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The Impacts of Carbon Emissions on Distribution Network Design: A Case Study

By

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Abstrait

Pour résoudre les problèmes environnementaux dans la distribution de marchandises, ce mémoire considère avec une préoccupation environnementale la conception de réseaux de distribution, lequel nous désignons comme le Conception Verte de Réseau de Distribution (CVRD). Nous formulons d'abord Un Modèle Générale de Conception de Réseau (MGCR). Nous présentons ensuite quatre modèles CVRD, qui sont les extensions de MGCR. Chacun de ces quatre modèles correspond à un groupe particulier de politiques environnementales. Les quatre environnement politiques sont strictes d'émission Cap, taxe sur le carbone, Cap-and-Trade et Cap-et-Offset. L'estimation précise des émissions est essentielle pour la CVRD. Nous expliquons en détail les deux modèles de calcul des émissions (un pour le transport routier et l'autre pour le transport ferroviaire), afin d'obtenir les valeurs d'émissions de chaque arc spécifique. Ces valeurs sont utilisées dans les modèles CVRD pour calculer les émissions totales d'un réseau particulier.

Une étude de cas est mise en œuvre. Nous utilisons les données réelles d'une société d'énergie canadienne et tentons de reconfigurer son réseau de distribution pour les dix années à venir. Les quatre modèles de CVRD ainsi que le MGCR sont résolus à optimalité sous les divers scénarios, sauf pour un scenario qui a des contraintes très strictes. Les solutions optimales sont analysées et comparées. Les résultats montrent que certaines politiques sont généralement plus performantes que les autres, réduisant à la fois les coûts et les émissions. De plus, il est confirmé que les émissions de CO2 n'influencent pas la décision de sélection d'entrepôt, car il n'y a pas de coûts fixes d'utilisation des installations. En outre, dans l'étude de cas, la sélection du mode de transport ne varie pas selon les émissions de CO2. Cependant, les émissions de CO2 ont un impact sur le portfolio des produits destinés aux entrepôts, le coût total et les émissions.

Abstract

To address the environmental issues in freight distribution, this thesis considers distribution network design with an environmental concern, which we denote as Green Distribution Network Design (GDND). We first formulate a general distribution network design (GeDND). We then present four GDND models, which are extensions of the GeDND model. Each of the four models corresponds to a particular type of environmental policy. The four environmental polices are Strict Emission Cap, Carbon Tax, Cap-and-Trade, and Cap-and-Offset. Accurately estimating emission is important for GDND. We explain in depth how to use two emission calculation models (one for road transport and the other for rail transport) to compute the arc-specific emission values. These values are used in the GDND models to calculate the total emissions from a particular network configuration.

A case study is implemented. We adopt the real data of a Canadian energy company to redesign its distribution network for the next ten years. All of the four GDND models as well as the GeDND model are solved to optimality under various scenarios except for one scenario, which has very strict constraints. The optimal solutions are analyzed and compared. The results show that some policies generally perform better than the other, producing both lower costs and lower emissions. Also, it is found that CO_2 emissions do not impact warehouse selection, as there are no fixed facility usage costs. Furthermore, the transport mode selection in the case study does not change with CO_2 emissions. However, CO_2 emissions do impact the assignment of products to warehouses, and total costs and emissions.

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1. Introduction

The negative impacts of global warming could be devastating:
"The effects of an increase in global temperature include a rise in sea levels and a change in the amount and pattern of precipitation, as well as a probable expansion of subtropical deserts------ (Lu et al., 2007)"

In 2013, the Intergovernmental Panel on Climate Change (IPCC) stated that the largest driver of global warming is carbon dioxide (CO_2) emissions from human activities (IPCC, 2013). Since the industrial revolution in the 18th century, CO_2 emissions due to human activities have stably increased. By 2011, the concentrations of CO_2 emissions exceeded the pre-industrial levels by about 40% (IPCC, 2013).

Among the various contributors to CO_2 emissions, the transport sector accounted for 23% of global CO_2 emissions, and 30% of the overall CO_2 emissions from fossil fuel combustion in 2005 (International Transport Forum, 2010). This is because right now, most transport still relies on fossil fuel, which contains high percentages of carbon. In the next few decades, the globally CO_2 emissions from transport are expected to increase by approximately 40% from 2007 to 2030 (International Transport Forum, 2010). By further checking the sources of the CO_2 emissions from the transport sector, freight transport was found to represent around one third of transport emissions (Regmif & Hanaoka, 2010). Therefore, it is inevitable that companies with freight transport will face more and more challenges from governmental regulations.

Around the world, governments and intergovernmental institutions mainly rely on four types of environmental policies: (1) Strict Emission Cap; (2) Carbon Tax; (3) Cap-and-Trade; (4) Carbon-and-Offset (The Congress of the United States, 2008). The policies of Strict Emission Cap and Carbon Tax are relatively simple. Basically, Strict Emission Cap means that governments impose hard emission constraints on companies during a planning horizon. Carbon Tax means that a tax is imposed on firms for emitting air pollutants (C2ES, 2011).

In the Cap-and-Trade mechanism, governments specify a quota of allowed GHG emissions for firms during a planning horizon. The quotas are determined either by auction or by allocation according to some rules. Within these quotas, firms do not need to pay, and they can sell the unused quota to other firms in an open carbon market. But, if the firms emit more than their quota, they need to buy emission allowances (C2ES, 2011).

In the Cap-and-Offset scheme, the Cap is also a government specified quota of allowed emissions for each entity. The Offset is the investment that a firm would make in carbon-reducing projects to offset emissions in excess of its specified quota. The Offset is essentially the same as the purchasing of emission credits in the Cap-and-Trade scheme, except that the underlying market mechanism is different. In Cap-and-Trade, the availability and pricing of emission credits are determined by a carbon exchange market, while the availability and pricing of offsets are determined by independent suppliers of the offsets (Guide et al., 2006). These explain why in some regions, such as California, a Cap-and-Offset scheme is actually managed under a Cap-and-Trade scheme, working as a compliance instrument to the Cap-and-Trade policies (California Air Resources Board, 2012). However, in Cap-and-Offset, firms do not benefit if they emit less than their specified caps as they cannot sell their unused emission quotas. This maybe the biggest difference between the two.

Fortunately, many companies have already taken on some practices to mitigate environmental risks. The ways that companies use to reduce emissions can be classified into two categories- green technologies practices and non-technical practices. Green technologies practices rely on using green products or technologies, such as electric vehicles and energy-efficient vehicles, while non-technical practices rely on better operations, such as training drivers to drive more energy efficiently. Green technologies practices were proved to be effective in reducing CO_2 emissions. However, according to a study commissioned by the European Commission, only technical options can hardly be sufficient to meet emission reduction targets of European countries (Skinner, 2010). Though the study focuses on European countries, it is also applicable to other countries or regions. Thus, more non-technical options are needed.

Green distribution network design (GDND) is a promising non-technical option. Compared to traditional distribution network design that usually only tries to minimize economic costs, GDND incorporates carbon costs or carbon constraints during the network design stage. This helps better balance the costs and emissions of a network. The benefits of GDND are obvious: GDND doesn't necessarily result in large capital investment, and its optimal solutions can also be easily implemented. However, total costs generally increase when addressing emissions in a network design. Also, different types of environmental policies exist. Research on how to incorporate emissions under each type of environmental policies is limited, let alone discussing their effect in reducing emissions.

To explore how CO_2 emissions impact distribution network design, we study a general distribution network design (GeDND) model. Based on this model, we propose four GDND models, each corresponding to a type of environmental policy. Accurately estimating emissions is important in GDND. We adopt an effective second-by-second microscope model to estimate road transport emissions, and a distance-based method to compute rail transport emissions. Based on these emission models, we obtain ways to compute values for arc-specific emission values, which are used for calculating total emissions of a network. A case study is implemented. The distribution network of a Canadian company is redesigned for the next 10 years. CPLEX 12.6.0.1 is used together with a C++ interface in a LINUX environment to find optimal solutions. Computational results are compared and analyzed to see: (1) how emission concerns impact the total costs and emissions under each type of environmental policy; (2) how emission concerns impact strategic decision-making, including transport mode and warehouse selection. Also, the four types of environmental policies are compared with their effect in reducing emissions while keeping a relatively low total cost.

Literature on green network design is scarce. The studies focusing on the impacts of CO_2 emissions on network design are even sparser. This thesis supplements the existing literature, and its contribution is threefold: (1) we formulate the GeDND model and four GNDN models based on a known general logistics network design model. Each of the four GNDN models corresponds to a type of environmental policy; (2) we test the potential impacts of the four types of policies using real data from a company. Thus providing managerial insights for the company; (3) instead of adopting highly integrated emission factors to compute emissions, we use arc-specific emission parameter to estimate total emissions in GDND. This helps capture the variation of total emissions and total emission costs among different optimal solutions.

The rest of this thesis is organized as follows. Section 2 reviews the existing literature. Section 3 presents the GeDND model and model extensions under different types of environmental policies. In Section 4, we introduce two emission calculation models (one for road transport and another for rail transport) based on which we compute the values for an emission parameter. In Section 5, we implement a case study. In section 6, we compare and analyze the optimal solutions from Section 5. In Section 7, we present our conclusions and indicate future research directions.

2. Literature Review

In this section, we first provide a brief overview on green supply chain management (GrSCM), which is supply chain management with an environmental concern (Wang et al., 2011). Then, we focus on the mathematical models for green supply chain network design (GSCND). Next, we review the impacts of CO_2 emissions on decision-making during network optimization. At last, we review the emission calculation methods (for road and rail transport only).

Through our literature survey, we find that many authors do not really distinguish CO_2 from Greenhouse gases (GHGs), Carbon footprint, Equivalent Carbon Dioxide and Carbon Dioxide Equivalent. As these are relevant concepts, our literature survey covers articles that consider any of them, in order to have a broad literature base.

2.1 Green Supply Chain Management

Similar to the term GrSCM, there are Green Logistics Management, GSCND, and GDND. In this thesis, Green Logistics Management is considered as the same as GrSCM. GSCND is considered as part of GrSCM, which is a broader concept. GSCND considers only the design and modeling of supply chain networks (SCN). GDND is considered as part of GSCND, because GSCND deals with a whole supply chain, while GDND deals with only the part that starts from plants and ends at customers.

Much research deals with GrSCM. Srivastava (2007) stated that since the conceptualization of GrSCM, about 1500 books, journal articles, and edited volumes have covered GrSCM. But, most of this research is empirical, and does not use mathematical models to solve problems. Therefore, this survey only covers review papers on GrSCM.

The earliest review paper comes from Srivastava (2007). At his time, no broad reference for GrSCM was available for regulatory bodies to refer to when formulating environmental policies. In the paper, he discussed a broad range of activities, including product design, material sourcing and selection, manufacturing processes, delivery of the final product to consumers, and end-of-life management of the product after its useful life. All of them are put under the scope of GrSCM. From this paper, it could be found that before 2007, research on green supply chain management mainly falls into three categories:

1. Articles about the importance of GrSCM;
2. Articles on green design (mainly on green products);
3. Articles on green operation (mainly on green manufacturing and remanufacturing, reverse logistics, and network design).

