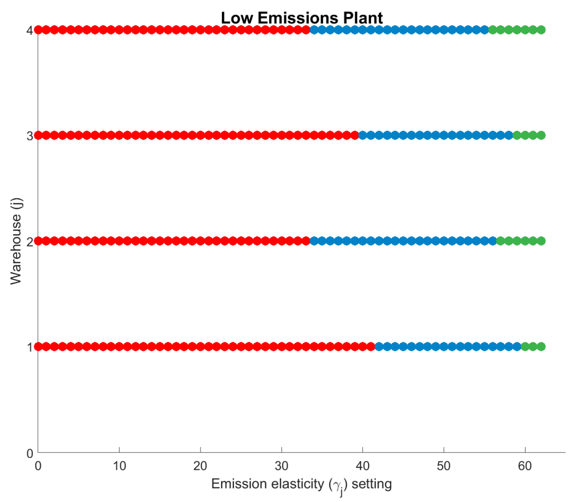
Table 3.7: Emission elasticity setting (EES) and the corresponding warehouse emission elasticities.

EES	γ_1	γ_2	γ_3	γ_4	EES	γ_1	γ_2	γ_3	γ_4
0	0	0	0	0	32	0.0084	0.2	0.046	0.072
1	0.00026	0.0063	0.0014	0.0023	33	0.0087	0.21	0.048	0.075
2	0.00053	0.013	0.0029	0.0045	34	0.0089	0.22	0.049	0.077
3	0.00079	0.019	0.0043	0.0068	35	0.0092	0.22	0.051	0.079
4	0.0011	0.025	0.0058	0.009	36	0.0095	0.23	0.052	0.081
5	0.0013	0.032	0.0072	0.011	37	0.0097	0.23	0.053	0.084
6	0.0016	0.038	0.0087	0.014	38	0.01	0.24	0.055	0.086
7	0.0018	0.044	0.01	0.016	39	0.01	0.25	0.056	0.088
8	0.0021	0.051	0.012	0.018	40	0.011	0.25	0.058	0.09
9	0.0024	0.057	0.013	0.02	41	0.011	0.26	0.059	0.093
10	0.0026	0.063	0.014	0.023	42	0.011	0.27	0.061	0.095
11	0.0029	0.07	0.016	0.025	43	0.011	0.27	0.062	0.097
12	0.0032	0.076	0.017	0.027	44	0.012	0.28	0.064	0.099
13	0.0034	0.082	0.019	0.029	45	0.012	0.28	0.065	0.1
14	0.0037	0.089	0.02	0.032	46	0.012	0.29	0.066	0.1
15	0.0039	0.095	0.022	0.034	47	0.012	0.3	0.068	0.11
16	0.0042	0.1	0.023	0.036	48	0.013	0.3	0.069	0.11
17	0.0045	0.11	0.025	0.038	49	0.013	0.31	0.071	0.11
18	0.0047	0.11	0.026	0.041	50	0.013	0.32	0.072	0.11
19	0.005	0.12	0.027	0.043	51	0.013	0.32	0.074	0.12
20	0.0053	0.13	0.029	0.045	52	0.014	0.33	0.075	0.12
21	0.0055	0.13	0.03	0.047	53	0.014	0.34	0.077	0.12
22	0.0058	0.14	0.032	0.05	54	0.014	0.34	0.078	0.12
23	0.006	0.15	0.033	0.052	55	0.014	0.35	0.079	0.12
24	0.0063	0.15	0.035	0.054	56	0.015	0.35	0.081	0.13
25	0.0066	0.16	0.036	0.057	57	0.015	0.36	0.082	0.13
26	0.0068	0.16	0.038	0.059	58	0.015	0.37	0.084	0.13
27	0.0071	0.17	0.039	0.061	59	0.015	0.37	0.085	0.13
28	0.0074	0.18	0.04	0.063	60	0.016	0.38	0.087	0.14
29	0.0076	0.18	0.042	0.066	61	0.016	0.39	0.088	0.14
30	0.0079	0.19	0.043	0.068	62	0.016	0.39	0.09	0.14
31	0.0081	0.2	0.045	0.07					

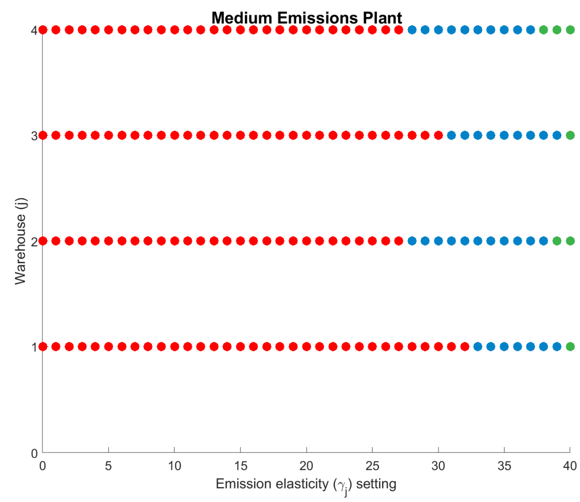
makes sense that the first warehouse to switch to an environmentally friendly alternative is warehouse 2 because it services over half of the total demand. In addition, this facility is the largest with the greatest environmental impact. The subsequent switches for the low level emitting plant occur at the emission elasticity settings 40, 42, 56, 57, 59, and 60. Similarly, subsequent switches for the medium level emitting plant occur at the emission elasticity settings 31, 33, 38, 39, and 40, and for the high level emitting plant at 24, 25, 26, and 29. For all plant emission levels, warehouse 1 is the slowest to switch to an environmentally friendly alternative, which is logical because it is the smallest and services the least customers. More information about the technology changes, warehouse demands, and carbon footprints, are found in Tables A.2, A.5, and A.8. Comparing the three cases illustrated in Figure 3.2, it is clear that technology changes occur earlier as the emission level at the plant increases. This due to the fact that the investment in lower technology has already been made in the low emitting technology at the plant. As a result, relatively higher emission elasticity settings are necessary to reach carbon footprint levels that will adversely impact demand enough to warrant further investment at the warehouses. What this indicates is that the technology selected at the plant has a significant impact on supply chain network design decisions when consumer emission elasticity is considered.

The same technology switches presented in Figure 3.2 are illustrated in Figures 3.3 to 3.5 using vertical black lines. These figures illustrate how the total emissions (red line) drop in a step-like function, with the steps occurring at the technology changes. Overlaid are the average carbon footprint emissions with respect the the percent demand change. The carbon footprint increases overall as the percent demand change increases, however, there are sharp drops when technology is changed. This is because after each technology change, total emissions in the supply chain drop significantly. The continued increase in emission elasticity results in lower demand, meaning that the emissions from the facilities are spread

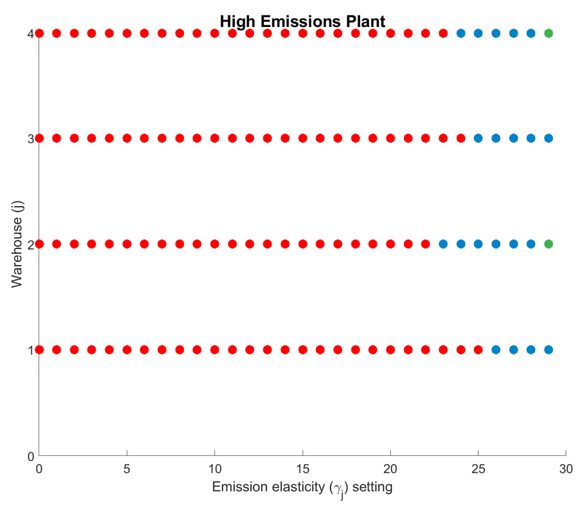
Figure 3.2: Technology selection with respect to emission elasticity setting for test case. Warehouse emission levels indicated by red (high), blue (medium), and green (low).



(a) Low emissions plant.



(b) Medium emissions plant.



(c) High emissions plant.

over fewer units of demand. To remedy this, rather than only offering different technology options at the facilities, also offer different operation capacities. Mathematically, this would be equivalent to having more technology options. Practically, this would be equivalent to outsourcing the warehousing activities to a third party, using only a portion of a shared warehouse. The values used to construct the graphs are found in Tables A.3, A.6, and A.9.

Tables 3.8 to 3.10 present an overview of the solutions for the test case. Tables A.1, A.4, and A.7 provide further insight into the results. With the low emitting plant in operation and demand having no sensitivity to emissions, the objective value would be \$3.76M, with total emissions of 8.73M kgCO_2 and demand of 4,003,000 units. As emission elasticity increases, the objective value is lower due to the decrease in demand, however, it is not until the emission elasticity setting reaches 34 that a technology switch occurs. The decrease in objective value is 44.86%, compared to 44.43% if no changes are made. While this drop in profit is significant, it should be pointed out that the test case under consideration is not based on a real case study. It is important to understand that these percentages are presented to illustrate the contrast between making an investment in green technology and not making any investments at all. The reduction in total emissions are significantly lower at 17.39%, as opposed to 2.72% if no technology change is made. The reason there is any reduction in emissions if no technology change is made, is because the reduced demand means there are fewer transported items. At the emission elasticity setting 34, the total demand is reduced by only 19.56%, which is far better than the lost sales of 24.16% if no technology change is made. These results indicate that the solution is better overall.

Similar observations are made for the medium and high level emission plants. With the medium emitting plant in operation and demand having no sensitivity to emissions, the objective value would be \$3.76M, with total emissions of 12.14M kgCO_2 and demand

Figure 3.3: Mean and total emissions for instance with the low level emissions plant. Technology changes indicated by vertical black line.

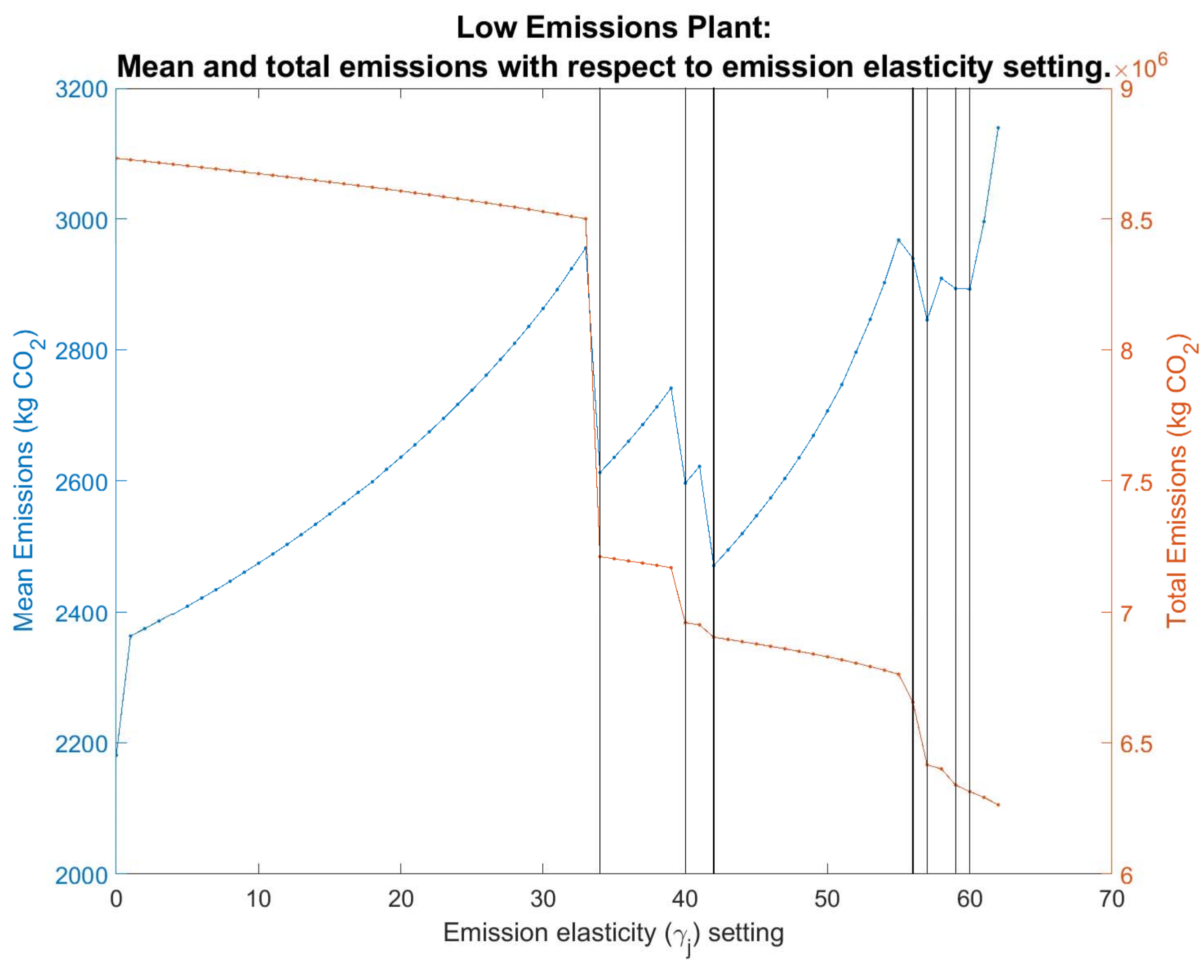


Figure 3.4: Mean and total emissions for instance with the medium level emissions plant. Technology changes indicated by vertical black line.

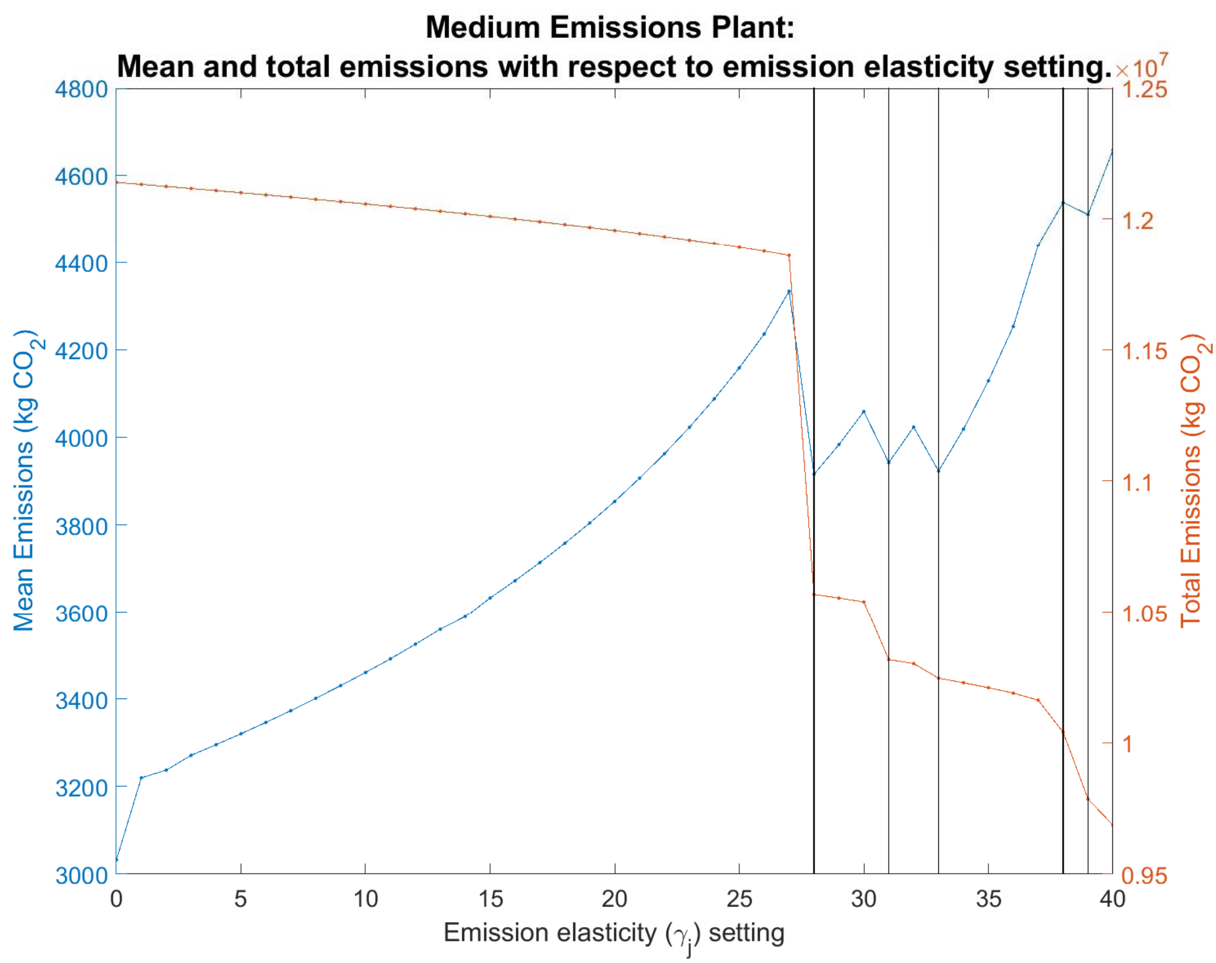
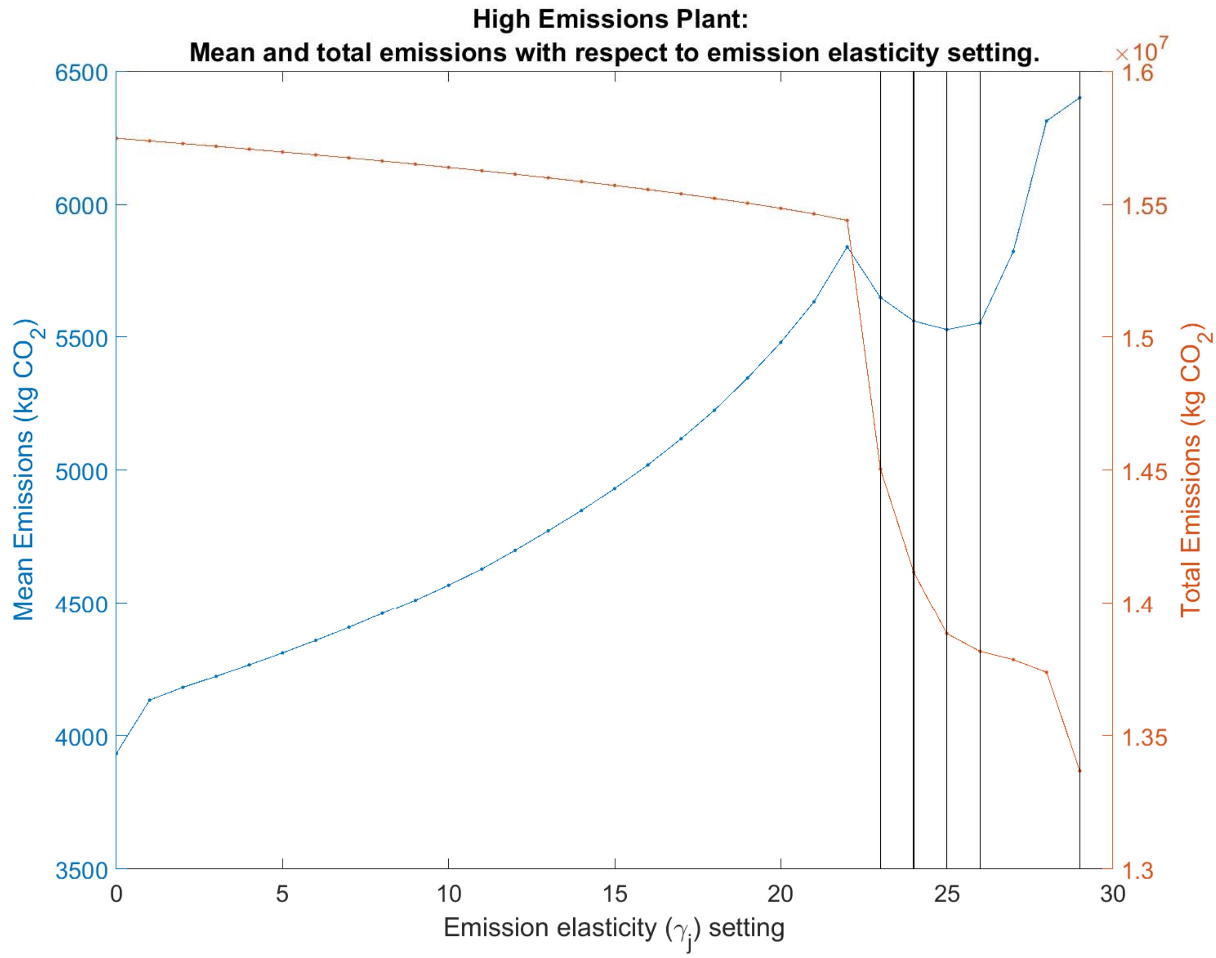