Dekker et al. (2012) presented a review that highlighted the contribution of operations research to green logistics. A broad range of aspects was covered, including transportation, product and inventory, facility, and supply and transport chain design. The transportation part is the focus of this paper. It covers the topics on: (1) transport mode choice; (2) intermodal transport; (3) equipment choice and efficiency; (4) fuel choice and carbon intensity. The paper concludes that more research using mathematical models is required to address the multitude of decisions needed to reduce emissions.

A recent review work by Luthra (2014) aims to provide an overview of the various issues of GrSCM, and suggests further research scopes and directions. The author analyzed the existing literature from many perspectives, including key components of GrSCM, frequency of GrSCM components, tool / techniques used (frequency) and model (frequency) and so on. The paper concludes that limited work has been done on green logistic models.

Pinto & Moreno (2014) focused on the mathematical models employed in GSCND. The decision variables of these models include facility location and capacity, technology selection, carbon market mechanism considerations, production operations, and transport operations. Pinto and Moreno classified these models according to the decision variables as in the following Table 1.

Table 1 Classification of decision variables in GSCND models (adapted from Pinto & Moreno, 2014)

Decision variables	Objective functions/ models
Facility location and capacity	Multi-objective mathematical model to find a balance between possible environmental damage and economic impact.
Technology Selection	1. Multi-objective model in which potential plants may be selected using different types of technologies 2. Long- term planning models to determine investment decisions relating to optimal selection, installation, and expansion of processes technological process
Carbon market mechanism consideration	Mixed integer linear programming (MILP) model for designing a green supply network integrating decisions related to "carbon trading".
Production Operations	1. Multi- period, discrete and continuous MILP model, which includes investment in energy generation systems within production planning. 2. Mathematical model to determine optimal production levels and product mix in the presence of various environmental restrictions and typical production planning limitations.
Transport Operations	1.Optimization model for freight consolidation in which CO2s emissions are computed for two transport modes (road and rail transport). 2. Linear programming and heuristic techniques to improve freight vehicle capacity use by accepting additional freight through in order to reduce CO2 emissions.

Pinto and Moreno concluded that: (1) the CO_2 market is an interesting alternative for managing CO_2 emissions via CO_2 credits. However, it is must be stressed that trading CO_2 credits do not directly lower GHG emissions; (2) the areas in which

GHGs emissions can be significantly reduced are production operations, transportation, and recycling.

Through these review papers, we find that there is a need to use mathematical models to solve GrSCM problems. Also, transportation seems to be a promising area for further emission reduction in a supply chain.

2.2 Mathematical Models with Green Supply Chain Network Design

Supply chain network design (SCND) is one of the most comprehensive strategic problems. It determines a portfolio of configuration parameters, including the number, location, capacity and type of various facilities in the network (Wang, 2011). It needs to be solved to optimality for the long-term efficiency of the entire supply chain. Most mathematical models consider economic factors such as fixed facility costs and operation costs. Recently, environmental issues began to be incorporated in SCND (Treitl & Jammernegg, 2011). In what follows, we present the work on the mathematical models of GSCND, which are the focus of this literature survey.

Hugo & Pistikopoulos (2005) developed a model for the long-term planning and design of SCN. One of the objective functions in this model aims to minimize the environmental impacts from emissions and wastes. The other aims to maximize the net profit value. The model incorporates a life cycle assessment criterion as part of the strategic investment decisions, and it considers plant location and plant capacity investments. Supply chain emissions are estimated by using life cycle analysis.

Ramudhin et al. (2008) developed a mixed-integer mathematical model with two objective functions to explore the “Carbon-Market Sensitive - Green Supply

Chain Network Design" problem, where carbon trading considerations are integrated within the SCND phase. One of the objective functions of the model minimizes total logistics costs. The other minimizes total CO_2 emissions from both production and transportation. Many strategic decisions were considered, including supplier selection, raw material selection, plant location, and transport mode selection. Transport emission is calculated by:

Transport emission= GHGs emission factor* Distance*Weight.

Here, GHGs emission factor represents the emission per ton per mile via a specific transport mode.

Pan et al. (2009) proposed a single objective model to explore emission reduction potential through freight consolidation between two French retail chains. The objective function of the model minimizes the sum of CO_2 emissions from three transport sections (upstream, midstream and downstream). Strategic decision variables in this paper include supplier selection, plant location, warehouse location and transport mode selection. A macroscopic model called MEET is used to estimate the emissions from both road and rail transport.

Wang et al. (2011) proposed a multi-objective optimization model to capture the trade-offs between total logistics cost and environmental influences. One of the objective functions in this model minimizes total costs, which include fixed setup costs, environmental protection investment, total transportation costs, and total handing costs. The other minimizes total CO_2 emissions, including emissions occurred from facility usage and on road. This model considers supplier selection, plant location, and plant capacity investment. An arc-dependent emission parameter e_{ij}^{p} is used to compute road transport emissions. The values of this parameter are obtained by:

$$e_{ij}^{p} = b_{ij} \times \text{Geographic distance between node } i \text{ and node } j.$$

However, the paper does not explain what b_{ij} represents.

Paksoy et al. (2011) developed a model for closed-loop SCND. The model has four objective functions. The first aims to minimize the transport costs from forward logistics, and different types of truck can be chosen. The second aims to minimize the transport costs from reverse logistics. The third minimizes total CO_2 emissions, which are produced by trucks on forward logistics. The last minimizes the purchasing costs minus the total opportunity profits. The opportunity profits are gained via using recyclable products. Different transport choices between echelons are considered. Arc-specific emission parameters are used to estimate forward logistics transport emissions. But, the paper does not mention how or where to obtain the values for these parameters.

Abdallah et al. (2012) developed a single-objective mixed integer model for the supply chain with carbon trading and environmental sourcing. The objective function of the model minimizes the sum of the fixed costs, distribution costs, procurement costs, and carbon emission costs associated with carbon trading. The model considers green procurement, plant location, plant capacity investment, warehouse location, and warehouse capacity investment. Emission from facility usage, emission derived from raw material production, and road transport emission are all included. Like many articles on GSCND, the paper uses an emission factor, which represents the emission per unit of weight per unit distance, to compute road transport emission.

Elhedhli & Merrick (2012) designed a single objective model for GSCND. Their objective function minimizes the fixed costs to set up facilities, the transport costs to move goods, and the emission costs from product shipment. Warehouse location and warehouse investment are considered in this model. An emission parameter (the emissions per unit distance per unit of weight) is the key to emission calculation. The emission parameter is obtained by referring to some concave lines representing the relationship between emissions and weights under different vehicle speeds. This relationship was found by researching the data set of the vehicle GHG emissions in the Mobile6 computer program and Speed Correction Factors. The Mobile6 computer program was funded by the Environmental Protection Agency of the United States (US EPA). The program contains an extensive database of CO_2 emissions for heavy-duty diesel vehicles obtained from full-scale experiment. From the database, emission factors for various vehicle weights can be obtained. Speed Correction Factors, outlined by the California Air Resources Board, are used to relate CO_2 emission levels with vehicle weights and speeds of travel. The authors combine the emission factors from the Mobile6 computer program and the Speed Correction Factors to obtain the emission rate.

Kannan et al. (2012) developed a single-objective model for reverse logistics network design. Its objective function minimizes the sum of transportation costs, fixed facility costs, and final disposal and landfill costs. The model considers the selection of collection / inspection centers. Carbon footprint from both transportation and reverse logistics operation are included. The paper uses an emission parameter, which represents the emission per unit of returned product per unit distance, to compute network emissions. It assumes that the value for this parameter is known.

Fahimnia et al. (2013) introduced a unified optimization model to explore the impact of carbon pricing on a closed-loop supply chain. The model has only one objective function, which minimizes the overall supply chain costs. Carbon emission costs, as part of the overall supply chain costs, are considered. The paper considers both forward and backward transport emissions. Emissions occurring from both product manufacturing and facility usage are included. The paper uses an arc-specific emission parameter to compute transport emissions. But, it does not explain how or where to obtain the values of this parameter. Even in its real case study, the paper only mentions that the values of this parameter were provided by a third-party logistics (3PL).

Martí et al. (2015) introduced a model with one objective function that minimizes the total supply chain costs per unit of time. The costs include inventory costs (holding cost in markets' warehouses and in transit, as well as ordering and shortage costs) and procurement costs (raw materials, manufacturing including labor and transport). One critical assumption with the model is that demands in market are stationary and stochastic. The model considers both plant location and transport mode selection. Emissions from warehousing, raw materials, manufacturing and transport are all included. Like most papers on green supply chain, the paper uses an emission factor, i.e., the emissions per unit of weight per unit distance, to compute emissions.

It seems that multi-objective models are more popular in supply chain network design. Multi-objective models usually do not consider specific environmental policies. Their emission concerns are expressed by independent objective functions minimizing the total emissions of networks. Articles with multi-objective models often focus on analyzing the trade-offs between logistics costs and emissions. But, recently, single objective models began to be more frequently developed. These models usually consider emissions under specific environmental polices. Their emission concerns are often expressed by incorporating carbon costs or emission constraints.

Decision variables tell what type of questions GSCND are dealing with. In Table 2 we summarize the models in this section from the perspective of their decision variables.

Table 2 Decision Variables of OR Models on Green Supply Chain Network Design

Authors	Supplier Selection/Raw Material Selection	Plant Location	Plant Capacity Investment	Warehouse Location	Warehouse Capacity Investment	Transport Mode Selection
Hugo et al. (2005)		✔	✔			
Ramudhin et al. (2008)	✔	✔				✔
Pan et al(2009)	✔	✔		✔		✔
Wang et al. (2011)	✔	✔	✔			
Paksoy et al.(2011)	✔					
Kannan et al.(2012)				✔		
Abdallah et al. (2012)	✔	✔	✔	✔	✔	
Fahimnia et al.(2013)						
Elhedhli et al.(2012)				✔	✔	

Table 2 suggests that transport mode selection, as a decision variable, is not very popular in GSCND. By 2009, only two articles include it. However, transport mode selection is an important decision variable that impacts network emissions. For example, Pan et al. (2009) found that by pooling the supply chain resources of two big retail companies, a reduction of 14% of CO_2 emission can be compared to their current road transport mode. But, if the companies use intermodal transport with at least two transport modes, they can save even up to 52% of CO_2 emissions.

Table 2 also indicates that limited research is done considering both transport mode selection and facility location in the SCND. Only Pan et al. (2009) considered both of them when designing a collaborative freight distribution network between two companies. This suggests that future research could incorporate both during in the SCND of a single company.

2.3 The Impacts of CO_2 Emissions in Supply Chain Management

Recently, researchers have started to model the impacts of CO_2 emissions and examine how CO_2 emissions could possibly affect decision making in supply chain management from the strategic level, such as network design, to the operational level, such as production planning.

At the strategic level, Elhedhli & Merrick (2012) developed a model to simultaneously minimize logistics costs and carbon costs by strategically locating warehouses within a distribution network. Test results indicate that the addition of carbon costs created a driving force to reduce the amount of vehicle kilometers travelled. Since the customer demands must still be met, the solution suggests that more distribution centers be opened to decrease vehicle travel distances.