Figure 3.5: Mean and total emissions for instance with the high level emissions plant. Technology changes indicated by vertical black line.



of 4,003,000 units. As emission elasticity increases, the objective value is lower due to the decrease in demand, however, it is not until the emission elasticity setting reaches 28 that a technology switch occurs. The decrease in objective value is 55.87%, compared to 56.56% if no changes are made, indicating that the switch results in a better solution. The reduction in total emissions are significantly lower at 12.94%, as opposed to 2.44% if no technology change is made. At the emission elasticity setting of 28, the total demand is reduced by only 25.46%, which is far better than the lost sales of 30.68% if no technology change is made.

Finally, with the high emitting plant in operation and no sensitivity to emissions, the objective value would be \$3.76M, with total emissions of 15.75M kgCO_2 and demand of 4,003,000 units. As emission elasticity increases, the objective value decreases due to the decrease in demand, however, it is not until percent demand change reaches 29% that a technology switch occurs. Although the medium level emissions technology at the warehouse costs more, the drop in the objective value is not significant with respect to demand change of 28%. Again, this is because the technology switch keeps sensitive demand, making up in part for the increased cost. The decrease in objective value is 61.50%, compared to 61.67% if no changes are made, indicated the switch results in a better solution. The reduction in total emissions are lower at 7.82%, as opposed to 2.04% if no technology change is made. That demand change of 29%, the total demand is reduced by 29.83%, which is far better than the lost sales of 33.42% if no technology change is made.

Finally, with the high emitting plant in operation and demand having no sensitivity to emissions, the objective value would be \$3.76M, with total emissions of 15.75M kgCO_2 and demand of 4,003,000 units. As emission elasticity increases, the objective value is lower due to the decrease in demand, however, it is not until the emission elasticity setting reaches 23 that a technology switch occurs. The decrease in objective value is 63.69%, compared to 64.55% if no changes are made, indicating that the switch results in a better solution. The total emissions are lower at 7.89%, as opposed to 2.13% if no technology change is made. At the emission elasticity setting of 23, the total demand is reduced by 31.03%, which is far better than the lost sales of 34.97% if no technology change is made. It is to be expected that the demand change and total demand reduced will approximately line up for this case because this supply chain is the bases for calculating the emission elasticity values used.

Once the emission elasticity setting increases past 60, 39 and 28 for low, medium, and high level emitting plants (respectively), the system is no longer profitable - indicated by negative objective values. This is because any further investments in low emitting technology options at the warehouses will not be profitable due to declining demand levels. It should be noted that past the emission elasticity setting of 46, 33, and 25 for low, medium, and high level emitting plants (respectively), it is no longer feasible to operate with all high emitting technologies at the warehouse. This illustrates that if the decision maker is not willing to make any changes, operation should cease.

Table 3.8: Low Emitting Plant: Comparison of solutions varying emission elasticity setting (EES).

EES	Obj Val	Total Em.	$\sum_k D_k$	Pct dec. wrt $\gamma_j = 0$			High WH tech, pct dec. wrt $\gamma_j = 0$		
	($ M)	(M kg CO_2)	(1000 units)	Obj Val	Em.	Demand	Obj Val	Em.	Demand
0	3.76	8.73	4003	0.00	0.00	0.00	0.00	0.00	0.00
1	3.72	8.72	3980	1.03	0.06	0.57	1.03	0.06	0.57
2	3.68	8.72	3958	2.08	0.13	1.12	2.08	0.13	1.12
3	3.64	8.71	3935	3.13	0.19	1.70	3.13	0.19	1.70
4	3.60	8.71	3912	4.19	0.26	2.27	4.19	0.26	2.27
5	3.56	8.70	3888	5.27	0.32	2.87	5.27	0.32	2.87
6	3.52	8.70	3864	6.36	0.39	3.47	6.36	0.39	3.47
7	3.48	8.69	3840	7.46	0.46	4.07	7.46	0.46	4.05
8	3.44	8.68	3816	8.58	0.53	4.67	8.57	0.53	4.67
9	3.40	8.68	3792	9.70	0.60	5.27	9.70	0.60	5.27
10	3.35	8.67	3767	10.85	0.67	5.90	10.84	0.67	5.90
11	3.31	8.67	3742	12.00	0.74	6.52	11.99	0.74	6.52
12	3.27	8.66	3716	13.18	0.81	7.17	13.18	0.81	7.17
13	3.22	8.65	3690	14.36	0.88	7.82	14.37	0.88	7.82
14	3.18	8.65	3664	15.58	0.96	8.47	15.58	0.96	8.47
15	3.13	8.64	3637	16.80	1.03	9.14	16.80	1.03	9.14
16	3.08	8.63	3610	18.04	1.11	9.82	18.04	1.11	9.82
17	3.04	8.63	3583	19.30	1.19	10.49	19.30	1.19	10.49
18	2.99	8.62	3555	20.57	1.26	11.19	20.58	1.26	11.19
19	2.94	8.61	3526	21.88	1.34	11.92	21.88	1.34	11.92
20	2.89	8.61	3498	23.21	1.42	12.62	23.21	1.42	12.62
21	2.84	8.60	3468	24.55	1.51	13.36	24.56	1.51	13.36
22	2.79	8.59	3438	25.93	1.59	14.11	25.93	1.59	14.11
23	2.73	8.58	3408	27.32	1.67	14.86	27.33	1.68	14.86
24	2.68	8.58	3377	28.75	1.76	15.64	28.76	1.76	15.64
25	2.63	8.57	3345	30.20	1.85	16.44	30.21	1.85	16.44
26	2.57	8.56	3313	31.69	1.94	17.24	31.70	1.94	17.24
27	2.51	8.55	3280	33.21	2.03	18.06	33.22	2.03	18.06
28	2.45	8.54	3246	34.77	2.13	18.91	34.78	2.13	18.91
29	2.39	8.54	3212	36.36	2.22	19.76	36.38	2.22	19.79
30	2.33	8.53	3176	37.99	2.32	20.66	37.72	2.31	20.51
31	2.27	8.52	3139	39.68	2.42	21.58	39.72	2.43	21.58
32	2.20	8.51	3101	41.44	2.53	22.53	41.46	2.53	22.53
33	2.14	8.50	3062	43.22	2.64	23.51	43.25	2.64	23.51
34	2.07	7.21	3220	44.86	17.39	19.56	44.43	2.72	24.16
35	2.02	7.20	3190	46.21	17.48	20.31	47.04	2.87	25.58
36	1.97	7.20	3160	47.60	17.57	21.06	49.04	2.99	26.66
37	1.92	7.19	3128	49.02	17.67	21.86	51.14	3.11	27.80
38	1.86	7.18	3096	50.49	17.77	22.66	53.34	3.24	28.98
39	1.81	7.17	3063	51.99	17.87	23.48	55.65	3.38	30.25
40	1.75	6.96	3072	53.52	20.31	23.26	58.11	3.53	31.58
41	1.69	6.95	3040	54.99	20.41	24.06	60.73	3.69	33.00
42	1.64	6.90	3016	56.51	20.95	24.66	63.58	3.85	34.52
43	1.58	6.89	2982	58.06	21.04	25.51	66.71	4.04	36.22
44	1.52	6.88	2947	59.66	21.14	26.38	70.20	4.24	38.12
45	1.45	6.88	2911	61.33	21.24	27.28	74.29	4.48	40.32
46	1.39	6.87	2874	63.02	21.34	28.20	79.35	4.78	43.07
47	1.32	6.86	2836	64.79	21.45	29.15	-	-	-
48	1.26	6.85	2796	66.64	21.56	30.15	-	-	-
49	1.18	6.84	2754	68.56	21.68	31.20	-	-	-
50	1.11	6.83	2709	70.63	21.80	32.33	-	-	-
51	1.02	6.82	2663	72.76	21.93	33.47	-	-	-
52	0.93	6.80	2610	75.18	22.08	34.80	-	-	-
53	0.84	6.79	2557	77.64	22.22	36.12	-	-	-
54	0.74	6.78	2499	80.31	22.38	37.57	-	-	-
55	0.63	6.76	2434	83.29	22.56	39.20	-	-	-
56	0.50	6.65	2418	86.60	23.78	39.60	-	-	-
57	0.40	6.42	2496	89.45	26.51	37.65	-	-	-
58	0.29	6.40	2435	92.23	26.69	39.17	-	-	-
59	0.17	6.34	2404	95.47	27.39	39.95	-	-	-
60	0.04	6.31	2340	98.84	27.68	41.54	-	-	-
61	-0.12	6.29	2248	103.07	27.93	43.84	-	-	-
62	-0.32	6.26	2129	108.56	28.25	46.81	-	-	-

Table 3.9: Medium Emitting Plant: Comparison of solutions varying emission elasticity setting (EES).

EES	Obj Val	Total Em.	$\sum_k D_k$	Pct dec. wrt $\gamma_j = 0$			High WH tech, pct dec. wrt $\gamma_j = 0$.		
	($ M)	(M kg CO_2)	(1000 units)	Obj Val	Em.	Demand	Obj Val	Em.	Demand
0	3.76	12.14	4003	0.00	0.00	0.00	0.00	0.00	0.00
1	3.71	12.13	3972	1.44	0.06	0.77	1.44	0.06	0.77
2	3.65	12.12	3940	2.90	0.13	1.57	2.91	0.13	1.57
3	3.60	12.12	3907	4.39	0.19	2.40	4.39	0.19	2.40
4	3.54	12.11	3875	5.90	0.26	3.20	5.90	0.26	3.20
5	3.48	12.10	3841	7.44	0.32	4.05	7.43	0.32	4.05
6	3.42	12.09	3807	9.00	0.39	4.90	8.99	0.39	4.87
7	3.36	12.08	3773	10.59	0.46	5.75	10.58	0.46	5.75
8	3.30	12.07	3737	12.21	0.53	6.65	12.21	0.53	6.65
9	3.24	12.07	3702	13.86	0.60	7.52	13.86	0.60	7.52
10	3.18	12.06	3665	15.54	0.68	8.44	15.55	0.68	8.44
11	3.11	12.05	3628	17.26	0.75	9.37	17.27	0.75	9.37
12	3.05	12.04	3589	19.02	0.83	10.34	19.02	0.83	10.34
13	2.98	12.03	3550	20.82	0.91	11.32	20.82	0.91	11.32
14	2.91	12.02	3511	22.61	0.98	12.29	22.66	0.99	12.32
15	2.84	12.01	3469	24.55	1.07	13.34	24.55	1.07	13.34
16	2.77	12.00	3427	26.48	1.15	14.39	26.48	1.15	14.39
17	2.69	11.99	3384	28.47	1.24	15.46	28.48	1.24	15.46
18	2.61	11.98	3340	30.52	1.33	16.56	30.53	1.33	16.56
19	2.53	11.97	3294	32.64	1.42	17.71	32.65	1.42	17.71
20	2.45	11.96	3246	34.83	1.51	18.91	34.84	1.51	18.91
21	2.37	11.94	3197	37.10	1.61	20.13	37.11	1.61	20.13
22	2.28	11.93	3146	39.46	1.71	21.41	39.48	1.71	21.43
23	2.19	11.92	3092	41.91	1.82	22.76	41.94	1.82	22.76
24	2.09	11.91	3037	44.48	1.93	24.13	44.53	1.93	24.16
25	1.99	11.89	2978	47.18	2.04	25.61	47.26	2.04	25.63
26	1.88	11.88	2916	50.03	2.16	27.15	50.15	2.17	27.20
27	1.76	11.86	2847	53.22	2.30	28.88	53.23	2.30	28.88
28	1.66	10.57	2984	55.87	12.94	25.46	56.56	2.44	30.68
29	1.57	10.55	2929	58.38	13.05	26.83	60.21	2.60	32.65
30	1.47	10.54	2871	61.04	13.17	28.28	64.32	2.77	34.87
31	1.36	10.32	2850	63.88	15.01	28.80	69.02	2.97	37.42
32	1.25	10.30	2788	66.74	15.14	30.35	74.81	3.21	40.54
33	1.14	10.25	2731	69.76	15.59	31.78	83.42	3.57	45.19
34	1.01	10.23	2659	73.10	15.74	33.57	-	-	-
35	0.87	10.21	2579	76.78	15.89	35.57	-	-	-
36	0.72	10.19	2492	80.80	16.06	37.75	-	-	-
37	0.52	10.16	2378	86.06	16.29	40.59	-	-	-
38	0.28	10.04	2292	92.66	17.29	42.74	-	-	-
39	0.03	9.79	2292	99.13	19.39	42.74	-	-	-
40	-0.28	9.69	2155	107.57	20.20	46.17	-	-	-

Table 3.10: High Emitting Plant: Comparison of solutions varying emission elasticity setting (EES).

EES	Obj Val	Total Em.	$\sum_k D_k$	Pct dec. wrt $\gamma_j = 0$			High WH tech, pct dec. wrt $\gamma_j = 0$		
	(\$ M)	(M kg CO_2)	(1000 units)	Obj Val	Em.	Demand	Obj Val	Em.	Demand
0	3.76	15.75	4003	0.00	0.00	0.00	0.00	0.00	0.00
1	3.69	15.74	3962	1.88	0.06	1.02	1.88	0.06	1.02
2	3.62	15.73	3921	3.80	0.13	2.05	3.79	0.13	2.05
3	3.55	15.72	3878	5.75	0.19	3.12	5.75	0.19	3.12
4	3.47	15.71	3835	7.75	0.26	4.20	7.74	0.26	4.20
5	3.39	15.70	3790	9.80	0.33	5.32	9.78	0.33	5.30
6	3.31	15.69	3745	11.89	0.40	6.45	11.89	0.40	6.45
7	3.23	15.67	3698	14.04	0.47	7.62	14.04	0.47	7.62
8	3.15	15.66	3650	16.24	0.54	8.82	16.25	0.54	8.82
9	3.07	15.65	3601	18.49	0.62	10.04	18.51	0.62	10.04
10	2.98	15.64	3551	20.82	0.69	11.29	20.85	0.69	11.32
11	2.89	15.63	3499	23.22	0.77	12.59	23.26	0.77	12.62
12	2.79	15.61	3444	25.74	0.86	13.96	25.76	0.86	13.96
13	2.70	15.60	3388	28.34	0.94	15.36	28.34	0.94	15.36
14	2.59	15.59	3329	31.03	1.03	16.84	31.03	1.03	16.84
15	2.49	15.57	3268	33.84	1.12	18.36	33.84	1.12	18.36
16	2.38	15.56	3205	36.78	1.22	19.94	36.78	1.22	19.94
17	2.26	15.54	3137	39.87	1.32	21.63	39.38	1.31	21.36
18	2.14	15.52	3067	43.14	1.43	23.38	43.16	1.43	23.41
19	2.01	15.50	2991	46.64	1.55	25.28	46.67	1.55	25.31
20	1.87	15.49	2910	50.38	1.67	27.30	50.45	1.67	27.35
21	1.71	15.46	2822	54.44	1.80	29.50	54.59	1.81	29.58
22	1.53	15.44	2718	59.23	1.96	32.10	59.22	1.96	32.10
23	1.37	14.51	2761	63.69	7.89	31.03	64.55	2.13	34.97
24	1.21	14.12	2725	67.90	10.35	31.93	71.05	2.34	38.50
25	1.03	13.88	2664	72.56	11.84	33.45	80.33	2.64	43.49
26	0.84	13.82	2562	77.64	12.26	36.00	-	-	-
27	0.61	13.79	2431	83.69	12.46	39.27	-	-	-
28	0.26	13.74	2229	93.03	12.76	44.32	-	-	-
29	-0.20	13.37	2162	105.30	15.11	45.99	-	-	-

3.6 Conclusions

In this chapter, a two-echelon e-commerce supply chain with emission sensitive demand problem is presented, along with a nonlinear mathematical model to solve it. The nonlinear model is reformulated using SOCP constraints, making the model tractable for commercial solvers. The solutions to a test case instance illustrates the impact a concious consumer has on the supply chain. The results provide insight for decision makers seeking a better understanding of how to best make supply chain investments in a more environmentally concious consumer market. This is especially helpful in understanding why making such investment will benefit the bottom line. Most importantly, is that there are clear points at which reconfiguration takes place, meaning large investments are not made continuously. This illustrates that warehouse technology choice makes a large impact in overall demand. This research is important for any e-commerce company wishing to market their products in a way that takes advantage of the growing environmentally concious customer base.

To improve this model further, a more realistic test case should be explored and different operation capacities at the warehouses should be made available. A more realistic test case would provide greater insight into the model's capabilities, while different operation capacities will remedy the issue of steadily increasing carbon footprint as emission elasticity increases. What will also help, is allowing for warehouses to close if satisfaction of demand is penalizing total profit. While this will reduce sales, it will significantly lower overall supply chain emissions. This model can also be improved by including price elasticity. This would be done by modelling price such that it increases as the carbon footprint of the item decreases - reflecting environmentally friendly products currently sold. The model can be made even more realistic by introducing a piece-wise linear or nonlinear demand function and modelling transportation costs to better reflect reality. The introduction economies of scale would aid in realistically representing transportation costs, providing a lower price as more products are shipped. Carbon policies should also be included in future iterations of this model, due to their increasing relevance in practice and literature. These attributes are not included this chapter because the focus is on reformulating the nonlinear carbon footprint constraint. They are, however, explored further in Chapter 5 when discussing avenues for future research.

Chapter 4

Three Echelon Green Supply Chain Network Design

4.1 Introduction

In this chapter, we consider a three-echelon supply chain, composed of a plant with technology choice, warehouse location selection and technology allocation, and customer zones with unique sensitivity to carbon footprint. As such, demand at customer zones is inversely proportional to carbon footprint. This is motivated by Klassen and McLaughlin (1996) and Kassinis and Soteriou (2003), who have established that there is a negative relationship between a company's impact on the environment and consumer demand. The problem is modelled as a nonlinear mixed integer program, transformed into a second-order mixed integer program, and solved. A test case is built and used for testing and analysis.

The three echelon supply chain problem is outlined in Section 4.2, along with the associated nonlinear model. The following section (Section 4.3) formulates and presents the final mathematical model. Section 4.4 presents a test case which is then used to illustrate the strengths of the model. Finally, concluding statements are presented in Section 4.5, which will summarize the findings and avenues for future research.

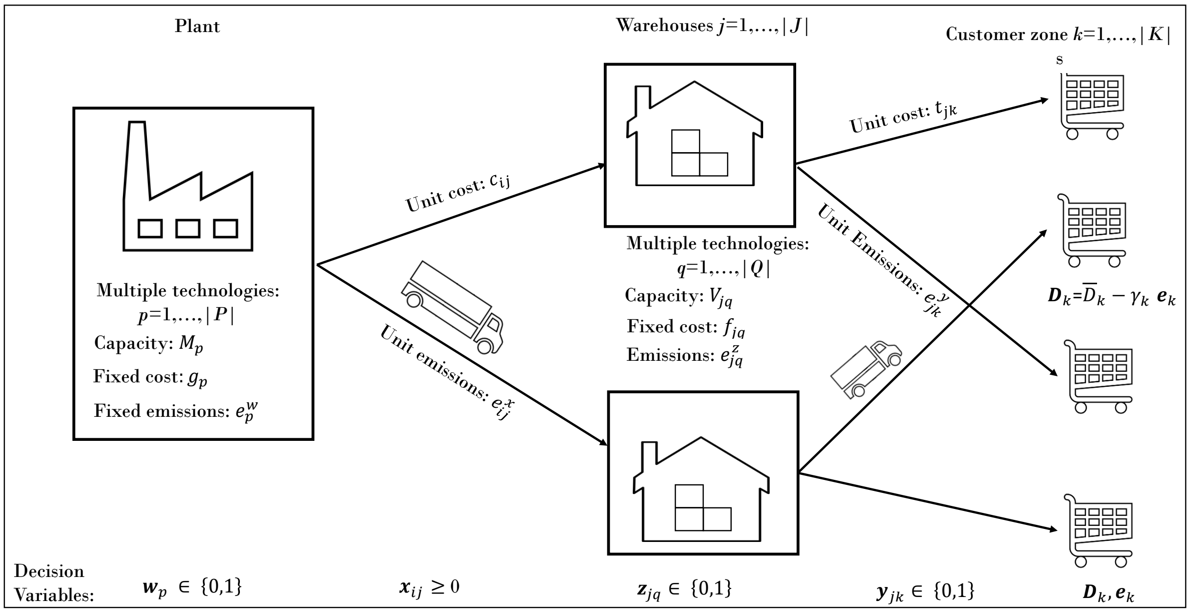
4.2 Problem description

The problem under consideration has a single plant and multiple warehouses, each with multiple technologies. The plant's technology options are denoted by index $p \in P$. The warehouse locations are denoted by index $j \in J$ and the technology options are denoted by index $q \in Q$. Among these technologies, at each location, there exists at least one low carbon alternative. M_p and V_{jq} represent the plant and warehouse capacities, respectively. There is also a fixed cost for opening and operating the plant (g_p) or a warehouse (f_{jq}), independent of flow volume. The emissions due to plant (e_p^w) and warehouse (e_{jq}^z) operations are also independent of flow volume.

Products are transported from the plants to open warehouses using a single-type of vehicle, so the cost (and emissions) to transport a single item is only dependent on distance traveled. These costs (c_j) and emissions (e_j^x) implicitly take into account the distance between the locations of the plant and warehouse j. Should the decision maker wish to include variable costs and/or emissions at the facilities, the facility cost/emissions can be reduced to a minimal level and the variabilities can be incorporated in the "transportation" parameters (c_j and e_j^x). As a result, c_j and e_j^x will no longer strictly represent transportation, but the variable cost and emissions from plant, transportation, and warehousing activities combined.

The customer zone locations are denoted by index $k \in K$. The cost (t_{jk}) and emissions (e_{jk}^y) for the transportation of a single item between open warehouses and customer zones

Figure 4.1: Schematic of the three-echelon GSCND with emission sensitive demand.



are similar, with both implicitly taking into account distance. Quality service is maintained by forcing single sourcing between warehouses and customer zones.

The demand at each customer zone is dependent on the per unit emissions of the product (carbon footprint). Each customer zone is assigned a carbon emission elasticity (γ_k), which represents the customer zone's demand sensitivity to per unit emissions. Each customer zone does, however, have a maximum annual demand, $\overline{D}_k$. This model does not capture demand price sensitivity, since the price is assumed to be set by the market and does not depend on the customer zone. The problem and the notation used are is illustrated in Figure 4.1 and Table 4.1, respectively.

Table 4.1: Definitions of parameters and decision variables

Sets	
P	set of plant technologies indexed by $p \in P$.
J	set of warehouse locations indexed by $j \in J$.
Q	set of warehouse technologies indexed by $q \in Q$.
K	set of customer zone locations indexed by $k \in K$.
Parameters	
π_k	market price of a single item in customer zone k.
g_p	annual cost to operate the plant with technology p.
f_{jq}	annual cost to open/operate warehouse j with technology q.
c_j	cost to transport a single unit of product from the plant to warehouse j.
t_{jk}	cost to transport a single unit of product from warehouse j to customer zone k.
e^w_p	annual emissions due to operation of the plant with technology p.
e^z_{jq}	annual emissions due to operation of warehouse j with technology q.
e^x_j	emissions due to transportation of a single unit of product from the plant to warehouse j.
e^y_{jk}	emissions due to transportation of a single unit of product from warehouse j to customer zone k.
$\overline{D}_k$	maximum annual consumer demand at customer zone k. $\overline{D}_k \geq 0$
γ_k	demand sensitivity to per unit emissions at customer zone k (emission elasticity).
M_p	capacity of the plant if using technology p.
V_{jq}	capacity of warehouse j using technology q.
M	very large number.
Decision Variables	
$\boldsymbol{w}_p$	equal to 1 if the plant is open using technology p, 0 otherwise.
$\boldsymbol{z}_{jq}$	equal to 1 if warehouse j is open using technology q, 0 otherwise.
$\boldsymbol{x}_j$	flow of product from the plant to warehouse j.
$\boldsymbol{y}_{jk}$	equal to 1 if there is product flow between warehouse j and customer zone k, 0 otherwise.
$\boldsymbol{D}_k$	demand at warehouse k.
$\boldsymbol{u}_{jk}$	flow of product between warehouse j and customer zone k.
$\boldsymbol{e}_k$	per unit product emissions at warehouse k.

The mathematical formulation for this three-echelon supply chain with emission-sensitive demand is:

$$
\begin{aligned}
(\mathrm{Loc_{NLP}}):\ \max\quad & \sum_k \pi_k \boldsymbol{D}_k - \sum_p g_p \boldsymbol{w}_p - \sum_j \sum_q f_{jq} \boldsymbol{z}_{jq} - \sum_j c_j \boldsymbol{x}_j - \sum_j \sum_k t_{jk} \boldsymbol{u}_{jk}, && (4.1)\\
\text{s.t.}\quad & \sum_j \boldsymbol{x}_j \le \sum_p M_p \boldsymbol{w}_p && p \in P, \quad (4.2)\\
& \sum_p \boldsymbol{w}_p = 1, && (4.3)\\
& \boldsymbol{x}_j \le \sum_q V_{jq} \boldsymbol{z}_{jq} && \forall j \in J, \quad (4.4)\\
& \sum_q \boldsymbol{z}_{jq} \le 1 && \forall j \in J, \quad (4.5)\\
& \boldsymbol{x}_j = \sum_k \boldsymbol{u}_{jk} && \forall j \in J, \quad (4.6)\\
& \sum_j \boldsymbol{y}_{jk} \le 1 && \forall k \in K, \quad (4.7)\\
& \boldsymbol{D}_k = \overline{D}_k - \gamma_k \boldsymbol{e}_k && \forall k \in K, \quad (4.8)\\
& \boldsymbol{e}_k = \frac{\sum_p e^w_p \boldsymbol{w}_p}{\sum_j \boldsymbol{x}_j} + \sum_j e^x_j \boldsymbol{y}_{jk} + \sum_j \frac{\sum_q e^z_{jq} \boldsymbol{z}_{jq} \boldsymbol{y}_{jk}}{\boldsymbol{x}_j} + \sum_j e^y_{jk} \boldsymbol{y}_{jk} && \forall k \in K, \quad (4.9)\\
& \boldsymbol{u}_{jk} \le \overline{D}_k \boldsymbol{y}_{jk} && \forall j \in J, k \in K, \quad (4.10)\\
& \boldsymbol{u}_{jk} \le \boldsymbol{D}_k && \forall j \in J, k \in K, \quad (4.11)\\
& \boldsymbol{u}_{jk} \ge \boldsymbol{D}_k - \overline{D}_k (1 - \boldsymbol{y}_{jk}) && \forall j \in J, k \in K, \quad (4.12)\\
& \boldsymbol{x}_j > 0; \boldsymbol{u}_{jk}, \boldsymbol{e}_k, \boldsymbol{D}_k \ge 0, && \forall j \in J, k \in K, \quad (4.13)\\
& \boldsymbol{w}_p, \boldsymbol{z}_{jq}, \boldsymbol{y}_{jk} \in \{0, 1\} && \forall j \in J, p \in P, q \in Q, k \in K \quad (4.14)
\end{aligned}
$$

($\mathrm{Loc_{NLP}}$) is constructed with objective (4.1) maximizing profit. The profit is calculated by subtracting total costs from revenue. The total costs include the cost to open/operate the plant using technology p, warehouses j using technologies q, and transportation from plant to warehouse and warehouse to customer zones. The revenue is simply the price of the product multiplied by the demand in customer zone k. The model ensures that facility capacities are not exceeded using constraints (4.2) and (4.4). Since only one plant is operating, there must be exactly one technology selected, as expressed by constraint (4.3). In contrast, the single technology selection constraint for the warehouse (constraint (4.5)) is not set to equality since the model may opt for the warehouse to be closed, however at most one technology may be selected per site. Constraint (4.6) stipulates that there must be flow balance at each warehouse, therefore no items are stored and it does not act as point of production. In order to ensure that each customer is only serviced by at most one warehouse, constraint (4.7). This is introduced to reflect high quality service, common in regular practice. As mentioned, demand is a function of the product's carbon footprint, which is presented in constraint (4.8). To calculate the carbon footprint for products at the warehouse, constraint (4.9) accounts for the average emissions at the facilities plus the per unit emissions along the transportation path to customer zone k.

To construct the carbon footprint constraint (4.9), the emissions from the plant are first accounted for. To ensure that only the emissions for the selected technology are taken into account, the plant emissions parameter e_p^w is multiplied by the binary variable $\boldsymbol{w}_p$. Since the carbon footprint is of concern, total emissions from the plant are divided by the total flow through, which is equivalent to total flow through all warehouses, $\sum_j \boldsymbol{x}_j$. Then, the per item emissions due to transportation from plant to warehouse is added. Since this parameter is already per unit, this parameter need not be divided by flow. To ensure that only flow that transports product that will end up at customer zone k is picked up, this parameter is multiplied by $\boldsymbol{y}_{jk}$. The emissions due to warehousing is then included. In a similar fashion to the plant, to ensure that only the emissions for the selected technology are taking into account, the warehouse emissions vector e_{jq}^z is multiplied by the binary vector $\boldsymbol{z}_{jq}$. Again, since the carbon footprint is of concern, total emissions from the warehouse is divided by the total flow through, $\boldsymbol{x}_j$. In addition, to ensure that only flow that will end up customer zone k is accounted for, the entirety of this element is multiplied by $\boldsymbol{y}_{jk}$ Finally, the per item emissions due to transportation from warehouse to customer zone is added. Since this parameter is also already per unit, it need not be divided by flow either. Instead, to ensure that the emissions are only included if the path transports product that will end up at customer zone k, this parameter is also multiplied by $\boldsymbol{y}_{jk}$. In order to ensure a zero does not exist in a denominator of constraint (4.9), this model stipulates that $\boldsymbol{x}_j > 0$. This is highly restrictive because it forces all the warehouses to be open, not leaving much for the model to determine. In response, the model is reformulated in Section 4.3 in order to address this.

Constraints (4.10) to (4.12) are included to allow $\boldsymbol{u}_{jk}$ to represent the flow from warehouse j to customer zone k, which is equivalent to $\boldsymbol{D}_k\boldsymbol{y}_{jk}$ $(\forall j \in J, k \in K)$. Finally, constraints (4.13) and (4.14) set bounds on all variables in the model.