Abdallah et al. (2012) found that the size of distribution centers could influence GHGs emissions in the entire supply chain. They formulated a mixed-integer linear model for reverse logistics network design. The model supports location choices for collecting used products and implementing recovery options, such as recycling and disposal options. Through sensitivity analysis, it was found that decreasing the size of facilities could reduce transport emissions.

Wang et al. (2011) introduced a model, which is based on the classical facility location model, to capture the trade-offs between total costs and environment influences. Facility location was set as a variable. "Capacity ratio", which is defined as the total network capacity over the total demand, was introduced. After conducting a sensitivity analysis, the authors found that: (1) at the same CO_2 emission level, larger capacity ratios led to less total costs; (2) for the same total costs, CO_2 emissions monotonically decreased along with the increase of capacity ratio.

At the tactical level, some papers conclude that if specific environmental policies are in place, CO_2 emissions are powerful enough to trigger transport mode switching. For example, Blauwens et al. (2006) investigated the effect of policy measures aiming at triggering mode shift in freight transport. The background was that road congestion resulted in extra emissions, thus some policies were made to force companies to switch to other transport modes. The author claimed that a combination of certain policy measures, such as those leading to an increase of road transport costs, could result in significant shifts from road transport to intermodal transport that produce less emissions.

There are also papers that question the power of CO_2 emissions in the SCND. Hoen et al. (2014) studied the effect of three emission regulations (Cap-and-Trade, Carbon Tax, and Strict Emission Cap) on transport mode selection under stochastic demands. They investigated the impact of these regulations on four particular products. They found that unless the emission-related charges or values of one or more of parameters (weight, distance, or unit cost) were extremely high, environmental policies could not lead to transport mode switching.

Hoen et al. (2010) investigated the effect of two regulation alternatives (an emission cost and an emission constraint) on transport mode selection. They analyzed a very simple situation: single product for delivery, an infinite horizon, and periodic review with stochastic demand. Their focus was on a decision maker who has to select one out of several available transport modes for a given product. They found that emission costs accounted for a relatively small portion of the total costs. Thus, they concluded that introducing emission costs via a direct emission tax or a market mechanism, such as Cap and Trade, was not likely to result in significant changes in transport modes. But, they believed that hard emission constraints could reduce carbon emissions by a large fraction.

Both Hoen et al. (2014) and Hoen et al. (2010) assumed that transport costs remained the same when different transport modes were chosen. They made this assumption because a 3PL was used. This may explain why they concluded some or all environmental polices were not powerful enough to trigger transport model switching.

At the operational level, Benjaafar et al. (2013) used the variants of traditional lot-sizing models to illustrate how carbon emission concerns could be integrated into operational decision-making process with regard to procurement, production, and inventory management. Carbon emissions under different environmental polices (Strict Emission Cap, Carbon Tax, Cap-and-Trade, and Cap-and-Offset) are incorporated in different ways. Numerical results show that: (1) under Strict Emission Cap, emissions can be significantly reduced without significantly affecting total costs; in one example, reducing emissions by 15% leads only to a 3% increase of costs; (2) carbon offsets enable tighter emission caps by mitigating the impacts of strict emission caps on costs; (3) under Cap-and-Trade, when the price of buying or selling emission credits is fixed, emission levels are not affected by emission caps. They are affected only by the price of carbon credits; (4) under Cap-and-Trade, a higher carbon price could lead to a lower total cost.

Benjaafar et al. (2013) focused on decision-making regarding production and procurement. They indicated that in the future, more operational decisions affecting emissions could be incorporated. Among them are facility location, transport mode selection, and so on. They also stated that other common models, such as newsvendor models and economic order quantity models, could be used to do similar analysis as in this article. In this thesis, we analyze how CO_2 emissions impact transport mode and warehouse selection based on a general model for the logistics network design.

2.4 Emission Estimation - Road and Rail Transport

According to the GHG Protocol (2005), developed by the World Resources Institute and the World Business Council on Sustainable Development (WBCSD), one either applies a fuel-based or a distance-based method to calculate CO_2 emissions. With the fuel-based method, CO_2 emission is often obtained by:

$$CO_2 \text{ emission} = \text{Fuel consumption} * CO_2 \text{ emission factor.}$$

Here the CO_2 emission factor is developed based on the fuel's heat content, the fraction of carbon in the fuel that is oxidized, and the carbon content coefficient. To know how much fuel is consumed, the simplest way is to refer to fuel receipts. However, fuel receipts are not always available. When fuel receipts are not in place but total fuel costs are available, we can still estimate fuel consumption by:

$$\text{Fuel consumption} = \text{Total fuel costs} / \text{Fuel price.}$$

For the distance-based method, CO_2 emission is often estimated by:

$$CO_2 \text{ emission} = \text{Distance} * \text{Weight} * \text{Emission factor.}$$

Here the emission factor represents the emission of shipping one unit of commodity for one unit of distance.

A handbook by the Department of Energy & Climate Change of UK classifies various emission calculation methods into three categories (see Figure 1). The first category, which is considered to be most accurate, uses fuel consumption amount to estimate emissions. The second one, which is considered to be less accurate than the first one, relies on travel distance and truckload to calculate emissions. The last one, which is considered to be the least accurate, relies only on travel distance to estimate emissions (GOV. UK, 2014).

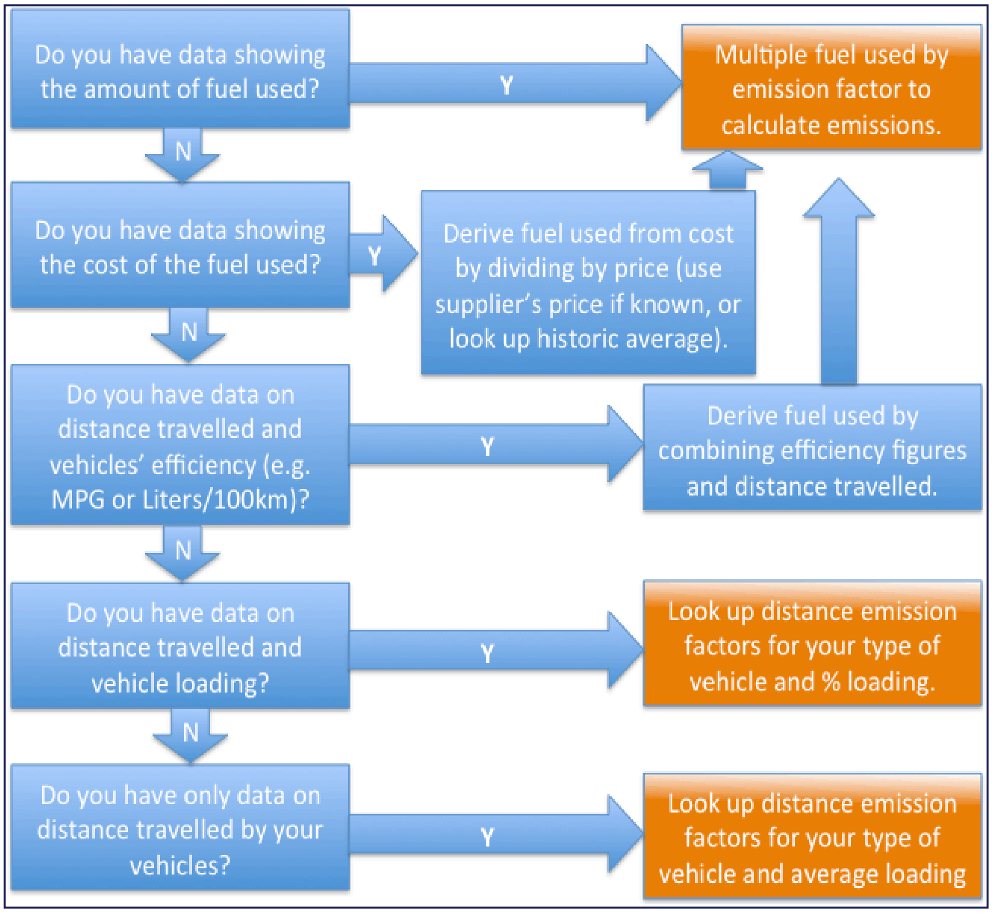

Figure 1 Decision tree for emission calculation methods selection (adapted from GOV. UK, 2014)

For road transport emission calculation, Demir et al. (2014) provided a relatively in-depth introduction to various fuel consumption models. They categorized fuel consumption models into three groups with increasing levels of complexity: factor models, macroscopic models, and microscopic models. Factor models mainly rely on emission factors to estimate emissions. The emission factors are derived from the mean values of repeated measurements over a particular driving cycle. Microscopic models require instantaneous vehicle kinematic variables, such as speed and acceleration, or more aggregated variables, such as the time spent in each traffic mode, cruise and acceleration. Macroscopic models use average aggregate network parameters to estimate network-wide emission rates.

Demir et al. (2014) implemented a three-point scale analysis of the microscopic and macroscopic models. Eight criteria, including robustness, reliability, and so on, are used. The results show that: (1) microscopic models seem more robust and reliable, but data requirements for them are also more significant than for macroscopic models; (2) macroscopic models have more technical support, which provides continuous improvement. They are also more capable of estimating other air pollutants.

Rail transport mainly has two types: the transport that uses electrical locomotives and the one that uses diesel locomotives. Literature on the fuel consumption models of rail transport is quite rare. The emission calculation handbook by the Department of Energy & Climate Change of UK explains how to use distanced-based methods to estimate rail transport emissions. According to it, distanced-based methods are the most common ways to estimate rail transport emissions (GOV. UK, 2014).

Hoen (2012) adopted the NTM model to calculate the CO_2 emissions from four types of transport modes: road, rail, marine, and air transport. The CO_2 emissions produced by electrical locomotive trains and by diesel locomotive trains are computed separately. The NTM model is a macroscopic one that considers distance, load factors, type of transport mode, positioning, empty return trips, topography, and type of road (urban, rural or motorway). It is responsive to other types of pollutants, and it is continuously improved (Demir et al., 2014). However, the values for some vehicle specific parameters, such as the fuel consumption factor of an empty vehicle and that of a fully loaded vehicle, often are hard to obtain.

Pan et al. (2009) considered two transport modes (road and rail transport) when designing a collaborative freight distribution network. They used the MEET mode, a macroscopic model, to estimate road and rail transport emissions. The emissions of a specific truckload are estimated by referring to the emissions of empty and full truckload. All parameter values were extracted from real-life experiments. However, these values were calibrated in 1999 based on European observations. Many corrections need to be done if they are to be used today and outside Europe (Demir et al., 2014).

Directly referring to fuel consumption is the most accurate way to estimate CO_2 emissions. However, information, such as fuel expenditure records and fuel receipts, usually are hard to obtain. In this thesis, we use the Comprehensive Modal Emission Model (CMEM) to estimate road transport fuel consumption and total emissions. This model was initially developed in the late 1990s, with sponsorship from the National Cooperative Highway Research Program (NCHRP) and the EPA, to fulfill the need for microscopic emission modeling (UCR, 2015). So far, scholars, such as Scora & Barth (2006), Barth & Boriboonsomsin (2008), Koç et al. (2014), and Demir et al. (2014), have already used this model. This model also has several hundreds registered users worldwide (UCR, 2015). Generally, CEME is believed to be an effective second-by-second microscope model.