In order to solve the model without emission elasticity, $(\mathrm{Loc}_{\mathrm{NLP}})$ must be simplified. The emission free model is presented as follows:

$$
\begin{aligned}
(\mathrm{Loc}_{\mathrm{NoEm}}):\ \max\quad & \sum_k \pi_k \boldsymbol{D}_k - \sum_p g_p \boldsymbol{w}_p - \sum_j \sum_q f_{jq}\boldsymbol{z}_{jq} - \sum_j c_j \boldsymbol{x}_j - \sum_j \sum_k t_{jk}\boldsymbol{u}_{jk}, && \\
\text{s.t.}\quad & (4.2), (4.4) - (4.7), (4.10) - (4.12) && \\
& \sum_p \boldsymbol{w}_p \leq 1 && (4.15) \\
& \sum_j \boldsymbol{u}_{jk} = \boldsymbol{D}_k && \forall k \in K, \quad (4.16) \\
& \boldsymbol{x}_j, \boldsymbol{u}_{jk}, \boldsymbol{D}_k \geq 0, && \forall j \in J, k \in K, \\
& \boldsymbol{w}_p, \boldsymbol{z}_{jq}, \boldsymbol{y}_{jk} \in \{0,1\} && \forall j \in J, p \in P, q \in Q, k \in K
\end{aligned}
$$

Because this model does not require the carbon footprint constraint (4.9), there is no longer a risk of dividing any variables by zero, if there is zero flow in the supply chain. As a result, the plant may close. It is for this reason that constraint (4.15) is included, replacing the highly restrictive constraint (4.3). Constraint (4.16) must also be included to ensure that demand to each customer zone is equal to exactly what is being transported to it.

In the following section, (Loc_{NLP}) will be reformulated to address the nonlinear carbon footprint constraints.

4.3 A SOCP reformulation

In order to solve (Loc_{NLP}) using a commercial solver, the nonlinear constraint (4.9) must be reformulated. In addition, the model is highly restrictive because flow to the warehouses must be non-zero in order to ensure that zeros do not exists in the denominator of constraint (4.9). In response, the nonlinearities and restrictiveness of the current model are addressed.

To begin linearizing constraint (4.9), variables $\boldsymbol{l}$, $\boldsymbol{r}_{jq}$, and $\boldsymbol{x}^T_{jq}$ are introduced such that

$$\boldsymbol{l} = \begin{cases} \dfrac{1}{\sum\limits_j \boldsymbol{x}_j}, & \text{if } \sum\limits_p \boldsymbol{w}_p = 1 \\ 0, & \text{otherwise,} \end{cases} \tag{4.17}$$

$$\boldsymbol{r}_{jq} = \begin{cases} \dfrac{\boldsymbol{z}_{jq}}{\boldsymbol{x}^T_{jq}} & \text{if } \boldsymbol{z}_{jq} = 1 \\ 0 & \text{if } \boldsymbol{z}_{jq} = 0 \end{cases} \qquad \forall j \in J, q \in Q \tag{4.18}$$

$$\boldsymbol{x}^T_{jq} \leq \left(\max_q V_{jq}\right) \boldsymbol{z}_{jq} \qquad \forall j \in J, q \in Q \tag{4.19}$$

$$\boldsymbol{x}^T_{jq} \leq \boldsymbol{x}_j \qquad \forall j \in J, q \in Q \tag{4.20}$$

$$\boldsymbol{x}^T_{jq} \geq \boldsymbol{x}_j - \left(\max_q V_{jq}\right)(1 - \boldsymbol{z}_{jq}) \qquad \forall j \in J, q \in Q \tag{4.21}$$

Equation (4.17) states that when the plant is in operation, let $\boldsymbol{l}$ be equal to the inverse of total flow in the supply chain (and through he plant). If the plant is closed, set $\boldsymbol{l} = 0$. Similarly, equation (4.18) states that when the warehouse is in operation, let $\boldsymbol{r}_{jq}$ be equal to the inverse of flow through warehouse j with technology q. If the warehouse is closed, set $\boldsymbol{r}_{jq} = 0$. Constraints (4.19) to (4.21) are included to ensure that $\boldsymbol{x}^T_{jq} = \boldsymbol{x}_j \boldsymbol{z}_{jq}$. The use of $\boldsymbol{x}^T_{jq}$ will be made clear shortly. In order to introduce equations (4.17) and (4.18) to the new model, they must be reformulated.

To reformulate equation (4.17), first let $\boldsymbol{x}^T = \sum_j \boldsymbol{x}_j$ and $\boldsymbol{W} = \sum_p \boldsymbol{w}_p$. These will be added as constraints to the model. Equation (4.17) can now be rewritten as the following quadratic constraint:

$$\boldsymbol{l}\boldsymbol{x}^T = \boldsymbol{W} \tag{4.22}$$

In order to add this as a second order cone programming (SOCP) constraint (a form that is more easily handled by the solver), $\boldsymbol{W}$ is squared (which is possible because $\boldsymbol{W} \in \{0, 1\}$), and the equality is relaxed:

$$\boldsymbol{l}\boldsymbol{x}^T \geq \boldsymbol{W}^2 \tag{4.23}$$

The equality can be relaxed, because the carbon footprint constraint is actively being minimized when $\gamma_k > 0$. As a result, $\boldsymbol{l}$ is being minimized as $\boldsymbol{x}^T$ is being maximized to increase revenue, making the solution only optimal if the constraint is active. In order to ensure $\boldsymbol{l}$ and $\boldsymbol{x}^T$ are both zero if the plant isn't open, the following constraints are also included:

$$\boldsymbol{l} \leq \sum_p \boldsymbol{w}_p \tag{4.24}$$

$$\boldsymbol{x}^T \leq \left(\sum_k \overline{D}_k \right) \sum_p \boldsymbol{w}_p \tag{4.25}$$

Equation (4.24) forces $\boldsymbol{l}$ to zero if the plant is closed, and sets an upper limit of one if it is open. Equation (4.25) forces total flow to zero if the plant is closed, and sets an upper limit as the sum of maximum flow from all customers. Introducing equations (4.24) and (4.25) add flexibility to the model, should one decide to have multiple plants.

In a similar fashion, equation (4.18) is reformulated. Equation (4.18) presents two cases which are equivalent to:

$$\boldsymbol{r}_{jq}\boldsymbol{x}_{jq}^T = \boldsymbol{z}_{jq} \qquad \text{if } \boldsymbol{z}_{jq} = 1 \qquad \forall j \in J, q \in Q \tag{4.26}$$

$$\boldsymbol{r}_{jq} = 0 \qquad \text{if } \boldsymbol{z}_{jq} = 0 \qquad \forall j \in J, q \in Q \tag{4.27}$$

Like before, equation (4.26) can be reformulated as a SOCP constraint by relaxing the equality and squaring the binary variable z_{jq}. The new equivalent set of constraints are:

$$\boldsymbol{r}_{jq}\boldsymbol{x}_{jq}^T \geq \boldsymbol{z}_{jq}^2 \qquad \forall j \in J, q \in Q, \tag{4.28}$$

$$\boldsymbol{r}_{jq} \leq \boldsymbol{z}_{jq} \qquad \forall j \in J, q \in Q, \tag{4.29}$$

This reformulation allows for flexibility in the model, in that the facility need only be open if non-zero flow exists at that point. At this point, constraints (4.19) to (4.21) are in use. The use of $\boldsymbol{x}_{jq}^T$ in lieu of $\boldsymbol{x}_j$ is necessary because it provides a stronger formulation, ensuring that the flow is specified for each technology at the warehouse.

Two sets of SOCP constraints have now been introduced. For completeness, equation (4.28) is derived as follows:

$$\begin{aligned}
\boldsymbol{r}_{jq}\boldsymbol{x}_{jq}^T &\geq \boldsymbol{z}_{jq}^2 \\
4\boldsymbol{r}_{jq}\boldsymbol{x}_{jq}^T &\geq 4\boldsymbol{z}_{jq}^2 \\
\left(\boldsymbol{r}_{jq} + \boldsymbol{x}_{jq}^T\right)^2 - \left(\boldsymbol{r}_{jq} - \boldsymbol{x}_{jq}^T\right)^2 &\geq 4\boldsymbol{z}_{jq}^2 \\
\left(\boldsymbol{r}_{jq} + \boldsymbol{x}_{jq}^T\right)^2 &\geq 4\boldsymbol{z}_{jq}^2 + \left(\boldsymbol{r}_{jq} - \boldsymbol{x}_{jq}^T\right)^2 \\
\boldsymbol{r}_{jq} + \boldsymbol{x}_{jq}^T &\geq \sqrt{4\boldsymbol{z}_{jq}^2 + \left(\boldsymbol{r}_{jq} - \boldsymbol{x}_{jq}^T\right)^2} \\
\boldsymbol{r}_{jq} + \boldsymbol{x}_{jq}^T &\geq \left\| \begin{bmatrix} 2\boldsymbol{z}_{jq} \\ \boldsymbol{r}_{jq} - \boldsymbol{x}_{jq}^T \end{bmatrix} \right\|
\end{aligned}$$

As mentioned before, introducing these SOCP constraints is possible because at optimality the demand will be maximized while the inverse variables are minimized, making these active constraints.

By introducing variables $\boldsymbol{l}$ and $\boldsymbol{r}_{jq}$ to the carbon footprint constraint, the variables in the denominator are eliminated. Adding equations (4.19)-(4.21), (4.24)-(4.23), and (4.28)-(4.29) to the model, the carbon footprint constraint may now take the form:

$$\boldsymbol{e}_k = \sum_p e_p^w \boldsymbol{w}_p \boldsymbol{l}(\sum_j \boldsymbol{y}_{jk}) + \sum_j e_j^x \boldsymbol{y}_{jk} + \sum_j \sum_q e_{jq}^z \boldsymbol{r}_{jq} \boldsymbol{y}_{jk} + \sum_j e_{jk}^y \boldsymbol{y}_{jk} \quad \forall k \in K$$

In addition to these changes, the plant (first) element of carbon footprint constraint is now multiplied by $\sum_j \boldsymbol{y}_{jk}$, ensuring that no carbon footprint from the plant is accounted for if there is no flow to customer zone k.

Though there are no longer terms in the denominator, there still exist non-linearities in the form of a binary-continuous multiplication. This is easily handled by introducing $\omega_p = \boldsymbol{w}_p \boldsymbol{l}$, $\boldsymbol{a}_{jqk} = \boldsymbol{r}_{jq}\boldsymbol{y}_{jk}$, $\boldsymbol{o}_{pk} = \omega_p(\sum_j \boldsymbol{y}_{jk})$, and the necessary linearisation constraints (see constraints (4.49) to (4.57)).

To summarize, the variables indicating flow to the warehouses have been taken out of the denominator of carbon footprint equation (constraint (4.39)) and equations (4.24)-(4.23) and (4.28)-(4.29) have been introduced. In addition, the plant (first) element of carbon footprint constraint is now multiplied by $\sum_j \boldsymbol{y}_{jk}$, ensuring that no carbon footprint from the plant is accounted for if there is no flow to customer zone k. It is for these reasons that the model is now able to accommodate zero flow to the warehouses when necessary. In addition, because the model can now accommodate zero flow to both customers and the warehouses, the plant can also close (see constraint (4.32)). Constraint (4.31) eliminates the risk of the plant closing when flow from it is needed. Closing the plant is preferable if it is not cost effective to open any part of the supply chain. It should also be noted that when $\gamma_k = 0$, the carbon footprint does not impact the demand at all, therefore ($\mathrm{Loc}_{\mathrm{NoEm}}$) should be solved instead.

After making the necessary changes to the carbon footprint constraint, and introducing the additional constraints, the model is now in its final form:

(Loc_{SOCP}):

$$\begin{aligned}
\max \quad & \sum_k \pi_k \boldsymbol{D}_k - \sum_p g_p \boldsymbol{w}_p - \sum_j \sum_q f_{jq} \boldsymbol{z}_{jq} - \sum_j c_j \boldsymbol{x}_j - \sum_j \sum_k t_{jk} \boldsymbol{u}_{jk}, && && (4.30)\\
\text{s.t.} \quad & \sum_j \boldsymbol{x}_j \leq \sum_p M_p \boldsymbol{w}_p, && && (4.31)\\
& \sum_p \boldsymbol{w}_p \leq 1, && && (4.32)\\
& \boldsymbol{x}_j \leq \sum_q V_{jq} \boldsymbol{z}_{jq} && \forall j \in J, && (4.33)\\
& \sum_q \boldsymbol{z}_{jq} \leq 1 && \forall j \in J, && (4.34)\\
& \boldsymbol{x}_j = \sum_k \boldsymbol{u}_{jk} && \forall j \in J, && (4.35)\\
& \sum_j \boldsymbol{y}_{jk} \leq 1 && \forall k \in K, && (4.36)\\
& \boldsymbol{D}_k \leq \overline{D}_k (\sum_j \boldsymbol{y}_{jk}) - \gamma_k \boldsymbol{e}_k && \forall k \in K, && (4.37)\\
& \sum_j \boldsymbol{y}_{jk} \leq M \boldsymbol{D}_k && \forall k \in K, && (4.38)\\
& \boldsymbol{e}_k = \sum_p e^w_p \boldsymbol{o}_{pk} + \sum_j e^x_j \boldsymbol{y}_{jk} + \sum_j \sum_q e^z_{jq} \boldsymbol{a}_{jqk} + \sum_j e^y_{jk} \boldsymbol{y}_{jk} && \forall k \in K, && (4.39)
\end{aligned}$$

$$\begin{aligned}
& \boldsymbol{x}^T = \sum_j \boldsymbol{x}_j && (4.40)\\
& \boldsymbol{W} = \sum_p \boldsymbol{w}_p && (4.41)\\
& \boldsymbol{l} \boldsymbol{x}^T \geq \boldsymbol{W}^2 && (4.42)\\
& \boldsymbol{l} \leq \sum_p \boldsymbol{w}_p && (4.43)
\end{aligned}$$

$$\begin{aligned}
& \boldsymbol{r}_{jq} \boldsymbol{x}^T_{jq} \geq \boldsymbol{z}^2_{jq} && \forall j \in J, q \in Q, && (4.44)\\
& \boldsymbol{r}_{jq} \leq \boldsymbol{z}_{jq} && \forall j \in J, q \in Q, && (4.45)
\end{aligned}$$

$$\boldsymbol{u}_{jk} \leq \overline{D}_k \boldsymbol{y}_{jk} \qquad \forall j \in J, k \in K, \tag{4.46}$$

$$\boldsymbol{u}_{jk} \leq \boldsymbol{D}_k \qquad \forall j \in J, k \in K, \tag{4.47}$$

$$\boldsymbol{u}_{jk} \geq \boldsymbol{D}_k - \overline{D}_k (1 - \boldsymbol{y}_{jk}) \qquad \forall j \in J, k \in K, \tag{4.48}$$

$$\omega_p \leq \boldsymbol{w}_p \qquad \forall p \in P, \tag{4.49}$$

$$\omega_p \leq \boldsymbol{l} \qquad \forall p \in P, \tag{4.50}$$

$$\omega_p \geq \boldsymbol{l} - (1 - \boldsymbol{w}_p) \qquad \forall p \in P, \tag{4.51}$$

$$\boldsymbol{a}_{jqk} \leq \boldsymbol{y}_{jk} \qquad \forall j \in J, q \in Q, k \in K, \tag{4.52}$$

$$\boldsymbol{a}_{jqk} \leq \boldsymbol{r}_{jq} \qquad \forall j \in J, q \in Q, k \in K, \tag{4.53}$$

$$\boldsymbol{a}_{jqk} \geq \boldsymbol{r}_{jq} - (1 - \boldsymbol{y}_{jk}) \qquad \forall j \in J, q \in Q, k \in K, \tag{4.54}$$

$$\boldsymbol{o}_{pk} \leq \sum_j \boldsymbol{y}_{jk} \qquad \forall p \in P, k \in K, \tag{4.55}$$

$$\boldsymbol{o}_{pk} \leq \omega_p \qquad \forall p \in P, k \in K, \tag{4.56}$$

$$\boldsymbol{o}_{pk} \geq \omega_p - (1 - \sum_j \boldsymbol{y}_{jk}) \qquad \forall p \in P, k \in K, \tag{4.57}$$

$$\boldsymbol{x}_{jq}^T \leq \left(\max_q V_{jq} \right) \boldsymbol{z}_{jq} \qquad \forall j \in J, q \in Q, \tag{4.58}$$

$$\boldsymbol{x}_{jq}^T \leq \boldsymbol{x}_j \qquad \forall j \in J, q \in Q, \tag{4.59}$$

$$\boldsymbol{x}_{jq}^T \geq \boldsymbol{x}_j - \left(\max_q V_{jq} \right) (1 - \boldsymbol{z}_{jq}) \qquad \forall j \in J, q \in Q, \tag{4.60}$$

$$\boldsymbol{x}_j, \boldsymbol{x}^T, \omega_p, \boldsymbol{r}_{jq}, \boldsymbol{l}, \boldsymbol{u}_{jk}, \boldsymbol{e}_k, \boldsymbol{D}_k, \boldsymbol{a}_{jqk}, \boldsymbol{o}_{pk}, \boldsymbol{x}_{jq}^T \geq 0, \qquad \forall p \in P, j \in J, q \in Q, k \in K, \tag{4.61}$$

$$\boldsymbol{w}_p, \boldsymbol{z}_{jq}, \boldsymbol{y}_{jk}, \boldsymbol{W} \in \{0, 1\} \qquad \forall j \in J, p \in P, q \in Q, k \in K \tag{4.62}$$

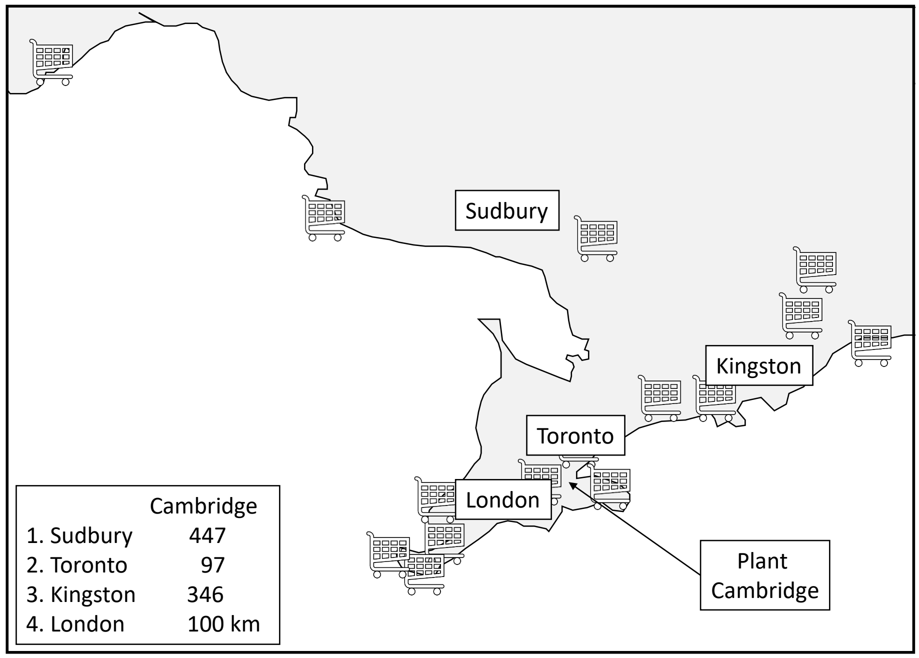
Constraints (4.30) to (4.36) remain the same as in (Loc$_{\text{NLP}}$), with the exception of relaxing the equality for constraint (4.32). Constraint (4.37) is modified slightly, multiplying $\overline{D}_k$ by $(\sum_j \boldsymbol{y}_{jk})$, in order to ensure that demand is set to zero if there is no flow to customer zone k and therefore no carbon footprint to measure. Additionally, the equality is relaxed, making the constraint easier to satisfy when solving. Once an optimal solution is found, the constraint is active because the objective directly maximizes demand, actively minimizing the carbon footprint variable. In addition to strengthening the formulation, constraint (4.38) is included to ensure that there is no connection between a warehouse and customer if there is no demand in the customer zone. Constraint (4.39) is now linearised, and constraints (4.40) to (4.57) allow for this linearisation to hold. As mentioned before, constraint (4.40) makes handling the summation of total flow through the warehouse easier by setting it equal to $\boldsymbol{x}^T$. The SOCP constraints (4.42) and (4.44) are also included, as discussed above, along with constraints (4.43), (4.45), and (4.58) to (4.60). Constraint (4.33) operates in two ways, to ensure warehouse capacity is not exceeded by flow through, and to ensure that $\boldsymbol{x}_j$ is zero if the warehouse is closed, supporting constraint (4.44).

As before, constraints (4.46) to (4.48) ensure that $\boldsymbol{u}_{jk} = \boldsymbol{D}_k \boldsymbol{y}_{jk}$ $(\forall j \in J, k \in K)$. In a similar vein, constraints (4.49) to (4.51) ensure that $\omega_p = \boldsymbol{l}\boldsymbol{w}_p$ $(\forall p \in P)$, constraints (4.52) to (4.54) ensure that $\boldsymbol{a}_{jqk} = \boldsymbol{y}_{jk}\boldsymbol{r}_{jq}$ $(\forall j \in J, q \in Q)$, and constraints (4.55) to (4.57) ensure that $\boldsymbol{o}_{pk} = \omega_p \sum_j \boldsymbol{y}_{jk}$ $(\forall p \in P, k \in K)$. Finally, constraints (4.61) and (4.62) set bounds on all variables in the model.

Now that the model is in its final form, numerical testing may be performed. Section 4.4 explores a test case, which reflects the potato chip industry. This will be followed by a discussion about the test results.

Figure 4.2: Map of plant, warehouse and customer zone locations.

		Population
1.	Toronto	5,429,524
2.	Ottawa	989,567
3.	Hamilton	693,645
4.	Kitchener	470,015
5.	London	383,437
6.	Oshawa	308,875
7.	Windsor	287,069
8.	St.Catharines-Niagara	229,246
9.	Barrie	145,614
10.	Guelph	132,397
11.	Kingston	117,660
12.	Kanata	117,304
13.	Milton	101,715
14.	Brantford	98,179
15.	Thunder Bay	93,952
16.	Sudbury	88,054
17.	Peterborough	82,094
18.	Sarnia	72,125
19.	Belleville	67,666
20.	Sault Ste.Marie	66,313
21.	WellandPelham	62,388
22.	NorthBay	50,396
23.	Cornwall	45,723
24.	Chatham	43,550
25.	Georgetown	42,123
26.	St.Thomas	41,813
27.	Woodstock	40,404
28.	Bowmanville	39,371
29.	Leamington	32,991
30.	Stouffville	32,634



4.4 Numerical testing

The green supply chain network design model is tested on a case study built for a hypothetical potato chip supply chain in the province of Ontario, Canada. A plant, located in the city of Cambridge, is used to serve demand for the 30 largest cities in the province through four distribution centres as depicted in Figure 4.2.

The product is produced at a single plant with three choices in technology, each having a unique fixed cost and fixed emission level. Based on population size and average consumption of potato chips in north America, the capacity is set for 1.5 million units. The fixed cost g_p and emissions e_p^w are set to $a_{0p}+a_{1p}(M_P)^{a_{2p}}$ and $b_{0p}+b_{1p}(MP)^{b2p}$, respectively to reflect economies of scale. The parameters used are presented in Table 4.2.

Table 4.2: Parameter values for plant with varying technology options.

Tech. p	M_p (000)	a_{0p}	a_{1p}	a_{2p}	g_p (000)	b_{0p}	b_{1p}	b_{2p}	e^w_p (tCO_2e)
1	1500	100	1.3	0.68	288	112	1.3	0.76	449
2	1500	100	2.6	0.68	476	112	0.6	0.76	268
3	1500	100	4	0.68	678	112	0.3	0.76	190

Table 4.3: Parameter values for warhouses with varying technology options.

		Sudbury ($j = 1$) $a_{0,1q} = 50, a_{1,1q} = 1.5, a_{2,1q} = 0.7$					Toronto ($j = 2$) $a_{0,2q} = 80, a_{1,2q} = 1.5, a_{2,2q} = 0.7$				
q	V_{jq}	f_{1q}	$b_{0,1q}$	$b_{1,1q}$	$b_{2,1q}$	e^z_{1q}	f_{2q}	$b_{0,2q}$	$b_{1,2q}$	$b_{2,2q}$	e^z_{2q}
1	200	91	50	1.3	0.7	103	121	50	1.3	0.7	103
2	400	116	60	0.6	0.75	114	146	60	0.6	0.75	114
3	800	158	70	0.3	0.8	133	188	70	0.3	0.8	133
		Kingston ($j = 3$) $a_{0,3q} = 60, a_{1,3q} = 1.5, a_{2,3q} = 0.7$					London ($j = 4$) $a_{0,4q} = 70, a_{1,4q} = 1.5, a_{2,4q} = 0.7$				
q	V_{jq}	f_{3q}	$b_{0,3q}$	$b_{1,3q}$	$b_{2,3q}$	e^z_{3q}	f_{4q}	$b_{0,4q}$	$b_{1,4q}$	$b_{2,4q}$	e^z_{4q}
1	200	101	50	1.3	0.7	103	111	50	1.3	0.7	103
2	400	126	60	0.6	0.75	114	136	60	0.6	0.75	114
3	800	168	70	0.3	0.8	133	178	70	0.3	0.8	133

Sudbury, Toronto, Kingston, and London are the four potential locations to establish a distribution centre (up to one each). Each could be operated using three technology types with unique capacity, emission and cost parameters. The fixed cost f_{jq} and emissions e^z_{jq} are set to $a_{0,jq} + a_{1,jq}(V_{jq})^{a_{2,jq}}$ and $b_{0,jq} + b_{1,jq}(V_{jq})^{b2,jq}$, respectively to reflect economies of scale. The capacity, fixed cost, and emissions are given by provided in Table 4.3

We consider the family-size bag of chips, which are 255 g each. A unit of chips will be one case of individual bags. Each case (approximately 24 in by 15 in by 12 in) contains 15 bags of chips. Each pallet contains 30 cases of chips. The retail price per 255 g bag

Table 4.4: Maximum demand per year (1000 cases).

j	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Max. Demand	762	139	97	66	54	43	40	32	20	19	16	16	14	14	13
j	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
Max. Demand	12	12	10	9	9	9	7	7	6	6	6	6	5	5	5

of chip to purchase is \$3, if we assume that there is a 50% mark up, then each bag has a wholesale cost of \$2. For each case of 15 bags, the price π_k would be \$30,000/1000 cases

According to Northern Plains Potato Growers Association (2011), "the average American eats over 4 pounds potato chips each year". In 2011, Americans consumed 1.5 billion pounds of potato chips." According to Statista (2017), in 2017 Lay's had 29.6% of the potato chip market share based on dollar sales. So if we let each bag be 255 g, then maximum demand is given by $\frac{1\ bag}{255\ g} \times \frac{4\ lbs}{year \cdot pp} \times \frac{453.6\ g}{lb} \times \frac{case}{15\ bags} \times \frac{29.6\%}{100\%} \times$population, which is equivalent to ($0.14 \times$ population) cases/year. Full details are given in Table 4.4.

Shipping will be done using 40 feet dry van trailers. Such a trailer carries 20 unstacked pallets of size 48" by 40", each having 30 cases of chips. This amounts to 600 cases per van, or 9000 bags per van. According to Barradas (2012), the average operating cost per vehicle is 1.38 USD/mile. With an exchange rate of 1.31 CAD/USD, the variable transportation costs is 1.12 CAD/km.

According to European Environment Agency (2011), CO_2 emissions per tonne-km for a transportation truck in 2011 was 78.37 gCO_2/tonne-km. With a truck weight of 28,000 lbs (12,700.58 kg), the emissions amount to 78.37 $gCO_2/t{\cdot}km \times 12{,}700.58\ kg = 1\ kgCO_2/km$. Therefore, the variable cost and emissions from the plant to the potential warehouse locations presented in Table 4.5

Table 4.5: Distance, cost, and emissions between plant and warehouse locations.

	Warehouse j			
	1	2	3	4
Distance to plant (km)	447	97	346	100
Unit delivery cost (\$/1000 cases): c_j	834	181	646	187
Unit delivery emissions ($kgCO_2$/1000 cases): e^x_j	0.75	0.16	0.58	0.17

Table 4.6: Distance between Distribution Centres and Customer Zones (km).

j/k	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	403	484	440	458	544	431	721	484	211	443	636	463	406	476	1003
2	0	449	68	108	191	60	369	112	110	93	265	389	56	104	1396
3	263	196	330	355	441	209	618	374	344	340	0	190	303	366	1630
4	192	628	128	110	0	239	191	184	255	120	444	568	143	94	1365
j/k	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**
1	0	397	643	558	307	507	127	584	646	403	556	492	444	700	375
2	400	138	290	187	699	134	357	435	293	54	203	142	76	347	48
3	634	185	540	84	933	396	449	181	543	301	453	389	191	597	252
4	545	310	103	366	665	207	502	614	115	161	27	55	255	170	224

Similarly, t_{jk} and e^y_{jk} are:

$$t_{jk} = \frac{1.12 \text{ CAD}}{\text{km}} \times \text{distance} \times \frac{1 \text{ van}}{600 \text{ cases}} \times \frac{1000 \text{ cases}}{1000 \text{ cases}} = \frac{1.87 \text{ CAD}}{1000 \text{ cases}}$$

$$e^y_{jk} = \frac{1 \text{ kgCO}_2}{\text{km}} \times \text{distance} \times \frac{1 \text{ van}}{600 \text{ cases}} \times \frac{1000 \text{ cases}}{1000 \text{ cases}} = \frac{1.67 \text{ kgCO}_2}{1000 \text{ cases}}$$

Finally, the distance between warehouses and customer zones is given in Table 4.6.

The locations for the plant, warehouses, and customer zones are visually illustrated in Figure 4.2. All emissions are in kg of CO_2 per year, demand is per 1000 units, price per unit is (CAD/1000 units), and other costs are in CAD per year. Based on the units selected, the environmental sensitivity variable (γ_k) will have the units (1000 units less/kg

CO_2). This means, for each kg of CO_2 increased per 1000 units of product, demand will decrease by 1000 units.

4.4.1 Results and Analysis

The model is solved for different emission elasticity parameters γ_k, ranging from 0.0001 to 0.01 with increments of 0.0001, 0.0002, and 0.0005. Table 4.7 displays the percentage decrease in profit, the percentage decrease in emissions, the demand served, the percentage decrease in demand, the average emissions per unit demand, and the percentage decrease in average emissions, all relative to the no-emission case. As expected, profits, demand and emissions decrease as customer sensitivity increases. We note that the average emissions range between 700 and 900 kgCO_2 per 1000 cases, which translates to 700 to 900 g CO_2/case or 47 to 60g per bag.

The last column of Table 4.7 gives the CPU time to solve (Loc_{SOCP}) to at least 1e-6 of optimality. The CPU time first increases, reaching a maximum of 787 seconds, and then starts dropping.

The percentage decreases in emissions, average emissions, profit and demand are displayed in Figure 4.3. Profit and demand, being linearly dependent, exhibit an increasing percentage decrease as γ_k increases. Percentage decrease in emissions and average emissions, on the other hand, follow staircase functions where the steps correspond to a change in the plant technology. It first starts at high, then switches to medium and finally to low. The distribution centres, however, keep the same configuration where only two distribution centres are used, one in Toronto and one in London, each with a high-emitting technology. These locations are selected because they are located closest to the highest demand customer zones, as well as being located in the highest customer density area.

Table 4.7: Solution results for varying emission elasticity values.

γ_k	% ↓ Profit	% ↓ Emissions	Demand (1000's)	% ↓ Demand	Avg. Emi. $CO_2/1000$	% ↓ Avg. Emis.	time (sec)
0	0	0	1459	0	888	0	0.2
0.0001	0.2	0.2	1456	0.2	888	0	2
0.0002	0.5	0.4	1452	0.5	889	-0.1	2.2
0.0004	0.9	0.8	1446	0.9	889	-0.1	8
0.0006	1.4	1.2	1439	1.4	890	-0.2	26.3
0.0008	1.8	1.7	1432	1.9	890	-0.2	39.3
0.001	2.3	2.1	1426	2.3	889	-0.1	62
0.0012	2.8	2.6	1419	2.7	889	-0.2	103.9
0.0014	3.2	2.9	1412	3.2	891	-0.3	275.1
0.0016	3.7	3.3	1405	3.7	891	-0.4	233.1
0.0018	4.1	17.4	1405	3.7	762	14.2	442.6
0.002	4.5	17.8	1400	4	760	14.4	425.8
0.0022	4.9	18.3	1394	4.5	759	14.5	341
0.0024	5.3	18.7	1387	4.9	760	14.4	392.3
0.0026	5.8	19.1	1381	5.4	759	14.5	261.5
0.0028	6.2	19.5	1375	5.8	758	14.6	710.3
0.003	6.6	19.8	1369	6.2	759	14.5	504.4
0.0035	7.6	20.9	1354	7.2	757	14.7	391.6
0.004	8.7	27.5	1346	7.8	698	21.4	542.7
0.0045	9.6	28.4	1332	8.7	696	21.6	786.5
0.005	10.5	29.2	1319	9.6	695	21.7	395.5
0.0055	11.4	29.9	1306	10.5	696	21.6	144.2
0.006	12.2	30.3	1295	11.2	697	21.5	151.6
0.0065	12.9	30.9	1284	12	698	21.4	280.2
0.007	13.6	31.3	1274	12.7	699	21.3	68.3
0.0075	14.3	31.7	1263	13.4	701	21.1	89.5
0.008	15	32.2	1254	14.1	701	21.1	84.9
0.0085	15.7	32.6	1244	14.7	702	20.9	75.6
0.009	16.3	33.1	1235	15.4	702	20.9	59.4
0.0095	17	33.3	1226	16	705	20.6	82.4
0.01	17.4	33.8	1219	16.5	703	20.8	26.4

Figure 4.3: Percent decreases in emissions, average emissions, profit and demand

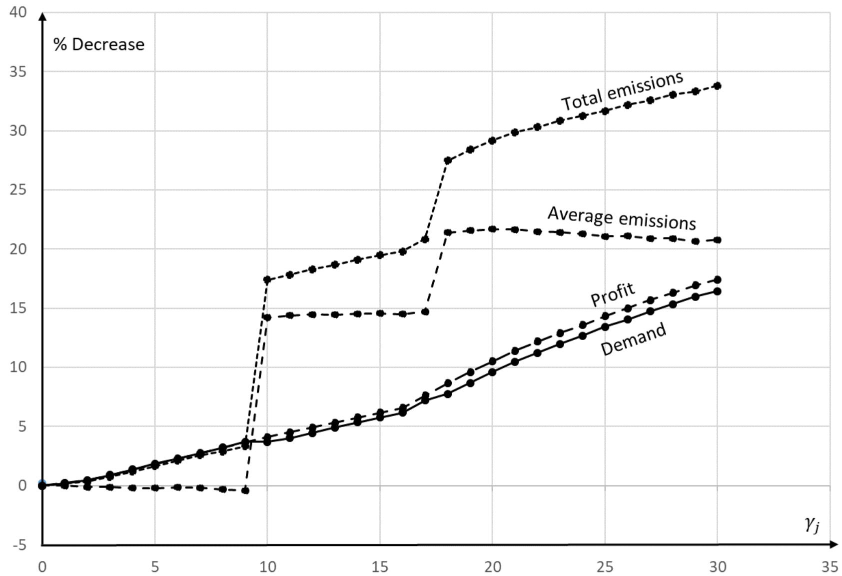


Table 4.8 provides the percentage of total emissions attributed to the plant (E_{Plant}), warehouses (E_{WH}), plan to warehouses (E_{P2WH}) and warehouses to customer zones (E_{WH2CZ}). On average, there is almost an even partition of emission among the four segments of the supply chain. The distribution makes sense since the plant will most certainly operate using the most power and therefore have the highest emissions. The warehouse will have lower emissions because these products need not be in a temperature controlled environment, however since more than one will be operating, the emissions are not negligible. The transportation emissions in the second echelon will be higher than the first because the number of consignees is higher, and a number customers are located in relatively remote locations.