It is difficult to use microscopic models to estimate emission for rail transport, because often we could not even determine the travel distance by each type of train. So, in this thesis, we use a distance-based method to calculate CO_2 emissions from rail transport, and we name this method as the ton-mile method.

3. Models for Green Distribution Network Design

The GeDND model in this thesis is derived from a general model for logistics network design developed by Cordeau et al. (2006). This general logistics network design model concerns decisions ranging from facility location and capacity choices to supplier and transport mode selection. This is beneficial as there are important interactions between these decisions. The model is flexible, as it can be easily adapted to handle other problem extensions, such as emission constraints and multiple planning periods. In the rest of this chapter, the GeDND model is firstly introduced. Then, four GDND models are presented as the extensions of the GeDND model. Each of the four models addresses a type of environmental policy.

3.1 General Distribution Network Design Model

The notations for the formulation of the GeDND model are:

Sets:

P	Set of potential plant locations
W	Set of potential warehouse locations
C	Set of customers
D	Set of destinations
K	Set of commodities
O	Set of origins
M	Set of vehicle types
O^k	Set of potential origins for commodity k
D^k	Set of potential destinations for commodity k
M_{od}	Set of vehicles types between o and d (There could be more than one type of vehicle for one transport mode)

M_{od}^{k} Set of vehicles types between o and d for commodity k

W^{k} Set of potential warehouse locations where commodity k can be stored

T Set of time periods

Parameters:

a_{c}^{kt} Demand of customer c for commodity k in period t

c_{o} Fixed cost for selecting origin o

c_{o}^{k} Fixed cost for assigning commodity k to origin o

c_{od}^{k} Fixed cost for providing commodity k to destination d from origin o

c_{od}^{m} Fixed cost for using transport mode m between o and d

c_{od}^{km} Unit cost for providing commodity k to d from o by vehicle type m

g_{w}^{k} Cost of holding one unit of commodity k in warehouse w for one period

q_{o} Capacity of origin o in equivalent units

g_{od}^{m} Capacity of vehicle type m between o and d in equivalent units

q_{o}^{k} Upper limit on the amount of commodity k shipped from origin o

q_{od}^{k} Upper limit on the amount of commodity k shipped from o to d

u_{o}^{k} Amount of capacity required by one unit of commodity k at origin o

u^{km} Amount of capacity required by one unit of commodity k in vehicle type m

Variables

X_{od}^{kmt} Amount of commodity k shipped from o to d by vehicle type m in period t

I_{w}^{kt} Inventory of commodity k in warehouse w at the end of period t

U_{o} =1 if origin o is selected, 0 otherwise

V_{o}^{k} =1 if commodity k is assigned to origin o, 0 otherwise

Y_{od}^{k} =1 if origin o provides commodity k to destination d, 0 otherwise

Z_{od}^{m} =1 if vehicle type m is selected between o and d, 0 otherwise

The objective function is:

$$\text{Min} \quad \sum_{o\in O}\Big[c_o U_o + \sum_{d\in D}\sum_{m\in M_{od}} c_{od}^{m}\, Z_{od}^{m}\Big] + \sum_{k\in K}\sum_{o\in O^k}\Big[c_o^k V_o^k + \sum_{d\in D^k}\Big[c_{od}^k Y_{od}^k + \sum_{t\in T}\sum_{m\in M_{od}^k} c_{od}^{km}\, X_{od}^{kmt}\Big]\Big] + \sum_{k\in K}\sum_{w\in W^k}\sum_{t\in T} g_w^k\, I_w^{kt} \tag{1}$$

subject to:

$$\sum_{o\in O^k}\sum_{m\in M_{ow}^k} X_{ow}^{kmt} - \sum_{d\in D^k}\sum_{m\in M_{wd}^k} X_{wd}^{kmt} + I_w^{k,t-1} - I_w^{kt} = 0 \qquad k\in K;\ w\in W^k; t\in T \tag{2}$$

$$\sum_{o\in O^k}\sum_{m\in M_{oc}^k} X_{oc}^{kmt} = a_c^{kt} \qquad k\in K;\ c\in C^k;\ t\in T \tag{3}$$

$$\sum_{k\in K}\sum_{d\in D^k}\sum_{m\in M_{od}^k} u_o^k X_{od}^{kmt} - q_0 U_0 \leq 0 \qquad o\in O; t\in T \tag{4}$$

$$\sum_{d\in D^k}\sum_{m\in M_{od}^k} X_{od}^{kmt} - q_o^k\, V_o^k \leq 0 \qquad k\in K;\ o\in O^k;\ t\in T \tag{5}$$

$$\sum_{m\in M_{od}^k} X_{od}^{kmt} - q_{od}^k\, Y_{od}^k \leq 0 \qquad k\in K;\ o\in O^k; d\in D^k\ ; t\in T \tag{6}$$

$$\sum_{k\in K} u^{km} X_{od}^{kmt} - q_{od}^m\, Z_{od}^m \leq 0 \qquad o\in O;\ d\in D; m\in M_{od}\ ;\ t\in T. \tag{7}$$

Objective function (1) minimizes the sum of all fixed and variable costs, including plant and warehouse selection costs, product assignment costs, vehicle selection costs, inventory-holding costs, and unit transport costs. Constraints (2) ensure the inventory balance at warehouses. Demand constraints are imposed in constraints (3). Constraints (4) impose capacity limits on plants and warehouses, whereas limits per commodity are enforced through constraints (5). Constraints (6) ensure that commodity k is transported from origin o to destination d only when origin o is selected to provide commodity k to destination d. Constraints (7) impose capacity constraints through vehicle type m.

3.2 Green Distribution Network Design Models

The formulations of the four GDND models are presented in this section. We concentrate mainly on how to incorporate CO_2 emissions in these models. The paper by Benjaafar et al. (2013) is used as a reference for incorporating emissions.

3.2.1 Model under Strict Emission Cap

To develop the GDND model under Strict Emission Cap, we only need to add an extra emission inequality to the GeDND model. If we denote the total emissions from all activities in period t as ET_t and the emission cap in period t as EC_t, the emission inequality takes the form:

$$ET_t \leq EC_t \qquad t \in T, \tag{8}$$

where ET_t is obtained by:

$$ET_t = \sum_{o \in O^k} \sum_{d \in D^k} \sum_{k \in K} \sum_{m \in M_{od}^k} e_{od}^{mt} X_{od}^{kmt} \qquad t \in T. \tag{9}$$

Here, e_{od}^{mt} represents the CO_2 emission generated from shipping one unit of commodity from origin o to destination d by vehicle type m in period t. It is an arc-specific emission parameter. Compared to highly integrated emission factors, e_{od}^{mt} considers origin, destination, vehicle type, and period. This helps capture the changes of total emissions among different network designs.

In this thesis, emissions from handling or storing products in warehouses are considered to be negligible. Thus, formula (9) does not include emissions of this type.

3.2.2 Model under Carbon Tax

The GDND model under Carbon Tax is similar to the GeDND model except the objective function. Let us denote c as the cost of emitting one unit of weight of CO_2 given a carbon tax. The objective function of this GDND model is as follows:

$$\text{Min} \quad \sum_{o\in O}\left[c_o U_o + \sum_{d\in D}\sum_{m\in M_{od}} c_{od}^{m} Z_{od}^{m}\right] + \sum_{k\in K}\sum_{o\in O^k}\left[c_o^k V_o^k + \sum_{d\in D^k}\left[c_{od}^k Y_{od}^k + \sum_{t\in T}\sum_{m\in M_{od}^k} c_{od}^{km} X_{od}^{kmt}\right]\right] + \sum_{k\in K}\sum_{w\in W^k}\sum_{t\in T} g_w^k I_w^{kt} + c\sum_{t\in T} ET_t \tag{10}$$

Here, we assume that c remains the same in all periods. In reality, it may change over time.

3.2.3 Model under Cap-and-Trade

The Cap-and-Trade mechanism alters both the objective function and the constraints of the GeDND model. The objective function of the GDND model under Cap-and-Trade is:

$$\text{Min} \quad \sum_{o\in O}\left[c_o U_o + \sum_{d\in D}\sum_{m\in M_{od}} c_{od}^{m} Z_{od}^{m}\right] + \sum_{k\in K}\sum_{o\in O^k}\left[c_o^k V_o^k + \sum_{d\in D^k}\left[c_{od}^k Y_{od}^k + \sum_{t\in T}\sum_{m\in M_{od}^k} c_{od}^{km} X_{od}^{kmt}\right]\right] + \sum_{k\in K}\sum_{w\in W^k}\sum_{t\in T} g_w^k I_w^{kt} + p\sum_{t\in T}(E_t^+ - E_t^-) \tag{11}$$

subject to constraints (2)-(7), and:

$$ET_t \leq EQ_t + E_t^+ - E_t^- \qquad t\in T \tag{12}$$

$$E_t^+,\ E_t^- \geq 0 \qquad t\in T. \tag{13}$$

Here, p is the price of buying or selling one unit of emission credit, and EQ_t denotes the free emission quota during period t. The variable E_t^+ denotes the amount of emission credits bought in period t while E_t^- denotes the amount of emission credits sold in period t. The assumption on p is that the selling price of emission credit equals the buying price, and this price remains the same in all periods. When we need to differentiate the price of buying from that of selling, the objective function can be modified by associating prices $p^{+}$and $p^{-}$with $E_t^{+}$and E_t^{-}, respectively. When we need to consider the changes of p as time goes on, p needs to be replaced by p_t, which is the average price of buying or selling one unit of emission credit in period t.

3.2.4 Model under Cap-and-Offset

The Cap-and-Offset mechanism also alters both the objective function and the constraints of the GeDND model. The objective function of the GDND model under Cap-and-Offset is:

$$\text{Min} \quad \sum_{o\in O}\left[c_o U_o + \sum_{d\in D}\sum_{m\in M_{od}} c_{od}^{m} Z_{od}^{m}\right] + \sum_{k\in K}\sum_{o\in O^k}\left[c_o^k V_o^k + \sum_{d\in D^k}\left[c_{od}^{k} Y_{od}^{k} + \sum_{t\in T}\sum_{m\in M_{od}^{k}} c_{od}^{km} X_{od}^{kmt}\right]\right] + \sum_{k\in K}\sum_{w\in W^k}\sum_{t\in T} g_w^k I_w^{kt} + \propto \sum_{t\in T} EI_t^{+} \qquad (14)$$

subject to constraints (2)-(7), and:

$$ET_t \le EQ_t + EI_t^{+} \qquad t\in T \qquad (15)$$

$$EI_t^{+} \ge 0 \qquad t\in T. \qquad (16)$$

Here, $\propto$ denotes the price per unit of carbon offset, and EI_t^{+} is the total amount of carbon offsets invested in period t.

4. Emission Parameter Calculation

In Chapter 3, we used formula (9) to compute the total period emissions of a distribution network.

$$ET_t = \sum_{o \in O^k} \sum_{d \in D^k} \sum_{k \in K} \sum_{m \in M_{od}^k} e_{od}^{mt} X_{od}^{kmt} \qquad t \epsilon T, \tag{9}$$

where e_{od}^{mt} represents the CO_2 emission of shipping one unit of commodity from origin o to destination d by vehicle type m in period t.