Table 4.8: Percentage emissions attributed to each different segments of the supply chain.

γ_k	E_{Plant}	E_{WH}	E_{P2WH}	E_{WH2CZ}	γ_k	Plant	WH	PtoWH	WHtoCZ
0	35	21	19	26	0.0035	26	26	22	26
0.0001	35	21	18	26	0.004	20	28	23	28
0.0002	35	21	18	26	0.0045	20	29	24	27
0.0004	35	21	18	26	0.005	21	29	24	27
0.0006	35	21	18	26	0.0055	21	29	24	26
0.0008	35	21	18	25	0.006	21	29	24	26
0.001	35	21	18	25	0.0065	21	30	23	26
0.0012	36	21	18	25	0.007	21	30	23	25
0.0014	36	21	18	25	0.0075	21	30	23	25
0.0016	36	21	18	24	0.008	22	30	23	25
0.0018	25	25	22	29	0.0085	22	30	23	24
0.002	25	25	22	28	0.009	22	31	23	24
0.0022	25	25	22	28	0.0095	22	31	23	24
0.0024	25	25	22	28	0.01	22	31	23	24
0.0026	26	25	22	27	min.	20	21	18	24
0.0028	26	26	22	27	avrg.	27	26	21	26
0.003	26	26	22	27	max.	36	31	24	29

4.4.2 Comparisons and Analysis

In order to assess the ability of the model to control the carbon footprint e_k, we compare four variations of the model:

- Case 0 (base case): no emissions
- Case 1: γ_k=0.005
- Case 2: γ_k=0.005 and $e_k \leq 750$ kgCO_2
- Case 3: $\gamma_k = \overline{D}_k/1800$

Case 2 imposes a hard constraint on the carbon footprint, not to exceed an expected value of 750 per 1000 cases, which translates to 50g per bag. In fact companies are starting to advertise this value as a means to showcase environmental commitment. Case 3 varies γ_k based on customer zone and maximum demand, allowing each customer zone to have a unique sensitivity level. The four scenarios are compared in Table 4.9 and 4.10.

According to Table 4.9 all customer zones are served under the base case. This is because the customer's are not concerned about the carbon footprint of the item, meaning demand may reach it's maximum level should facilities allow. For case 1, customer zone 15 (Thunder Bay) is dropped. This is because it is the most remote customer, requiring significant emissions to transport the product to this customer zone. Case 2 serves only 5 customer zones (Toronto, Oshawa, Milton, Georgetown, and Stouffville). This is because by capping emissions, only the cities closest to Toronto (the largest warehouse) can feasibly be served. In contrast, case 3 serves 25 out of the 30 zones. The customer zones no longer served include Ottawa, Thunder Bay, Sudbury, Sault Ste. Marie, and Cornwall. By calculating the emission elasticity in this way, these customer zones would have γ_k equal

Table 4.9: Comparison of customer zone (CZ) demand and emissions under the four scenarios.

	Demand				Emissions				Demand				Emissions		
CZ	base	case1	case2	case3	case1	case2	case3	CZ	base	case1	case2	case3	case1	case2	case3
1	762	760	759	523	472	566	566	16	12	6	0	0	1139	0	1233
2	139	131	0	0	1614	0	1314	17	12	8	0	6	702	0	796
3	97	93	0	60	780	679	679	18	10	6	0	4	739	0	1049
4	66	62	0	38	750	0	746	19	9	5	0	5	784	0	878
5	54	51	0	27	567	0	884	20	9	0.62	0	0	1675	0	1731
6	43	38	26	27	965	666	666	21	9	4	0	5	912	0	789
7	40	36	0	14	885	0	1181	22	7	2	0	2	1067	0	1161
8	32	28	0	18	874	0	753	23	7	1	0	0	1197	0	1291
9	20	15	0	12	992	0	749	24	6	2	0	3	759	0	1054
10	19	15	0	11	767	721	721	25	6	3	3	4	562	656	656
11	16	9	0	7	1307	0	1008	26	6	3	0	3	612	0	904
12	16	10	0	2	1120	0	1214	27	6	3	0	4	659	0	803
13	14	10	11	9	805	659	659	28	5	2	0	3	599	0	693
14	14	10	0	8	724	739	739	29	5	0.75	0	2	850	0	1144
15	13	0	0	0	0	0	0	30	5	2	2	3	552	646	646

Table 4.10: Percent decreases in profit, emissions, and demand under different scenarios.

Case	γ_k	% $\downarrow$ Profit	% $\downarrow$ Em.	$\sum_k D_k$ (1000 units)	% $\downarrow$ Demand
0	0	0	0	1459	0
1	0.005	10.51	29.19	1319	9.6
2	$e_k \leq 750$	45.88	64.75	800	45.17
3	$\overline{D}_k/1800$	46.02	60.44	800	45.17

to 0.077, 0.0072, 0.0067, 0.005, and 0.0039, respectively. These customer zones are not served because these sensitivity values are too high to justify serving that zone. This is clear because Thunder Bay has $\gamma_{15} = 0.0072$, which is lower than case 1 in which it was also not served.

Only 800 units of demand are served under cases 2 and 3, however, the cases are delivered to different customer zones. Profit for both is identical, except that carbon footprint for case 2 is capped at 750 $kgCO_2$, which could be used for promotional purposes. Note that customer zone 2 is closed under cases 2 and 3, which may suggest that a it should be considered as a potential location for a distribution centre.

As the sensitivity parameter increases, as predicted, demand decreases. Starting at $\gamma_k = 0.005$, some customer zones stop being served completely. For $\gamma_k = 0.005$, customer zone 13 (Milton) is the only customer zone not served. The reason for this is that Milton consistently has the highest carbon footprint up until this point, meaning that total demand will be impacted greatly. The loss of customer zones being serviced continues for $\gamma_k =$ 0.0055 (customer zone 20), 0.006 (customer zones 23 and 29), 0.007 (customer zone 22), 0.008 (customer zone 24), 0.0085 (customer zones 27 and 28), and 0.009 (customer zones 26 and 30). This adds up to a total of 10 customer zones no longer serviced once testing is complete. The customer zones that are no longer serviced are grouped near the end of the customer zone indices. This is because the customer zones are sequenced based on population size, which impacts the maximum demand that can be achieved. As a result, the customer zones with lower maximum demand are more vulnerable to being unserviced due to sensitivity and carbon footprint. Customer zones that remain serviced have relatively lower carbon footprints. All this information is available in Table A.10.

4.5 Conclusions

This chapter considers a three echelon green supply chain network design problem with emission sensitive demand. A mixed integer programming formulation is presented and reformulated so that it may be solved using commercial solvers. The solutions to the test case instance illustrates the impact a concious consumer has on the supply chain. The results highlight how without proper adaptation, companies can lose out on revenue if the supply chain is not used to take advantage of minimizing the carbon footprint for the consumer. Most telling, is that there are clear points at which reconfiguration takes place, meaning large investments are not made continuously. The various cases based on the test case illustrate that by making seemingly minor changes to requirements (e.g. capping carbon footprint) may result in major reconfiguration decisions or loss in sales.

This research is particularly important because as more and more information is gathered about consumers, emissions sensitivity values may be approximated, and key demographics can be targeted. This research would be key for any company looking to market their products in a way that sets them apart from the competition. The model presented in this chapter can be extended by including price elasticity as in Yalabik and Fairchild (2011), using a piece-wise linear or nonlinear demand function, incorporating economies of scale in transportation costs, and adding carbon policies.

Chapter 5

Conclusion and Future Research

Green SCND is at the forefront of SCND research. Further, allowing demand to be a function of the consumer's sensitivity to the product's carbon footprint is even more novel. This thesis starts with an in depth review of current GSCND literature, and then introduces two new green e-commerce and SCND models.

Chapter 2 illustrates the growing interest in GSCND literature, though the focus remains chiefly on the incorporation of environmental policy. It is clear that a supply chain system is complex, and therefore a single policy is not ideal for all players. That being said, each may be optimized to maximize profit for all. The chapter also discusses the different ways in which emissions may be included in SCND models, highlighting the need for as much information as possible in order to make informed decisions. As models become more realistic, they inevitably become more complex. This review motivated Chapters 3 and 4 due to the lack of literature on SCND models with demand being a function of carbon footprint.

In response to Chapter 2, Chapter 3 presents a two-echelon e-commerce supply chain with emissions sensitive demand. This model selects the technologies used at the warehouses and the demand level served in order to maximize profit. The carbon footprint of the product is calculated using nonlinear constraints which are dealt with using SOCP. This leads to a SOCP reformulation which can be directly solved using commercial solvers. Results highlight the fact that it is important to have many options for the warehouse in terms of technology and capacity, allowing the level of demand captured to be maximized. More importantly, the model indicates clear points at which reconfiguration is necessary in order to maximize sales and therefore maximize profit. It also highlights the need for different capacity options at the warehouses, in order to ensure that carbon footprints are minimized as demand changes.

Chapter 4 builds upon Chapter 3 by presenting a three-echelon SCND problem with emissions sensitive demand. The model determines which technology will be used at the plant, which warehouses will be operational and with which technology, the flow of products between the echelons, and, most importantly, the level of demand served at customer zones. Like Chapter 3, the carbon footprint is found using SOCP constraints. The model is important because it gives decision makers a tool to find solutions to a highly complex problem. The analysis presented illustrates when switching to a higher cost lower emitting technology makes up for lost sales, thereby maximizing profit. This is important because it allows the decision maker to know precisely when these types of investments pay off and when it is no longer profitable to serve a certain market.

As consumers are often driven more-so by product price than any other factor, future work should incorporate price elasticity. Due to the current structure of the supply chain models, this will lead to further nonlinearities in the model. As a result, it will require a more dedicated approach.

As mentioned in Chapters 3 and 4, the linear demand model is motivated by the price and emission sensitivity demand function presented in Yalabik and Fairchild (2011). Using a linear demand function leads to a more manageable formulation of the supply chain models. This is however a downfall of the presented models, since demand is unlikely to follow a strictly linear correlation to emissions. To better model consumer demand, a piece-wise linear or nonlinear demand function could also be incorporated into the model. Depending on the function structure of the nonlinear demand, incorporating it into the model will require further reformulation to make it tractable. Finally, future work could incorporate economies of scale in transportation costs. This is especially true for the three-echelon model presented in Chapter 4.

Also lacking in both models is the inclusion of carbon policies. As discussed in Chapter 2, policy makers are including carbon policies more than ever, making it especially relevant. Incorporating an environmental policy into both of the presented models will help decision makers understand how environmental sensitivity and price further push supply chain configuration to greener alternatives.

APPENDICES

Appendix A

Appendix

A.1 Two-Echelon Supply Chain

Table A.1: Low level emissions plant: Solution results for varying emission elasticity setting (EES).

EES	% ↓ Profit	% ↓ Emissions	Demand (1000's)	% ↓ Demand	Avg. Emi. $CO_2/1000$	% ↓ Avg. Emis.	time (sec)
0	0	0	4003	0	2181	0.00	0.1
2	2.08	0.13	3958	1.12	2203	-1.01	0.1
4	4.19	0.26	3912	2.27	2226	-2.06	0.1
6	6.36	0.39	3864	3.47	2251	-3.21	0.1
8	8.58	0.53	3816	4.67	2276	-4.36	0.1
10	10.85	0.67	3767	5.9	2302	-5.55	0.1
12	13.18	0.81	3716	7.17	2330	-6.83	0.1
14	15.58	0.96	3664	8.47	2360	-8.21	0.1
16	18.04	1.11	3610	9.82	2392	-9.67	0.2
18	20.57	1.26	3555	11.19	2425	-11.19	0.2
20	23.21	1.42	3498	12.62	2460	-12.79	0.2
22	25.93	1.59	3438	14.11	2499	-14.58	0.1
24	28.75	1.76	3377	15.64	2540	-16.46	0.2
26	31.69	1.94	3313	17.24	2584	-18.48	0.2
28	34.77	2.13	3246	18.91	2632	-20.68	0.1
30	37.99	2.32	3176	20.66	2685	-23.11	0.1
32	41.44	2.53	3101	22.53	2744	-25.81	0.1
34	44.86	17.39	3220	19.56	2240	-2.71	0.1
36	47.6	17.57	3160	21.06	2277	-4.40	0.1
38	50.49	17.77	3096	22.66	2319	-6.33	0.2
40	53.52	20.31	3072	23.26	2265	-3.85	0.2
42	56.51	20.95	3016	24.66	2288	-4.91	0.2
44	59.66	21.14	2947	26.38	2336	-7.11	0.1
46	63.02	21.34	2874	28.2	2389	-9.54	0.1
48	66.64	21.56	2796	30.15	2449	-12.29	0.1
50	70.63	21.8	2709	32.33	2520	-15.54	0.1
52	75.18	22.08	2610	34.8	2607	-19.53	0.1
54	80.31	22.38	2499	37.57	2712	-24.35	0.2
56	86.6	23.78	2418	39.6	2752	-26.18	0.2
58	92.23	26.69	2435	39.17	2629	-20.54	0.2
60	98.84	27.68	2340	41.54	2698	-23.70	0.1
62	108.56	28.25	2129	46.81	2942	-34.89	0.1

Table A.2: Low level emissions plant: Low (L) vs. medium (M) vs. high (H) emission technology selected, varying emission elasticity setting (EES).