In fact, many of the reviewed papers in Chapter 2 use a similar formula to compute network emissions. But, none of them explain in depth how they obtain the values of the emission parameters in their paper. This chapter explains how we compute the value of e_{od}^{mt}, which is essential for accurately estimating total emissions.

In the rest of this chapter, we first introduce how to compute the value of e_{od}^{mt} for road transport. Then, we introduce the way to compute the value of e_{od}^{mt} for rail transport.

4.1 Emission Values Calculation for Road Transport

We compute the value of e_{od}^{mt} for road transport based on the Comprehensive Modal Emission Model (CMEM). The fuel consumption F^m (in liters) of vehicle type m over a distance L with speed v and vehicle total weight G^m (curb weight plus vehicle payload, in kilogram) is calculated as:

$$F^{\,m} = \lambda({f_r}^m N^m V^m L/v + G^m \gamma^m \alpha L + \beta^m \gamma^m L v^2), \tag{17}$$

where:

$$\lambda = \xi/(\phi\psi) \tag{18}$$

$$\gamma^m = 1/1000 n_f \eta \tag{19}$$

$$\alpha = \tau + g sin\theta + g C_r cos\theta \quad (20)$$

$$\beta^m = 0.5 C^m \rho A^m. \quad (21)$$

Here, ${f_r}^m N^m V^m L/v$ is the engine module, which is linear in the travel time. The term $G^m \gamma^m \alpha L$ is the weight module. Finally, $\beta^m \gamma^m L v^2$ is the speed module, which is quadratic in speed.

There are two types of parameters. The first is vehicle-common parameters. The values for these parameters remain the same no matter which truck is being used (see Table 3). The second is vehicle-specific parameters. The values for these parameters vary when different types of trucks are used[1].

Table 3 BD truck type Vehicle-common parameters (Koç et al., 2014)

Notation	Description	Typical values
ξ	Fuel-to-air mass ratio	1
g	Gravitational constant $(\mathrm{m/s^2})$	9.81
ρ	Air density $(\mathrm{kg/m^3})$	1.2041
C_r	Coefficient of rolling resistance	0.01
η	Efficiency parameter for diesel engines	0.45
ϕ	Heating value of a typical diesel fuel $(\mathrm{kj/g})$	44
ψ	Conversion factor $(\mathrm{g/s\ to\ liter/s})$	737
n_f	Vehicle drive train efficiency	0.45
v^l	Lower speed limit (m/s)	5.5
v^u	Upper speed limit $(\mathrm{m/s})$	27.8
θ	Road angle	0
τ	Acceleration $(\mathrm{m/s^2})$	0

[1]Some symbols for parameters and variables from Koç et al. (2014) have been replaced by the new ones in Table 3, in order to be consistent with the notation introduced in Chapter 3.

The notations for vehicle-specific parameters are:

w^m Curb weight of vehicle type m (kg)

Q^m Maximum payload of vehicle type m (kg)

f_r^m Engine friction factor of vehicle type m (kg/rev/liter)

N^m Engine speed of vehicle type m (rev/s)

V^m Engine displacement of vehicle type m (liter)

C^m Coefficient of aerodynamics drag of vehicle type m

A^m *Frontal surface area of vehicle type* m (m^2)

Based on formula (17), the value of e_{od}^{mt} for road transport is estimated by:

$$e_{od}^{mt} = f_{co2}\lambda({f_r}^m N^m V^m L_{od}/v_{od}^{mt} + G_{od}^{mt}\gamma^m \alpha L_{od} + \beta^m \gamma^m L_{od}(v_{od}^{mt})^2)/\, Q_{od}^{mt}$$

$$o \in O; d \in D\ ;\ m\ \in M_{od}^1\ \ t \in\ T, \tag{22}$$

$$\mathrm{G}_{od}^{mt} = Q_{od}^{mt} + w^m. \tag{23}$$

Here, f_{co2} is the CO_2 emission of burning one unit of weight or volume of fuel. It is believed that fuel consumption and CO_2 emission are proportionally related (Koç et al., 2014). Thus, CO_2 emissions can be estimated through fuel consumptions using f_{co2}. The parameters L_{od} is the distance between origin o to destination d v_{od}^{mt} is the average speed of truck type m from origin o to destination d in period t, G_{od}^{mt} is the average total weight (curb weight plus payload) of truck type m traveling from origin o to destination d in period t, Q_{od}^{mt} is the average payload of truck type m traveling from origin o to destination d in period t, w^m is the curb weight of vehicle type m, and M_{od}^1 is the available truck types between origin o to destination d.

4.2 Emission Values Calculation for Rail Transport

With the ton-mile method, the emission of shipping one unit of commodity over distance L is calculated by:

$$E_{rail} = fL, \tag{24}$$

where f is an emission factor based on average loading and fuel efficiency for various rail freight operations (GOV. UK, 2014).

Based on formula (24), the value of e_{od}^{mt} for rail transport can be estimated by:

$$e_{od}^{mt} = f_t^m L_{od} \qquad o \in O; d \in D\ ; m \in M_{od}^2;\ t \in\ T, \qquad (25)$$

where f_t^m denotes the CO_2 emission of shipping one unit of commodity for one unit of distance by vehicle type m in period t, L_{od} is the distance between origin o and destination d, and M_{od}^2 is the set of train types between origin o and destination $d.$ The values of f_t^m can be obtained from governmental reports, such as the 2014 Emission Factor Report by the EPA (EPA, 2014). For example, this report indicates that the average CO_2 emission of shipping one ton of products for one mile by US trains in 2014 is 0.026 kilogram (kg).

5. Case study: an Energy Company

BD is a leading energy company in the world (the case company is named as BD due to confidentiality reasons). The company has a refinery plant in Ontario, where it produces 99 categories of bulk lubricant oil products that are sold all over North America. In 2014, BD sold more than 40 million US gallons (USG) of these products to its 168 customers in North America. It is assumed that the yearly demand of these products will increase continuously in the next ten years. By 2024, the total demand is expected to triple. Also, it is assumed that its customer base will not change much in the next decade.

BD is in the process of optimizing many aspects of its logistics network. Among those is the distribution of its bulk lubricant oil products in North America. The current distribution network for these products has five warehouses and one plant (see Figure 7). Between the plant and the warehouses, part of the products are shipped by trains, while the rest are by trucks. Between the warehouses and end customers, trucks do all the shipments. In the new distribution network design, BD wants to determine the optimal number of warehouses and the best combination of transport modes for the next 10 years. BD can choose warehouses and transport modes from its current available ones. Besides, BD has realized the necessity to incorporate environmental considerations in its network design phase. Therefore, we implement both the GeDND and GDND for BD.

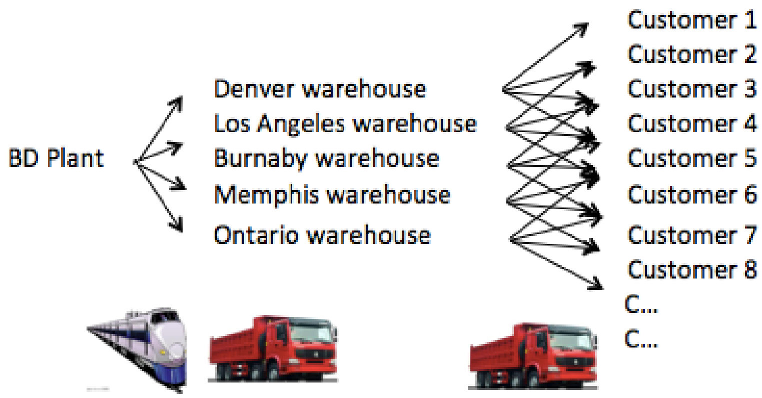

Figure 2 Current network structure of BD

In the rest of this chapter, we first compute the value of the parameter e_{od}^{mt}. Then, we design an optimal distribution network using the GeDND model. Later on, we adopt the four GDND models to design optimal green distribution network for BD, separately.

5.1 Emission Parameter Calculation for BD

This section explains how we compute the value of e_{od}^{mt} to calculate BD's total network emissions. As BD can choose both road and rail transport, the value of e_{od}^{mt} for road and rail transport are computed separately in the following sections.

5.1.1 Road Transport

To compute the value of e_{od}^{mt} by the CEME model, we need to know the values of vehicle specific parameters, which are determined by the specific truck types used in BD's distribution network. However, it is impossible to know exactly what types of trucks BD will use in the next ten years. We assume that the truck types BD will use in the next ten years remain almost the same as the ones in current period, except that the fuel efficiencies of the future trucks will be higher. With this assumption, we compute the value of e_{od}^{mt} for the future network by:

$$e_{od}^{mt} = \varpi^t e_{od}^{m0} \quad o \in O; d \in D\,; m \in M_{od}^1;\ t \in T, \tag{26}$$

where e_{od}^{m0} represents the CO_2 emission of shipping one unit of commodity from origin o to destination d by vehicle type m in period 0, ϖ^t is the emission reduction coefficient in period t, and T is the set of 10 periods (each period is one year). The parameter ϖ^t is derived from the projected improvement of engine efficiency of trucks in period t when compared with current period 0. We assume that ϖ^t is less than one, because in reality the engine efficiency of vehicles is improving all the time. This is partly stimulated by governmental regulations. To know more about how the values of ϖ^t are obtained, the reader is referred to Appendix 2 of this thesis.

The values for e_{od}^{m0} are obtained by:

$$e_{od}^{m0} = f_{co2}\lambda({f_r}^m N^m V^m L_{od}/v_{od}^{m0} + G_{od}^{m0}\gamma^m \alpha L_{od} + \beta^m \gamma^m L_{od}(v_{od}^{m0})^2)/\,\mathrm{Q}_{od}^{m0}$$
$$o \in O; d \in D\,;\ m \in M_{od}^1\,. \tag{26}$$

Here, v_{od}^{m0} represents the average speed of vehicle type m from origin o to destination d in period 0, G_{od}^{m0} is the average total weight (curb weight plus payload) of vehicle type m traveling from origin o to destination d in period 0, Q_{od}^{m0} is the average payload of vehicle type m traveling from origin o to destination d in period 0, and M_{od}^1 is the set of truck types between origin o to destination d.

The arc distances are all known; BD provided them all. The values of vehicle common parameters remain the same as those from Koç et al. (2014) (see Table 3 in Section 4.1). We need to determine the values for vehicle specific parameters and the value for f_{co2}.

We started by collecting the details of the trucks used in BD's current network.

However, it is difficult to get such detailed information as the engine types and curb weights of the trucks, because BD is using a 3PL for its distribution service. What we did is to utilize the known information to make assumptions about the trucks and then get the values of vehicle specific parameters. We learned from BD that a homogenous fleet is used, and the average payload of the trucks is 23,470 USG. We also learned that the weight of 1 USG of products equals to 1 kg or 2.205 US pounds (lbs). Thus, the average payload of the trucks is 23,470 kg or 51,751 lbs. With this information, we investigated the North American truck market. Then, we made assumptions about the details of the trucks used in BD's current network (see Table 4) and the values of vehicle specific parameters (see Table 5). For example, in the US, a truck that can carry more than 25,000 lbs of goods belongs to Class 8 (EPA & NHTSA, 2015). So, we assume that BD is using Class 8 trucks. Class 8 trucks in the US mostly use diesel fuel. We thus assume that f_{co2} is 2.70 kg per liter by referring to the EPA emission report (EPA, 2014). To know more how we made all those assumptions, the reader is referred to Appendix 1 of this thesis.

Table 4 BD truck type

Truck	Class 8 sleeper cab
	DD15L Detroit Diesel Engine
	Middle roof
	53-feet trailer with Max volume 3800 cubic feet
	Maximum Weight of 80,000lbs from governmental regulation

Table 5 BD truck specific parameters

Notation	Description	Heavy duty
w^m	Curb weight of vehicle type m (kg)	13,040.78
Q^m	Maximum payload of vehicle type m (kg)	34,068
f_r^m	Engine friction factor of vehicle type m (kg/rev/liter)	0.15
N^m	Engine speed of vehicle type m (rev/s)	22.5
V^m	Engine displacement of vehicle type m (liter)	14.8
C^m	Coefficient of aerodynamics drag of vehicle type m	0.87
A^m	Frontal surface area of vehicle type m (m^2)	5.6

5.1.2 Rail Transport

Similar to road transport, we also use e_{od}^{m0} as a reference to compute the values of e_{od}^{mt} for rail transport by:

$$e_{od}^{mt} = \varpi^t e_{od}^{m0} \qquad o \in O; d \in D\,; m \in M_{od}^2;\ t \in\ T, \tag{27}$$

where:

$$e_{od}^{m0} = f_0^m L_{od} \qquad o \in O; d \in D\,; m \in M_{od}^2;\ t \in\ T. \tag{28}$$

Here, e_{od}^{m0} represents the CO_2 emission of shipping one unit of commodity from from origin o to destination d by vehicle type m in current period 0, and f_0^m is the CO_2 emission of shipping one unit of commodity for one unit of distance by vehicle type m in current period 0. We also adopt the parameter ϖ^t to account for the improvement of engine efficiency of trains.

It is difficult to know what types of trains are used in the current network. It is even more difficult to know the exact distances traveled by each type of train. We thus assume that f_0^m is fixed, no matter which type of train is used. According to the emission report by the EPA (EPA, 2014), the CO_2 emission of shipping one ton of products for one mile by rail transport is 0.026 kg. Hence, f_0^m= 0.026 kg / ton-mile.

5.2 General Distribution Network Design

The formulation of the GeDND model was coded in C++ with CPLEX 12.6.0.1 (Cordeau et al., 2006). The optimality tolerance was set to 0.01. The maximum computating time was 7200 seconds. The problem was solved on one of two Intel(R) Xeon(R) CPU X5675 3.07 GHz processors of a machine with 96 GB of RAM.

It took 2.38 seconds to find a solution with an optimality gap of 0.079%. All of the five warehouses were selected. Whenever there was a cheaper transport mode on an arc, the solution always chose the cheaper one. To protect confidentiality, the total cost and emission of the solution are not disclosed. They are set as the baselines for comparison in the following part of this chapter.

5.3 Green Distribution Network Design

So far, none of the four types of environmental polices has an actual impact on freight transport by 3PLs in the US (GOV. UK, 2014). However, they all have a chance to be enforced in the USA within the next 10 years. Thus, we explore GDND under each type of environmental policy. In this section, all the GDND problems were solved on the same machine with the same optimality tolerance and the same maximum computing time as the GeDND problem. This ensures that the results are comparable.

5.3.1 Distribution Network Design under Strict Emission Cap

The GeDND problem from Section 5.2 is imposed with neither emission constraints nor carbon costs. Thus, the total emission of its optimal solution ($\sum_{t \in T} ET_t$), if not the highest, is high. We name this emission as the baseline emission, and we use it as the basis to set up nine caps for the total emissions of the coming ten years as in Table 6. Then, each cap emission is further divided among the 10 years to obtain 10 period emission caps as in Table 7. The period emission caps are determined based on the period demand. For example, for scenario 1, the emission cap for the first period (EC_1) is computed by:

$$EC_1 = ET_1^b * 99\%$$

ET_1^b= (Per1 demand/Total demand)*Baseline emission,

where "Total demand" covers the demands from all 10 periods.

Table 6 Total emission caps set up

Base	Total emission cap of Scenario 1	Total emission cap of Scenario 2	Total emission cap of Scenario 3	Total emission cap of Scenario 4	Total emission cap of Scenario 5	Total emission cap of Scenario 6	Total emission cap of Scenario 7	Total emission cap of Scenario 8	Total emission cap of Scenario 9
Baseline emission	99% of Baseline emission	97% of Baseline emission	95% of Baseline emission	92% of Baseline emission	90% of Baseline emission	87% of Baseline emission	86% of Baseline emission	85% of Baseline emission	84% of Baseline emission

Table 7 Period emission caps set up

Base	EC_t (Scenario 1)	EC_t (Scenario 2)	EC_t (Scenario 3)	EC_t (Scenario 4)	EC_t (Scenario 5)	EC_t (Scenario 6)	EC_t (Scenario 7)	EC_t (Scenario 8)
ET_1^b	99% of ET_1^b	97% of ET_1^b	95% of ET_1^b	92% of ET_1^b	90% of ET_1^b	87% of ET_1^b	86% of ET_1^b	85% of ET_1^b
ET_2^b	99% of ET_2^b	97% of ET_2^b	95% of ET_2^b	92% of ET_2^b	90% ofET_2^b	87% of ET_2^b	86% of ET_2^b	85% of ET_2^b
ET_3^b	99% of ET_3^b	97% of ET_3^b	95% of ET_3^b	92% of ET_3^b	90% ofET_3^b	87% of ET_3^b	86% of ET_3^b	85% of ET_3^b
ET_4^b	99% of ET_4^b	97% of ET_4^b	95% of ET_4^b	92% of ET_4^b	90% ofET_4^b	87% of ET_4^b	86% of ET_4^b	85% of ET_4^b
ET_5^b	99% of ET_5^b	97% of ET_5^b	95% of ET_5^b	92% of ET_5^b	90% ofET_5^b	87% of ET_5^b	86% of ET_5^b	85% of ET_5^b
ET_6^b	99% of ET_6^b	97% of ET_6^b	95% of ET_6^b	92% of ET_6^b	90% ofET_6^b	87% of ET_6^b	86% of ET_6^b	85% of ET_6^b
ET_7^b	99% of ET_7^b	97% of ET_7^b	95% of ET_7^b	92% of ET_7^b	90% ofET_7^b	87% of ET_7^b	86% of ET_7^b	85% of ET_7^b
ET_8^b	99% of ET_8^b	97% of ET_8^b	95% of ET_8^b	92% of ET_8^b	90% ofET_8^b	87% of ET_8^b	86% of ET_8^b	85% of ET_8^b
ET_9^b	99% of ET_9^b	97% of ET_9^b	95% of ET_9^b	92% of ET_9^b	90% ofET_9^b	87% of ET_9^b	86% of ET_9^b	85% of ET_9^b
ET_{10}^b	99% of ET_{10}^b	97% of ET_{10}^b	95% of ET_{10}^b	92% of ET_{10}^b	90% ofET_{10}^b	87% of ET_{10}^b	86% of ET_{10}^b	85% of ET_{10}^b

From scenario 1 to scenario 9, the emission caps become stricter and stricter. We found an optimal solution for all scenarios except for scenario 9. For scenario 9, no feasible solutions were found, as its emission caps are too strict. All solutions were found in less than 8 seconds, and their optimality gaps were less than 0.95%**.** All of the five warehouses of BD were selected. Whenever there was a cheaper transport mode on an arc, the solution always chose the cheaper one. Here we notice that the result of transport mode selection remain the same as that in GeDND in Section 5.2. This is because the cheaper transport mode, which is rail transport here, is also the one with lower emissions. So, when all the arcs in GeDND have already chosen the cheaper mode, the arcs in GDND will continue to choose the cheap one, in order to keep both emission and cost low.

Comparisons between the result of the GeDND and each of those to scenarios 1-9 are given in Figure 3. The total cost and emission (denoted as "Base" in Figure

3) of the GeDND are set as the baselines for comparison.

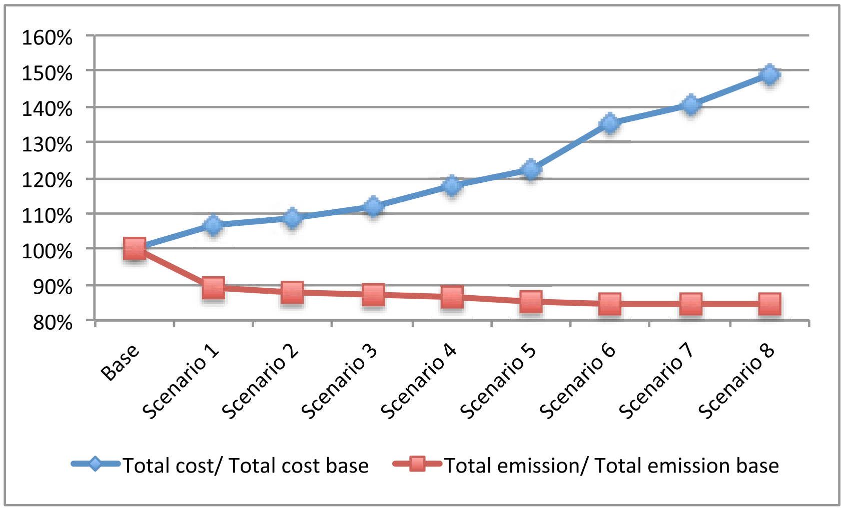

Figure 3 Total costs and emissions of the optimal solutions under Strict Emission Cap

Figure 3 indicates that from Scenario 1 to 8, when emission caps become stricter, total emissions drop but total costs increase. This is achieved by selecting shorter routes for some of the product shipment when the emission constraints become tighter. For example, product A is assigned to Warehouse Los Angeles in scenario 1, but is assigned to Warehouse Memphis in scenario 7. In scenario 7, the emission from shipping product A is lower than in scenario 1, because the shipping distance via Warehouse Memphis is shorter than the shipping distance via Warehouse Los Angeles. However, much higher warehouse-related costs occur when using warehouse Memphis. So, the shipment for product A in scenario 7 emits less that in scenario 1, but costs much more.

Figure 3 indicates that when emission caps are loose, such as from scenario 1 to 3, BD has a good chance to reduce emission by around 10% while also causing around 10% increase in cost. But, when emission caps are very strict, such as in scenario 8, an emission reduction of 16% may cause 49% more of cost.

5.3.2 Distribution Network Design under Carbon Tax

To see how Carbon Tax impacts optimal distribution network designs, a broad range of potential values for c (the price of emitting one unit of weight of CO_2 given a carbon tax) were selected arbitrarily among its possible value scope (see Table 8). The scope was determined by referring to the carbon taxes in other countries. For example, in British Columbia in 2012, the carbon tax was at 30 Canadian dollars per metric ton. In Ireland, the carbon tax was at 10 euro per metric ton in 2012 (CTC, 2015).