EES	$\boldsymbol{z}_{jq}$	$\boldsymbol{D}_j$ / $\boldsymbol{e}_j$ (1, 2, 3, 4)	EES	$\boldsymbol{z}_{jq}$	$\boldsymbol{D}_j$ / $\boldsymbol{e}_j$ (1, 2, 3, 4)
0	HHHH	[115, 2403, 602, 883]	32	HHHH	[88, 1870, 463, 681]
		-			[3254, 2635, 3017, 2787]
1	HHHH	[114, 2390, 598, 878]	33	HHHH	[87, 1847, 457, 673]
		[2682, 2094, 2470, 2204]			[3286, 2665, 3048, 2820]
2	HHHH	[114, 2376, 595, 873]	34	HMHM	[86, 1962, 454, 718]
		[2693, 2105, 2481, 2216]			[3248, 2051, 3008, 2145]
3	HHHH	[113, 2363, 591, 868]	35	HMHM	[85, 1945, 449, 712]
		[2705, 2117, 2493, 2227]			[3278, 2068, 3036, 2162]
4	HHHH	[112, 2349, 588, 863]	36	HMHM	[84, 1928, 443, 705]
		[2718, 2128, 2504, 2240]			[3309, 2086, 3066, 2181]
5	HHHH	[111, 2335, 584, 858]	37	HMHM	[83, 1910, 437, 699]
		[2730, 2140, 2516, 2252]			[3342, 2104, 3097, 2201]
6	HHHH	[111, 2321, 580, 852]	38	HMHM	[81, 1892, 430, 692]
		[2743, 2151, 2528, 2265]			[3376, 2124, 3130, 2222]
7	HHHH	[110, 2307, 576, 847]	39	HMHM	[80, 1874, 424, 685]
		[2756, 2163, 2541, 2278]			[3414, 2144, 3165, 2243]
8	HHHH	[109, 2293, 573, 842]	40	HMMM	[79, 1859, 455, 680]
		[2770, 2176, 2553, 2291]			[3434, 2149, 2554, 2249]
9	HHHH	[108, 2278, 569, 836]	41	HMMM	[78, 1840, 450, 672]
		[2783, 2188, 2567, 2306]			[3474, 2169, 2575, 2271]
10	HHHH	[108, 2264, 565, 831]	42	MMMM	[84, 1822, 445, 666]
		[2797, 2201, 2581, 2320]			[2813, 2187, 2594, 2290]
11	HHHH	[107, 2249, 561, 825]	43	MMMM	[83, 1802, 440, 658]
		[2812, 2215, 2594, 2335]			[2838, 2210, 2617, 2315]
12	HHHH	[106, 2234, 557, 819]	44	MMMM	[82, 1781, 434, 650]
		[2827, 2229, 2609, 2349]			[2864, 2234, 2642, 2340]
13	HHHH	[105, 2219, 553, 814]	45	MMMM	[81, 1760, 429, 642]
		[2842, 2243, 2623, 2365]			[2891, 2260, 2669, 2368]
14	HHHH	[104, 2203, 549, 808]	46	MMMM	[80, 1738, 423, 634]
		[2858, 2260, 2638, 2381]			[2920, 2286, 2696, 2396]
15	HHHH	[104, 2187, 545, 802]	47	MMMM	[79, 1715, 417, 625]
		[2874, 2275, 2654, 2397]			[2950, 2314, 2725, 2427]
16	HHHH	[103, 2171, 540, 796]	48	MMMM	[77, 1691, 411, 616]
		[2891, 2290, 2670, 2414]			[2983, 2344, 2756, 2459]
17	HHHH	[102, 2155, 536, 790]	49	MMMM	[76, 1666, 405, 607]
		[2908, 2306, 2686, 2431]			[3017, 2377, 2789, 2494]
18	HHHH	[101, 2139, 532, 783]	50	MMMM	[75, 1639, 398, 597]
		[2923, 2321, 2702, 2449]			[3055, 2414, 2825, 2532]
19	HHHH	[100, 2122, 527, 777]	51	MMMM	[74, 1612, 391, 586]
		[2944, 2340, 2720, 2467]			[3096, 2453, 2865, 2573]
20	HHHH	[99, 2105, 523, 771]	52	MMMM	[72, 1580, 383, 574]
		[2962, 2358, 2738, 2487]			[3147, 2501, 2913, 2625]
21	HHHH	[99, 2087, 518, 764]	53	MMMM	[70, 1548, 375, 562]
		[2982, 2376, 2757, 2506]			[3197, 2549, 2962, 2677]
22	HHHH	[98, 2070, 514, 757]	54	MMMM	[69, 1514, 367, 549]
		[3002, 2396, 2776, 2527]			[3254, 2603, 3016, 2735]
23	HHHH	[97, 2052, 509, 751]	55	MMMM	[67, 1475, 357, 534]
		[3023, 2415, 2796, 2548]			[3321, 2667, 3080, 2804]
24	HHHH	[96, 2033, 504, 744]	56	MMML	[66, 1446, 350, 557]
		[3044, 2436, 2816, 2570]			[3360, 2702, 3116, 2577]
25	HHHH	[95, 2014, 500, 736]	57	MLML	[65, 1527, 348, 556]
		[3067, 2457, 2838, 2593]			[3329, 2429, 3083, 2540]
26	HHHH	[94, 1995, 495, 729]	58	MLML	[63, 1492, 338, 542]
		[3090, 2479, 2860, 2617]			[3402, 2484, 3152, 2598]
27	HHHH	[93, 1976, 490, 722]	59	MLLL	[61, 1461, 351, 531]
		[3114, 2502, 2883, 2641]			[3461, 2523, 2947, 2641]
28	HHHH	[92, 1956, 484, 714]	60	LLLL	[64, 1420, 341, 515]
		[3139, 2526, 2907, 2667]			[3252, 2590, 3014, 2713]
29	HHHH	[91, 1935, 479, 706]	61	LLLL	[61, 1365, 328, 494]
		[3166, 2551, 2932, 2694]			[3357, 2691, 3115, 2820]
30	HHHH	[90, 1914, 474, 698]	62	LLLL	[58, 1293, 311, 467]
		[3193, 2577, 2959, 2722]			[3501, 2829, 3254, 2972]
31	HHHH	[89, 1892, 468, 690]			
		[3222, 2604, 2987, 2754]			

Table A.3: Low level emissions plant: Mean carbon footprint and total emissions, varying emission elasticity setting (EES).

EES	mean($\boldsymbol{e}_j$)	Total Em. (M kg CO_2)	EES	mean($\boldsymbol{e}_j$)	Total Em. (M kg CO_2)
0	-	8.73	32	2923.57	8.51
1	2362.47	8.72	33	2954.98	8.5
2	2373.85	8.72	34	2613.09	7.21
3	2385.45	8.71	35	2636.1	7.2
4	2397.33	8.71	36	2660.44	7.2
5	2409.44	8.7	37	2685.86	7.19
6	2421.81	8.7	38	2712.88	7.18
7	2434.45	8.69	39	2741.49	7.17
8	2447.37	8.68	40	2596.81	6.96
9	2461.18	8.68	41	2622.35	6.95
10	2474.86	8.67	42	2471.25	6.9
11	2488.89	8.67	43	2494.97	6.89
12	2503.52	8.66	44	2520	6.88
13	2518.39	8.65	45	2547.03	6.88
14	2534.12	8.65	46	2574.37	6.87
15	2549.86	8.64	47	2603.93	6.86
16	2566.07	8.63	48	2635.46	6.85
17	2582.78	8.63	49	2669.26	6.84
18	2598.87	8.62	50	2706.89	6.83
19	2617.92	8.61	51	2746.75	6.82
20	2636.29	8.61	52	2796.24	6.8
21	2655.29	8.6	53	2846.09	6.79
22	2675.02	8.59	54	2902.15	6.78
23	2695.38	8.58	55	2967.89	6.76
24	2716.66	8.58	56	2938.74	6.65
25	2738.47	8.57	57	2845.31	6.42
26	2761.16	8.56	58	2908.84	6.4
27	2785.06	8.55	59	2893.1	6.34
28	2809.8	8.54	60	2892.41	6.31
29	2835.64	8.54	61	2995.83	6.29
30	2862.79	8.53	62	3138.78	6.26
31	2891.71	8.52			

Table A.4: Medium level emissions plant: Solution results for varying emission elasticity setting (EES).

EES	% ↓ Profit	% ↓ Emissions	Demand (1000's)	% ↓ Demand	Avg. Emi. $CO_2/1000$	% ↓ Avg. Emis.	time (sec)
0	0	0	4003	0	3032	0.00	0.1
2	2.9	0.13	3940	1.57	3077	-1.48	0.1
4	5.9	0.26	3875	3.2	3125	-3.07	0.1
6	9	0.39	3807	4.9	3176	-4.75	0.1
8	12.21	0.53	3737	6.65	3231	-6.56	0.1
10	15.54	0.68	3665	8.44	3290	-8.51	0.1
12	19.02	0.83	3589	10.34	3354	-10.62	0.1
14	22.61	0.98	3511	12.29	3423	-12.90	0.1
16	26.48	1.15	3427	14.39	3501	-15.47	0.1
18	30.52	1.33	3340	16.56	3586	-18.27	0.1
20	34.83	1.51	3246	18.91	3683	-21.47	0.1
22	39.46	1.71	3146	21.41	3793	-25.10	0.2
24	44.48	1.93	3037	24.13	3920	-29.29	0.2
26	50.03	2.16	2916	27.15	4073	-34.33	0.1
28	55.87	12.94	2984	25.46	3542	-16.82	0.2
30	61.04	13.17	2871	28.28	3671	-21.08	0.1
32	66.74	15.14	2788	30.35	3695	-21.87	0.2
34	73.1	15.74	2659	33.57	3847	-26.88	0.1
36	80.8	16.06	2492	37.75	4089	-34.86	0.1
38	92.66	17.29	2292	42.74	4381	-44.49	0.1
40	107.57	20.2	2155	46.17	4495	-48.25	0.2

Table A.5: Medium level emissions plant: Low (L) vs. medium (M) vs. high (H) emission technology selected, varying emission elasticity setting (EES).

EES	$\boldsymbol{z}_{jq}$	$\frac{\boldsymbol{D}_j}{\boldsymbol{e}_j}$				EES	$\boldsymbol{z}_{jq}$	$\frac{\boldsymbol{D}_j}{\boldsymbol{e}_j}$			
		1	2	3	4			1	2	3	4
0	HHHH	[115,	2403,	602,	883]	21	HHHH	[92,	1920,	481,	704]
		-						[4223,	3633,	3999,	3771]
1	HHHH	[114,	2384,	597,	876]	22	HHHH	[90,	1890,	473,	693]
		[3539,	2952,	3327,	3062]			[4279,	3689,	4054,	3829]
2	HHHH	[113,	2365,	592,	869]	23	HHHH	[89,	1858,	465,	681]
		[3557,	2969,	3345,	3080]			[4338,	3748,	4112,	3893]
3	HHHH	[112,	2346,	587,	862]	24	HHHH	[87,	1824,	457,	668]
		[3590,	3003,	3378,	3114]			[4402,	3813,	4175,	3961]
4	HHHH	[111,	2326,	582,	855]	25	HHHH	[86,	1789,	449,	655]
		[3615,	3027,	3402,	3139]			[4472,	3884,	4244,	4035]
5	HHHH	[110,	2306,	577,	847]	26	HHHH	[84,	1751,	440,	641]
		[3640,	3051,	3426,	3165]			[4547,	3961,	4319,	4116]
6	HHHH	[109,	2286,	572,	840]	27	HHHH	[82,	1710,	430,	625]
		[3666,	3077,	3452,	3191]			[4643,	4059,	4413,	4219]
7	HHHH	[108,	2266,	567,	832]	28	HMHM	[82,	1810,	427,	665]
		[3693,	3103,	3478,	3219]			[4551,	3347,	4319,	3445]
8	HHHH	[107,	2245,	562,	824]	29	HMHM	[80,	1778,	418,	653]
		[3721,	3131,	3506,	3249]			[4627,	3406,	4395,	3505]
9	HHHH	[106,	2223,	556,	816]	30	HMHM	[78,	1744,	408,	641]
		[3750,	3159,	3534,	3278]			[4713,	3471,	4480,	3572]
10	HHHH	[105,	2201,	551,	808]	31	HMMM	[76,	1716,	428,	630]
		[3780,	3188,	3564,	3310]			[4768,	3505,	3888,	3608]
11	HHHH	[104,	2179,	545,	800]	32	HMMM	[74,	1678,	419,	616]
		[3812,	3219,	3595,	3342]			[4868,	3579,	3961,	3685]
12	HHHH	[103,	2156,	539,	791]	33	MMMM	[78,	1641,	410,	602]
		[3845,	3254,	3627,	3376]			[4245,	3652,	4033,	3761]
13	HHHH	[102,	2133,	533,	783]	34	MMMM	[76,	1596,	399,	586]
		[3879,	3288,	3660,	3411]			[4338,	3750,	4126,	3859]
14	HHHH	[101,	2109,	527,	774]	35	MMMM	[74,	1548,	388,	569]
		[3908,	3317,	3689,	3442]			[4447,	3861,	4234,	3974]
15	HHHH	[99,	2084,	521,	765]	36	MMMM	[72,	1495,	376,	549]
		[3952,	3361,	3732,	3487]			[4568,	3986,	4355,	4103]
16	HHHH	[98,	2059,	515,	755]	37	MMMM	[69,	1426,	360,	524]
		[3991,	3400,	3771,	3528]			[4750,	4175,	4536,	4297]
17	HHHH	[97,	2033,	508,	746]	38	MMML	[66,	1360,	345,	521]
		[4033,	3441,	3811,	3571]			[4906,	4339,	4692,	4213]
18	HHHH	[96,	2006,	502,	736]	39	MLML	[64,	1383,	336,	509]
		[4076,	3485,	3854,	3616]			[4940,	4134,	4725,	4241]
19	HHHH	[94,	1979,	495,	726]	40	LLLL	[63,	1290,	327,	475]
		[4122,	3531,	3899,	3664]			[4963,	4399,	4755,	4513]
20	HHHH	[93,	1950,	488,	715]						
		[4171,	3580,	3947,	3715]						

Table A.6: Medium level emissions plant: Mean carbon footprint and total emissions), varying emission elasticity setting (EES).

EES	mean($\boldsymbol{e}_j$)	Total Em. (M kg CO_2)	EES	mean($\boldsymbol{e}_j$)	Total Em. (M kg CO_2)
0	-	12.14	21	3906.65	11.94
1	3219.88	12.13	22	3962.53	11.93
2	3237.48	12.12	23	4022.72	11.92
3	3271.24	12.12	24	4087.86	11.91
4	3295.53	12.11	25	4158.6	11.89
5	3320.58	12.1	26	4235.87	11.88
6	3346.48	12.09	27	4333.58	11.86
7	3373.27	12.08	28	3915.3	10.57
8	3401.54	12.07	29	3983.34	10.55
9	3430.47	12.07	30	4058.78	10.54
10	3460.53	12.06	31	3941.96	10.32
11	3491.8	12.05	32	4023.37	10.3
12	3525.24	12.04	33	3922.91	10.25
13	3559.42	12.03	34	4018.51	10.23
14	3588.73	12.02	35	4128.95	10.21
15	3632.95	12.01	36	4253.07	10.19
16	3672.36	12	37	4439.5	10.16
17	3713.91	11.99	38	4537.38	10.04
18	3757.85	11.98	39	4509.88	9.79
19	3804.3	11.97	40	4657.26	9.69
20	3853.46	11.96			

Table A.7: High level emissions plant: Solution results for varying emission elasticity setting (EES).

EES	% ↓ Profit	% ↓ Emissions	Demand (1000's)	% ↓ Demand	Avg. Emi. $CO_2/1000$	% ↓ Avg. Emis.	time (sec)
0	0	0	4003	0	3934	0.00	0
1	1.88	0.06	3962	1.02	3972	-0.97	0.1
2	3.8	0.13	3921	2.05	4011	-1.96	0.1
3	5.75	0.19	3878	3.12	4053	-3.02	0.1
4	7.75	0.26	3835	4.2	4096	-4.12	0.1
5	9.8	0.33	3790	5.32	4142	-5.29	0.1
6	11.89	0.4	3745	6.45	4188	-6.46	0.1
7	14.04	0.47	3698	7.62	4239	-7.75	0.1
8	16.24	0.54	3650	8.82	4291	-9.07	0.1
9	18.49	0.62	3601	10.04	4346	-10.47	0.1
10	20.82	0.69	3551	11.29	4404	-11.95	0.1
11	23.22	0.77	3499	12.59	4466	-13.52	0.1
12	25.74	0.86	3444	13.96	4533	-15.23	0.1
13	28.34	0.94	3388	15.36	4604	-17.03	0.2
14	31.03	1.03	3329	16.84	4682	-19.01	0.1
15	33.84	1.12	3268	18.36	4765	-21.12	0.1
16	36.78	1.22	3205	19.94	4854	-23.39	0.1
17	39.87	1.32	3137	21.63	4954	-25.93	0.1
18	43.14	1.43	3067	23.38	5061	-28.65	0.1
19	46.64	1.55	2991	25.28	5184	-31.77	0.1
20	50.38	1.67	2910	27.3	5321	-35.26	0.2
21	54.44	1.8	2822	29.5	5480	-39.30	0.1
22	59.23	1.96	2718	32.1	5681	-44.41	0.1
23	63.69	7.89	2761	31.03	5254	-33.55	0.1
24	67.9	10.35	2725	31.93	5181	-31.70	0.1
25	72.56	11.84	2664	33.45	5212	-32.49	0.2
26	77.64	12.26	2562	36	5393	-37.09	0.1
27	83.69	12.46	2431	39.27	5671	-44.15	0.1
28	93.03	12.76	2229	44.32	6164	-56.69	0.1
29	105.3	15.11	2162	45.99	6183	-57.17	0.1

Table A.8: High level emissions plant: Low (L) vs. medium (M) vs. high (H) emission technology selected, varying emission elasticity setting (EES).

EES	$\boldsymbol{z}_{jq}$	$\frac{\boldsymbol{D}_j}{\boldsymbol{e}_j}$ 1	2	3	4	EES	$\boldsymbol{z}_{jq}$	$\frac{\boldsymbol{D}_j}{\boldsymbol{e}_j}$ 1	2	3	4
0	HHHH	[115,	2403,	602,	883]	15	HHHH	[94,	1960,	493,	720]
		-						[5243,	4664,	5024,	4795]
1	HHHH	[114,	2379,	596,	874]	16	HHHH	[93,	1922,	484,	706]
		[4453,	3867,	4241,	3976]			[5331,	4753,	5111,	4887]
2	HHHH	[113,	2353,	590,	865]	17	HHHH	[91,	1881,	474,	691]
		[4501,	3914,	4288,	4025]			[5427,	4851,	5207,	4989]
3	HHHH	[111,	2328,	583,	855]	18	HHHH	[89,	1838,	464,	676]
		[4542,	3955,	4329,	4067]			[5532,	4959,	5311,	5099]
4	HHHH	[110,	2302,	577,	846]	19	HHHH	[87,	1792,	453,	659]
		[4585,	3998,	4371,	4111]			[5650,	5081,	5429,	5225]
5	HHHH	[109,	2275,	570,	836]	20	HHHH	[85,	1743,	441,	640]
		[4629,	4043,	4416,	4157]			[5781,	5215,	5559,	5364]
6	HHHH	[108,	2248,	563,	826]	21	HHHH	[82,	1690,	429,	621]
		[4676,	4090,	4462,	4205]			[5930,	5369,	5708,	5524]
7	HHHH	[106,	2220,	556,	816]	22	HHHH	[80,	1626,	414,	598]
		[4726,	4139,	4510,	4256]			[6130,	5580,	5908,	5738]
8	HHHH	[105,	2191,	549,	805]	23	HMHH	[78,	1690,	407,	586]
		[4778,	4191,	4562,	4311]			[6101,	4900,	5878,	5716]
9	HHHH	[104,	2161,	542,	794]	24	HMHM	[76,	1647,	395,	607]
		[4828,	4242,	4613,	4364]			[6202,	4979,	5980,	5081]
10	HHHH	[102,	2131,	535,	783]	25	HMMM	[73,	1596,	405,	589]
		[4885,	4298,	4669,	4422]			[6349,	5099,	5461,	5204]
11	HHHH	[101,	2100,	527,	771]	26	MMMM	[75,	1532,	390,	565]
		[4945,	4361,	4728,	4484]			[5856,	5298,	5652,	5405]
12	HHHH	[99,	2067,	519,	759]	27	MMMM	[72,	1452,	371,	536]
		[5012,	4432,	4797,	4557]			[6118,	5570,	5915,	5682]
13	HHHH	[98,	2033,	511,	747]	28	MMMM	[67,	1328,	344,	491]
		[5087,	4505,	4869,	4632]			[6595,	6071,	6395,	6191]
14	HHHH	[96,	1997,	502,	734]	29	MLML	[63,	1293,	326,	480]
		[5162,	4581,	4943,	4711]			[6799,	6049,	6601,	6152]

Table A.9: High level emissions plant: Mean carbon footprint and total emissions, varying emission elasticity setting (EES).