Table 8 Value settings for c (the price of emitting one unit of weight of CO_2 given a carbon tax)

C (US Dollar/ kg)
0.000003
0.00003
0.0003
0.003
0.036
0.06
0.09
0.12
0.15
0.3
0.6
1.2
4.8
7.2
9.6
13
20
30
60
120

Each value of c creates a different scenario. For each scenario, an optimal solution was found in less than 3 seconds. The optimality gaps lay between 0.22% and 0.56%. All of the five warehouses of BD were selected. Whenever there was a cheaper transport mode on an arc, the solution always chose the cheaper one. The total costs, total logistics costs, and total emissions (in comparison with the base scenario) of the optimal solutions are given in Table 9 and Figure 4.

Table 9 Total costs and emissions of the optimal solutions under Carbon Tax

c (US dollor/ kg)	Total cost/Total cost base	Total logistics cost (Total cost minus total emission cost)	Total emisson/Total emission base
Base(*c=0*)	100.00%	100.00%	100.00%
0.000003	100.00%	100.00%	100.00%
0.00003	100.00%	100.00%	100.00%
0.0003	100.01%	100.00%	100.00%
0.003	100.15%	100.00%	100.00%
0.036	101.77%	100.00%	100.00%
0.06	102.95%	100.04%	98.22%
0.09	104.40%	100.05%	98.09%
0.12	105.85%	100.06%	97.80%
0.15	107.30%	100.09%	97.47%
0.3	114.49%	100.19%	96.69%
0.6	128.90%	100.88%	94.72%
1.2	156.05%	102.46%	90.57%
4.8	313.50%	106.60%	87.42%
7.2	416.13%	110.72%	86.03%
9.6	517.68%	112.05%	85.69%
13	660.97%	114.30%	85.29%
20	955.03%	115.50%	85.13%
30	1374.49%	117.81%	84.96%
60	2628.38%	125.26%	84.61%
120	5125.63%	137.39%	84.31%

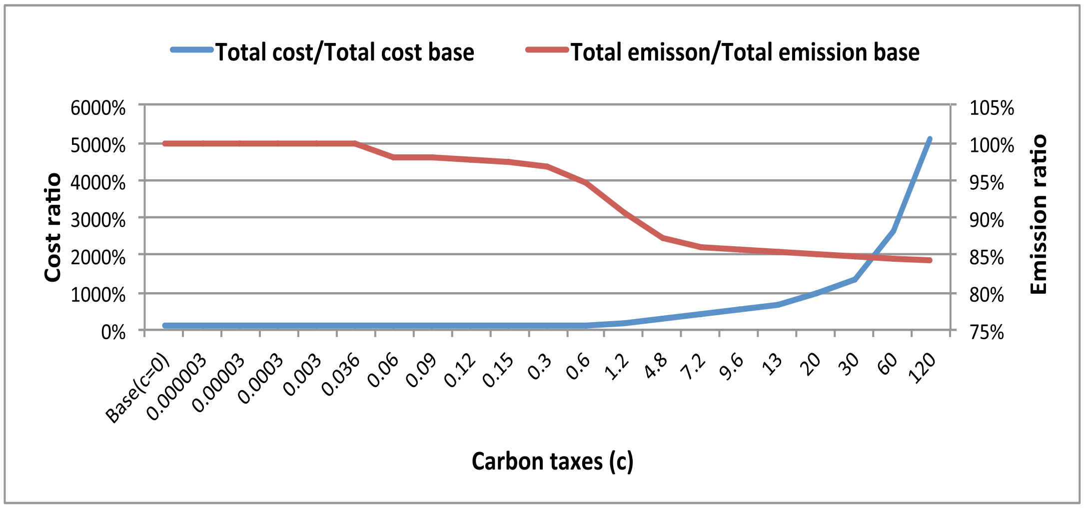

Figure 4 Total costs and emissions of the optimal solutions under Carbon Tax

Figure 4 shows that when c increases from zero to 0.003, the total emissions of the optimal solutions almost do not change. This suggests that c is too small to trigger emission reduction. When c increases from 0.003 to 0.06, there is a slight emission reduction of 2% accompanying a slight cost increase of 3%. When c increases from 0.06 to 7.2, the total emission drops by 12%, but the total cost increases by 314%. When c is beyond 7.2, the total emissions almost do not change anymore, though the total costs increase wildly. This is because all products have already been assigned a shortest route from origin to destination.

5.3.3 Distribution Network Design under Cap-and-Trade

Let us recall the objective function (11) for this problem:

$$\text{Min} \quad \sum_{o\in O}\left[c_o U_o + \sum_{d\in D}\sum_{m\in M_{od}} c_{od}^{m} Z_{od}^{m}\right] + \sum_{k\in K}\sum_{o\in O^k}\left[c_o^k V_o^k + \sum_{d\in D^k}\left[c_{od}^k Y_{od}^k + \sum_{t\in T}\sum_{m\in M_{od}^k} c_{od}^{km} X_{od}^{kmt}\right]\right] + \sum_{k\in K}\sum_{w\in W^k}\sum_{t\in T} g_w^k I_w^{kt} + p\sum_{t\in T}(E_t^+ - E_t^-) \tag{11}$$

subject to constraints (2)-(7), and:

$$ET_t \leq EQ_t + E_t^+ - E_t^- \qquad t\in T \tag{12}$$

$$E_t^+, E_t^- \geq 0, \qquad t\in T. \tag{13}$$

Here, p is the price of buying or selling one unit of emission credits, EQ_t is the free emission quota in period t, E_t^+ denotes the amount of emission credits bought in period t, and E_t^- denotes the amount of emission credits sold in period t. When $E_t^+ - E_t^- > 0$, it means that during period t, more emission credits are bought than sold, and vice-versa.

To see how Cap-and-Trade may impacts the optimal distribution network design, a group of values for p, ranging from very low to very high, are selected arbitrarily as in Table 10.

Table 10 Value settings for emission credits (p)

p **(US Dollar/ kg)**
0.000003
0.00003
0.0003
0.003
0.036
0.6
1.2
4.8
20
30

Similar to the method used in Section 5.3.1 to determine emission caps, we first use the baseline emission to set up 8 total free emission quotas. Then, each quota is further divided among the 10 periods to get 10 period free emission quotas EQ_t as in Table 11.

Table 11 Value settings for period free emission quota (EQ_t)

Base	EQ_t (Scenario 1)	EQ_t (Scenario 2)	EQ_t (Scenario 3)	EQ_t (Scenario 4)	EQ_t (Scenario 5)	EQ_t (Scenario 6)	EQ_t (Scenario 7)	EQ_t (Scenario 8)
ET_1^b	99% of ET_1^b	97% of ET_1^b	95% of ET_1^b	92% of ET_1^b	90% of ET_1^b	87% of ET_1^b	86% of ET_1^b	85% of ET_1^b
ET_2^b	99% of ET_2^b	97% of ET_2^b	95% of ET_2^b	92% of ET_2^b	90% of ET_2^b	87% of ET_2^b	86% of ET_2^b	85% of ET_2^b
ET_3^b	99% of ET_3^b	97% of ET_3^b	95% of ET_3^b	92% of ET_3^b	90% of ET_3^b	87% of ET_3^b	86% of ET_3^b	85% of ET_3^b
ET_4^b	99% of ET_4^b	97% of ET_4^b	95% of ET_4^b	92% of ET_4^b	90% of ET_4^b	87% of ET_4^b	86% of ET_4^b	85% of ET_4^b
ET_5^b	99% of ET_5^b	97% of ET_5^b	95% of ET_5^b	92% of ET_5^b	90% of ET_5^b	87% of ET_5^b	86% of ET_5^b	85% of ET_5^b
ET_6^b	99% of ET_6^b	97% of ET_6^b	95% of ET_6^b	92% of ET_6^b	90% of ET_6^b	87% of ET_6^b	86% of ET_6^b	85% of ET_6^b
ET_7^b	99% of ET_7^b	97% of ET_7^b	95% of ET_7^b	92% of ET_7^b	90% of ET_7^b	87% of ET_7^b	86% of ET_7^b	85% of ET_7^b
ET_8^b	99% of ET_8^b	97% of ET_8^b	95% of ET_8^b	92% of ET_8^b	90% of ET_8^b	87% of ET_8^b	86% of ET_8^b	85% of ET_8^b
ET_9^b	99% of ET_9^b	97% of ET_9^b	95% of ET_9^b	92% of ET_9^b	90% of ET_9^b	87% of ET_9^b	86% of ET_9^b	85% of ET_9^b
ET_{10}^b	99% of ET_{10}^b	97% of ET_{10}^b	95% of ET_{10}^b	92% of ET_{10}^b	90% of ET_{10}^b	87% of ET_{10}^b	86% of ET_{10}^b	85% of ET_{10}^b

Combining the values of EQ_t and p, we create 42 scenarios. The time to find an optimal solution for each scenario lay between 2.21 and 2.89 seconds. The optimality gap ranged from 0.09% to 0.6%. All of the five warehouses were selected for each scenario. Whenever there was a cheaper transport mode on an arc, the solution always chose the cheaper one.

The total costs and emissions as a proportion of their respective value in the base scenario are given in Table 12. In this table, the cost of a scenario is divided by the cost of the base scenario. Similarly, the emission of a scenario is divided by the emission of the base scenario. We note that some negative values are associated with the cost ratios. For example, the scenario with EQ_t = 99% of base and p=30 has a total cost of around -90%, implying that the total cost from this scenario is negative. Furthermore, the total emission from this scenario is 85%. This means that the total emission of the optimal solution of this scenario accounts for only 85% of the total emission of the base scenario. However, the emission quota for this scenario is 99% of the total emission of the base scenario. So, the unused emission quota (99% of base minus 85% of base) is sold in carbon market. As the price of carbon credit (p) is so high here: 30 US dollars per kg, the profit from selling the unused emission quota reduces the total cost to a negative value.