EES	mean($\boldsymbol{e}_j$)	Total Em. (M kg CO_2)
0	-	15.75
1	4134.35	15.74
2	4181.96	15.73
3	4223.18	15.72
4	4266.24	15.71
5	4311.24	15.70
6	4358.37	15.69
7	4407.82	15.67
8	4460.45	15.66
9	4511.65	15.65
10	4568.50	15.64
11	4629.44	15.63
12	4699.56	15.61
13	4773.34	15.60
14	4849.20	15.59
15	4931.53	15.57
16	5020.35	15.56
17	5118.55	15.54
18	5225.17	15.52
19	5346.43	15.50
20	5479.96	15.49
21	5632.60	15.46
22	5838.65	15.44
23	5648.65	14.51
24	5560.49	14.12
25	5528.28	13.88
26	5552.75	13.82
27	5821.42	13.79
28	6312.90	13.74
29	6400.04	13.37

A.2 Three Echelon Supply Chain

Table A.10: Technology selection indicated by low (L), medium (M), or high (H) while varying γ_k. If a facility is closed, then it will be denoted by (C). The last 30 columns present demand served stacked at customer zone k stacked over the respective carbon footprint. Demand is in 1000 units.

γ_j	w_p	z_{jq}															$\frac{D_k}{e_k}$															
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
0	H	CHCH	[762,	139,	97,	66,	54,	43,	40,	32,	20,	19,	16,	16,	14,	14,	13,	12,	12,	10,	9,	9,	9,	7,	7,	6,	6,	6,	6,	5,	5,	5]
0.0001	H	CHCH	[762,	139,	97,	66,	54,	43,	40,	32,	20,	19,	16,	16,	14,	14,	13,	12,	12,	10,	9,	9,	9,	7,	7,	6,	6,	6,	6,	5,	5,	5]
			[637,	1725,	891,	861,	678,	1076,	996,	985,	1103,	878,	1418,	1625,	916,	835,	2953,	1586,	867,	850,	948,	1786,	1023,	1515,	1361,	870,	946,	723,	770,	764,	961,	717]
0.0002	H	CHCH	[762,	139,	97,	66,	54,	43,	40,	32,	20,	19,	16,	16,	14,	14,	12,	12,	12,	10,	9,	9,	9,	7,	7,	6,	6,	6,	6,	5,	5,	5]
			[637,	1727,	893,	863,	680,	1078,	998,	987,	1105,	880,	1420,	1627,	918,	837,	2955,	1588,	1197,	852,	949,	1788,	1025,	1232,	1362,	872,	727,	725,	772,	764,	963,	717]
0.0004	H	CHCH	[762,	138,	97,	66,	54,	43,	40,	32,	20,	19,	15,	15,	14,	14,	12,	11,	12,	10,	9,	8,	9,	7,	6,	6,	6,	6,	6,	5,	5,	5]
			[639,	1730,	896,	866,	683,	1081,	1001,	990,	1108,	883,	1423,	1630,	921,	840,	2958,	1591,	1200,	855,	951,	1791,	1028,	1234,	1364,	875,	729,	728,	775,	766,	966,	719]
0.0006	H	CHCH	[762,	138,	96,	65,	54,	42,	39,	31,	19,	18,	15,	15,	13,	13,	11,	11,	11,	9,	8,	8,	8,	6,	6,	5,	6,	6,	6,	5,	4,	5]
			[641,	1733,	899,	869,	686,	1084,	1004,	993,	1111,	886,	1426,	1633,	924,	843,	2961,	1594,	1203,	858,	953,	1794,	1031,	1236,	1366,	878,	731,	731,	778,	768,	969,	721]
0.0008	H	CHCH	[761,	138,	96,	65,	53,	42,	39,	31,	19,	18,	15,	15,	13,	13,	11,	11,	11,	9,	8,	8,	8,	6,	6,	5,	5,	5,	5,	4,	4,	4]
			[642,	1737,	903,	873,	690,	1088,	1008,	997,	1115,	890,	1430,	1637,	928,	847,	2965,	1598,	872,	862,	1300,	1798,	1035,	1237,	1367,	882,	732,	735,	782,	769,	973,	722]
0.001	H	CHCH	[761,	137,	96,	65,	53,	42,	39,	31,	19,	18,	15,	14,	13,	13,	10,	11,	11,	9,	8,	7,	8,	6,	6,	5,	5,	5,	5,	4,	4,	4]
			[643,	1742,	908,	878,	695,	1093,	1013,	1002,	1120,	895,	1435,	1642,	933,	852,	2970,	1310,	1212,	867,	955,	1803,	1040,	1238,	1368,	887,	963,	740,	787,	770,	978,	723]
0.0012	H	CHCH	[761,	137,	96,	65,	53,	42,	39,	31,	19,	18,	14,	14,	13,	13,	9,	10,	11,	9,	8,	7,	8,	6,	5,	5,	5,	5,	5,	4,	4,	4]
			[645,	1745,	911,	881,	698,	1096,	1016,	1005,	1123,	898,	1438,	1645,	936,	855,	2973,	1606,	875,	870,	957,	1806,	1043,	1240,	1370,	890,	966,	743,	790,	772,	981,	725]
0.0014	H	CHCH	[761,	137,	96,	65,	53,	41,	39,	31,	18,	18,	14,	14,	13,	13,	9,	10,	10,	9,	8,	6,	8,	6,	5,	5,	5,	5,	5,	4,	4,	4]
			[646,	1749,	915,	885,	702,	1100,	1020,	1009,	1127,	902,	1442,	1649,	940,	859,	2977,	1610,	1219,	874,	958,	1810,	869,	1241,	1371,	894,	736,	747,	794,	773,	985,	726]
0.0016	H	CHCH	[761,	136,	96,	65,	53,	41,	38,	30,	18,	18,	14,	13,	12,	13,	8,	9,	10,	9,	7,	6,	8,	5,	5,	5,	5,	5,	5,	4,	3,	4]
			[648,	1753,	919,	889,	706,	1104,	1024,	1013,	1131,	906,	1446,	1653,	944,	863,	2981,	1614,	1223,	878,	960,	1814,	871,	1243,	1373,	898,	738,	751,	798,	775,	989,	728]
0.0018	M	CHCH	[761,	136,	96,	65,	53,	41,	38,	30,	18,	18,	14,	13,	13,	13,	8,	9,	10,	9,	8,	6,	8,	5,	5,	5,	5,	5,	5,	4,	3,	4]
			[519,	1624,	790,	760,	577,	975,	895,	884,	1002,	777,	1317,	1524,	815,	734,	2852,	1485,	1094,	749,	831,	1685,	742,	1114,	1244,	769,	609,	622,	669,	646,	860,	599]
0.002	M	CHCH	[761,	136,	95,	64,	53,	41,	38,	30,	18,	17,	13,	13,	12,	13,	7,	10,	10,	8,	7,	6,	7,	5,	5,	4,	5,	5,	5,	4,	3,	4]
			[520,	1627,	793,	763,	580,	978,	898,	887,	1005,	780,	1320,	1527,	818,	737,	2855,	1187,	1097,	752,	832,	1688,	925,	1115,	1245,	772,	610,	625,	672,	647,	863,	600]
0.0022	M	CHCH	[761,	135,	95,	64,	53,	41,	38,	30,	18,	17,	13,	13,	12,	12,	7,	9,	10,	8,	7,	5,	7,	5,	4,	4,	5,	5,	5,	4,	3,	4]
			[521,	1630,	796,	766,	583,	981,	901,	890,	1008,	783,	1323,	1530,	821,	740,	2858,	1491,	751,	755,	833,	1691,	928,	1116,	1246,	775,	611,	628,	675,	648,	866,	601]
0.0024	M	CHCH	[761,	135,	95,	64,	53,	41,	38,	30,	18,	17,	13,	12,	12,	12,	6,	8,	10,	8,	7,	5,	7,	4,	4,	4,	5,	4,	4,	3,	3,	4]
			[522,	1633,	799,	769,	586,	984,	904,	893,	1011,	786,	1326,	1533,	824,	743,	2861,	1494,	752,	758,	834,	1694,	931,	1117,	1247,	778,	612,	631,	678,	649,	869,	602]
0.0026	M	CHCH	[761,	135,	95,	64,	52,	40,	38,	30,	17,	17,	13,	13,	12,	12,	6,	8,	9,	8,	7,	5,	7,	4,	4,	4,	4,	4,	4,	3,	3,	3]
			[522,	1636,	802,	772,	589,	987,	907,	896,	1014,	789,	1329,	1170,	827,	746,	2864,	1497,	1106,	761,	834,	1697,	934,	1117,	1247,	781,	612,	634,	681,	649,	872,	602]
0.0028	M	CHCH	[761,	134,	95,	64,	52,	40,	37,	29,	17,	17,	12,	12,	12,	12,	5,	9,	10,	8,	7,	4,	6,	4,	4,	4,	4,	4,	4,	3,	3,	3]
			[523,	1640,	806,	776,	593,	991,	911,	900,	1018,	793,	1333,	1540,	831,	750,	2868,	1190,	753,	765,	835,	1701,	938,	1118,	1248,	785,	861,	638,	685,	650,	876,	603]
0.003	M	CHCH	[760,	134,	95,	64,	52,	40,	37,	29,	17,	17,	12,	11,	11,	12,	4,	8,	9,	8,	6,	4,	7,	4,	3,	4,	4,	4,	4,	3,	2,	3]
			[524,	1643,	809,	779,	596,	994,	914,	903,	1021,	796,	1336,	1543,	834,	753,	2871,	1191,	1113,	768,	836,	1704,	747,	1119,	1249,	788,	614,	641,	688,	651,	879,	604]
0.0035	M	CHCH	[760,	133,	94,	63,	52,	39,	37,	29,	16,	16,	11,	11,	11,	11,	3,	8,	9,	7,	6,	3,	6,	3,	3,	3,	4,	4,	4,	3,	2,	3]
			[526,	1651,	817,	787,	604,	1002,	922,	911,	1029,	804,	1344,	1551,	842,	761,	2879,	1193,	756,	776,	838,	1712,	949,	1121,	1251,	796,	616,	649,	696,	653,	887,	606]
0.004	L	CHCH	[760,	133,	94,	63,	52,	39,	37,	29,	16,	16,	11,	10,	11,	11,	2,	7,	9,	7,	6,	2,	5,	3,	2,	3,	4,	4,	3,	3,	2,	3]
			[470,	1598,	764,	734,	551,	949,	869,	858,	976,	751,	1291,	1498,	789,	708,	2797,	1137,	700,	723,	782,	1659,	896,	1065,	1195,	743,	560,	596,	643,	597,	834,	550]
0.0045	L	CHCH	[760,	132,	94,	63,	51,	39,	36,	28,	16,	16,	10,	9,	10,	11,	0.41,	7,	9,	7,	5,	1,	6,	2,	2,	3,	3,	3,	3,	2,	1,	3]
			[471,	1606,	772,	742,	559,	957,	877,	866,	984,	759,	1299,	1506,	797,	716,	2798,	1138,	701,	731,	783,	1667,	694,	1066,	1196,	751,	561,	604,	651,	598,	842,	551]
0.005	L	CHCH	[760,	131,	93,	62,	51,	38,	36,	28,	15,	15,	9,	10,	10,	10,	0,	6,	8,	6,	5,	0.62,	4,	2,	1,	2,	3,	3,	3,	2,	0.75,	2]
			[472,	1614,	780,	750,	567,	965,	885,	874,	992,	767,	1307,	1120,	805,	724,	0,	1139,	702,	739,	784,	1675,	912,	1067,	1197,	759,	562,	612,	659,	599,	850,	552]
0.0055	L	CHCH	[759,	130,	93,	62,	51,	38,	35,	27,	14,	15,	9,	10,	10,	10,	0,	5,	8,	6,	5,	0,	5,	1,	3.3e-07,	2,	3,	3,	2,	2,	0.28,	2]
			[474,	1623,	789,	759,	576,	974,	894,	883,	1001,	776,	1316,	1122,	814,	733,	0,	1141,	704,	748,	786,	0,	697,	1069,	1199,	768,	564,	621,	668,	601,	859,	554]
0.006	L	CHCH	[759,	129,	92,	61,	51,	37,	35,	27,	14,	14,	8,	9,	9,	10,	0,	5,	8,	5,	4,	0,	5,	0.58,	0,	1,	3,	2,	2,	1,	0,	2]
			[476,	1628,	794,	764,	581,	979,	899,	888,	1006,	781,	1321,	1124,	819,	738,	0,	1143,	706,	753,	788,	0,	699,	1071,	0,	773,	566,	626,	673,	603,	0,	556]
0.0065	L	CHCH	[759,	128,	92,	61,	50,	37,	34,	26,	13,	14,	10,	9,	9,	9,	0,	5,	7,	5,	4,	0,	3,	0.036,	0,	0.93,	2,	2,	2,	1,	0,	1]
			[477,	1636,	802,	772,	589,	987,	907,	896,	1014,	789,	919,	1125,	827,	746,	0,	1144,	707,	761,	789,	0,	934,	1071,	0,	781,	567,	634,	681,	604,	0,	557]
0.007	L	CHCH	[759,	128,	91,	61,	50,	36,	34,	26,	13,	13,	10,	8,	8,	9,	0,	4,	7,	5,	3,	0,	4,	0,	0,	0.49,	2,	2,	1,	0.77,	0,	1]
			[478,	1643,	809,	779,	596,	994,	914,	903,	1021,	796,	920,	1126,	834,	753,	0,	1145,	708,	768,	790,	0,	701,	0,	0,	788,	568,	641,	688,	605,	0,	558]
0.0075	L	CHCH	[758,	127,	91,	60,	49,	36,	33,	25,	12,	13,	9,	8,	8,	8,	0,	3,	7,	4,	3,	0,	4,	0,	0,	0.05,	2,	1,	0.8,	0.45,	0,	0.8]
			[480,	1648,	814,	784,	601,	999,	919,	908,	1026,	801,	922,	1128,	839,	758,	0,	1147,	710,	773,	792,	0,	703,	0,	0,	793,	570,	646,	693,	607,	0,	560]
0.008	L	CHCH	[758,	126,	90,	60,	49,	35,	33,	25,	12,	13,	9,	7,	9,	8,	0,	2,	6,	4,	3,	0,	3,	0,	0,	0,	1,	0.75,	0.37,	0.15,	0,	0.52]
			[480,	1658,	824,	794,	611,	1009,	929,	918,	1036,	811,	922,	1128,	573,	768,	0,	1147,	710,	783,	792,	0,	703,	0,	0,	0,	570,	656,	703,	607,	0,	560]
0.0085	L	CHCH	[758,	125,	90,	59,	49,	34,	32,	24,	11,	12,	8,	6,	9,	7,	0,	2,	6,	3,	2,	0,	3,	0,	0,	0,	1,	0.37,	0,	0,	0,	0.23]
			[482,	1664,	830,	800,	617,	1015,	935,	924,	1042,	817,	924,	1130,	575,	774,	0,	1149,	712,	789,	794,	0,	705,	0,	0,	0,	572,	662,	0,	0,	0,	562]
0.009	L	CHCH	[758,	124,	89,	59,	48,	34,	32,	24,	14,	12,	8,	6,	6,	7,	0,	2,	6,	3,	2,	0,	3,	0,	0,	0,	0.85,	0,	0,	0,	0,	0]
			[483,	1672,	838,	808,	625,	1023,	943,	932,	666,	825,	925,	1131,	863,	782,	0,	1150,	713,	797,	795,	0,	706,	0,	0,	0,	573,	0,	0,	0,	0,	0]
0.0095	L	CHCH	[757,	123,	89,	58,	48,	33,	31,	23,	10,	11,	7,	5,	9,	8,	0,	1,	5,	2,	1,	0,	2,	0,	0,	0,	0.55,	0,	0,	0,	0,	0]
			[484,	1679,	845,	815,	632,	1030,	950,	939,	1057,	832,	926,	1132,	577,	657,	0,	1151,	714,	804,	796,	0,	707,	0,	0,	0,	574,	0,	0,	0,	0,	0]
0.01	L	CHCH	[757,	122,	88,	58,	48,	33,	30,	23,	13,	11,	7,	5,	8,	6,	0,	0.49,	5,	2,	1,	0,	2,	0,	0,	0,	0.26,	0,	0,	0,	0,	0]
			[484,	1686,	852,	822,	639,	1037,	957,	946,	667,	839,	926,	1132,	577,	796,	0,	1151,	714,	811,	796,	0,	707,	0,	0,	0,	574,	0,	0,	0,	0,	0]

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