Table 12 Total costs and emissions of the optimal solutions under Cap-and-Trade

EQ_t \ p		0.000003	0.00003	0.0003	0.003	0.036	0.6	1.2	4.8	20	30
0.99 of Base	Total cost	100%	100%	100%	100%	100%	100%	98%	79%	-21%	-90%
	Total emission	100%	100%	100%	100%	100%	95%	90%	87%	85%	85%
0.97 of Base	Total cost	100%	100%	100%	100%	100%	100%	99%	84%	-2%	-60%
	Total emission	100%	100%	100%	100%	100%	95%	90%	87%	85%	85%
0.95 of Base	Total cost	100%	100%	100%	100%	100%	101%	100%	89%	18%	-31%
	Total emission	100%	100%	100%	100%	100%	95%	90%	87%	85%	85%
0.92 of Base	Total cost	100%	100%	100%	100%	100%	102%	102%	96%	48%	14%
	Total emission	100%	100%	100%	100%	100%	95%	90%	87%	85%	85%
0.90 of Base	Total cost	100%	100%	100%	100%	100%	102%	103%	100%	68%	43%
	Total emission	100%	100%	100%	100%	100%	95%	91%	87%	85%	85%
0.87 of Base	Total cost	100%	100%	100%	100%	100%	103%	105%	107%	97%	88%
	Total emission	100%	100%	100%	100%	100%	95%	91%	87%	85%	85%
0.86 of Base	Total cost	100%	100%	100%	100%	100%	103%	105%	110%	107%	102%
	Total emission	100%	100%	100%	100%	100%	95%	90%	87%	85%	85%
0.85 of Base	Total cost	100%	100%	100%	100%	100%	104%	106%	112%	117%	117%
	Total emission	100%	100%	100%	100%	100%	95%	90%	87%	85%	85%

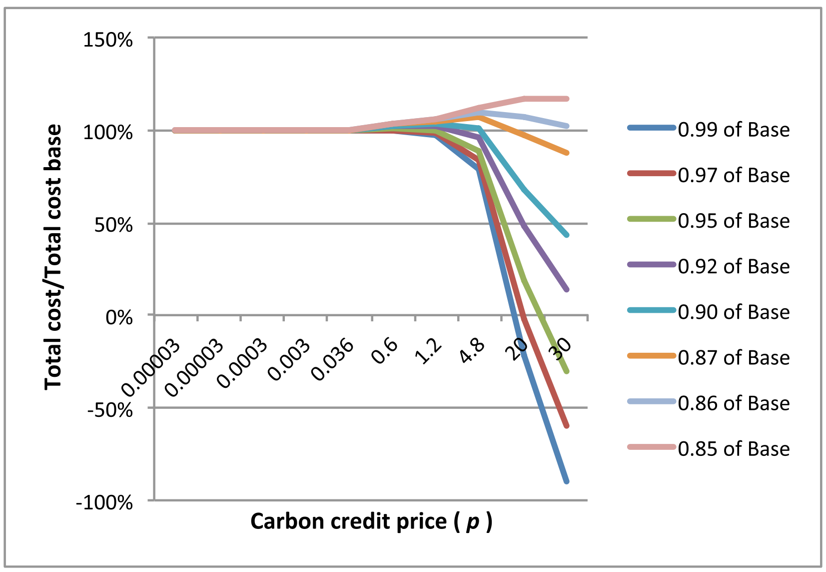

Figure 5 Total costs of the optimal solutions under Cap-and-Trade

Figure 5 shows the total costs (in comparison with the base scenario) of the optimal solutions. One can see that when p is beyond 0.036, loose emission caps lead to a cost reduction, while strict mission caps lead to a cost increase.

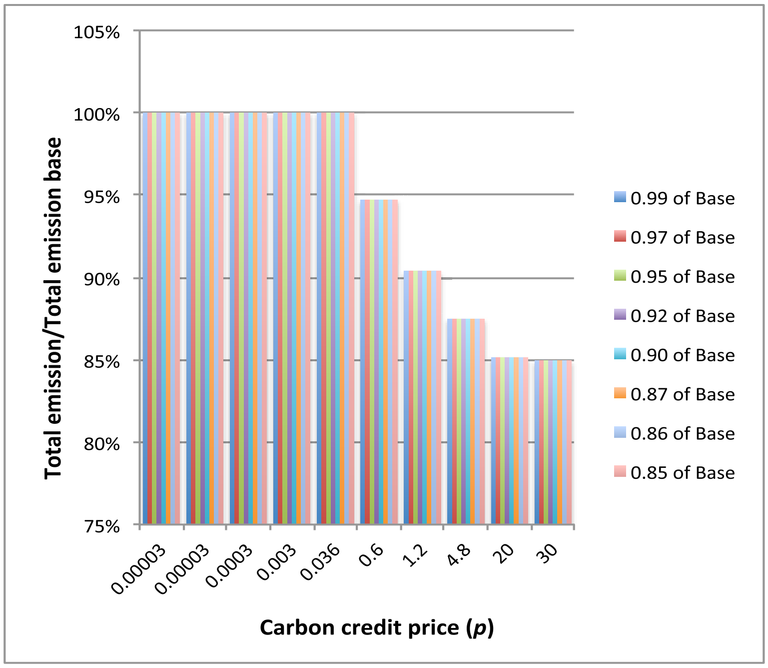

Figure 6 Total emissions of the optimal solutions under Cap-and-Trade

Figure 6 indicates when the price of carbon credit (p) is fixed, the total emissions of the optimal solutions remain the same, no matter how the free emission quotas change. This is because during each network optimization process, there is always a balance point, at which reducing emissions through network adjustment costs as much as buying emission rights. The secenarios with the same p value share the same balance point. The process of network adjustment stops once reaching this balance point, because after this point, it is cheaper to buy emission credits in order to emit more than the free emission. However, total emissions drop along with the increase of p. This is because when p increases, the balance point moves. At the new balance point, reducing emission through network adjustment costs more, because more emsssion is reduced. Thus, the total emission is lower once p becomes bigger.

5.3.4 Distribution Network Design under Carbon-and-Offset

Let us recall the objective function (14) for this problem:

$$\text{Min} \quad \sum_{o\in O}\Big[c_o U_o + \sum_{d\in D}\sum_{m\in M_{od}} c_{od}^{m} Z_{od}^{m}\Big] + \sum_{k\in K}\sum_{o\in O^k}\Big[c_o^k V_o^k + \sum_{d\in D^k}\Big[c_{od}^{k} Y_{od}^{k} + \sum_{t\in T}\sum_{m\in M_{od}^{k}} c_{od}^{km} X_{od}^{kmt}\Big]\Big] + \sum_{k\in K}\sum_{w\in W^k}\sum_{t\in T} g_w^k I_w^{kt} + \propto \sum_{t\in T} EI_t^{+} \quad (14)$$

subject to constraints (2)-(7), and:

$$ET_t \le EQ_t + EI_t^{+} \qquad t\in T \qquad (15)$$

$$EI_t^{+} \ge 0, \qquad t\in T. \qquad (16)$$

Here, the parameter $\propto$ denotes the price per unit of carbon offsets, and EI_t^{+} denotes the total amount of carbon offset invested in period t.

The same groups of values of EQ_t from Section 5.3.3 are used to set the values of EQ_t under Carbon-and-Offset. Also, we use the same group of values of p from Section 5.3.3 to set the values of $\propto$.

Combining the values of EQ_t and $\propto$, we create 42 scenarios. The time to find an optimal solution for each scenario lay between 2.35 to 6.01 seconds. The optimality gap ranged from 0.07% to 0.6%. For each solution, all of the five warehouses were selected. Whenever there was a cheaper transport mode on an arc, the solution always chose the cheaper one.

The total costs and emissions (in comparison with the base scenario) of the optimal solutions are given in Table 13. This table shows that when p=30, 15% of emission reduction could be achieved, and it always accompanies a cost increase.

Table 13 Total costs and emissions of the optimal solutions under Carbon-and-Offset

EQ_t \ ∝ (US Dollar/kg)		0.000003	0.00003	0.0003	0.003	0.036	0.6	1.2	4.8	20	30
99% of Base	Total cost	100.00%	100.00%	100.00%	100.00%	100.02%	100.04%	100.04%	100.04%	100.04%	100.04%
	Total emission	100.00%	100.00%	100.00%	100.00%	100.00%	99.00%	99.00%	99.00%	99.00%	99.00%
97% of Base	Total cost	100.00%	100.00%	100.00%	100.00%	100.05%	100.12%	100.12%	100.12%	100.12%	100.12%
	Total emission	100.00%	100.00%	100.00%	100.00%	100.00%	97.00%	97.00%	97.00%	97.00%	97.00%
95% of Base	Total cost	100.00%	100.00%	100.00%	100.01%	100.09%	100.80%	100.80%	100.80%	100.80%	100.80%
	Total emission	100.00%	100.00%	100.00%	100.00%	100.00%	95.00%	95.00%	95.00%	95.00%	95.00%
92% of Base	Total cost	100.00%	100.00%	100.00%	100.01%	100.14%	101.69%	102.05%	102.05%	102.05%	102.05%
	Total emission	100.00%	100.00%	100.00%	100.00%	100.00%	94.72%	92.00%	92.00%	92.00%	92.00%
90% of Base	Total cost	100.00%	100.00%	100.00%	100.01%	100.23%	103.18%	104.64%	107.54%	109.40%	109.40%
	Total emission	100.00%	100.00%	100.00%	100.00%	100.00%	94.72%	90.57%	87.49%	87.00%	87.00%
87% of Base	Total cost	100.00%	100.00%	100.00%	100.02%	100.25%	103.46%	105.39%	109.91%	113.35%	113.35%
	Total emission	100.00%	100.00%	100.00%	100.00%	100.00%	94.72%	90.57%	90.00%	90.00%	90.00%
86% of Base	Total cost	100.00%	100.00%	100.00%	100.02%	100.25%	103.46%	105.39%	109.91%	113.35%	113.35%
	Total emission	100.00%	100.00%	100.00%	100.00%	100.00%	94.72%	90.38%	87.49%	86.00%	86.00%
85% of Base	Total cost	100.00%	100.00%	100.00%	100.02%	100.27%	103.77%	105.97%	112.61%	117.69%	118.03%
	Total emission	100.00%	100.00%	100.00%	100.00%	100.00%	94.72%	90.38%	87.49%	85.14%	85.00%

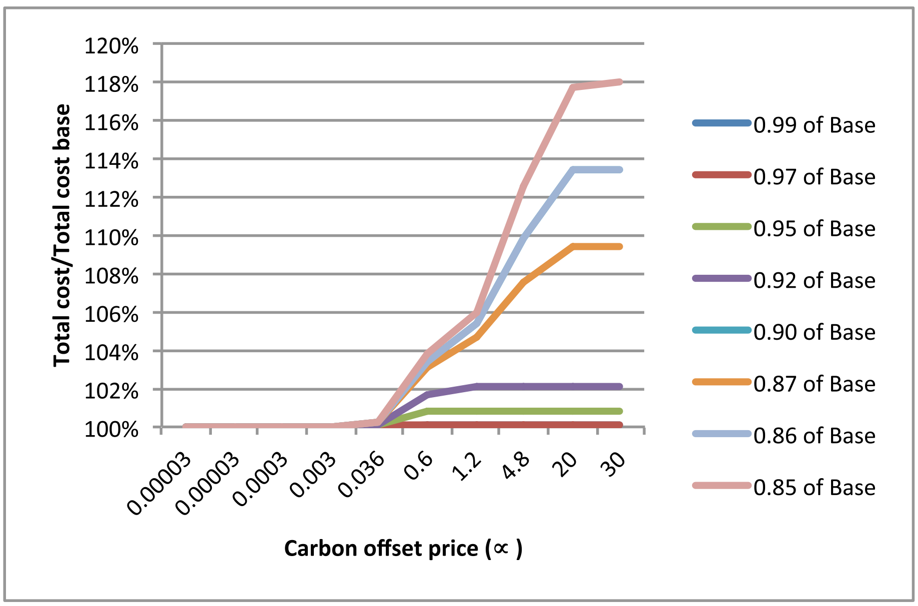

Figure 7 Total costs of the optimal solutions under Cap-and-Offset

Figure 7 demonstrates the total costs (in comparison with the base scenario) of the optimal solutions. When the value of ∝ is fixed, the lower the free emission quotas are, the higher the total costs are.

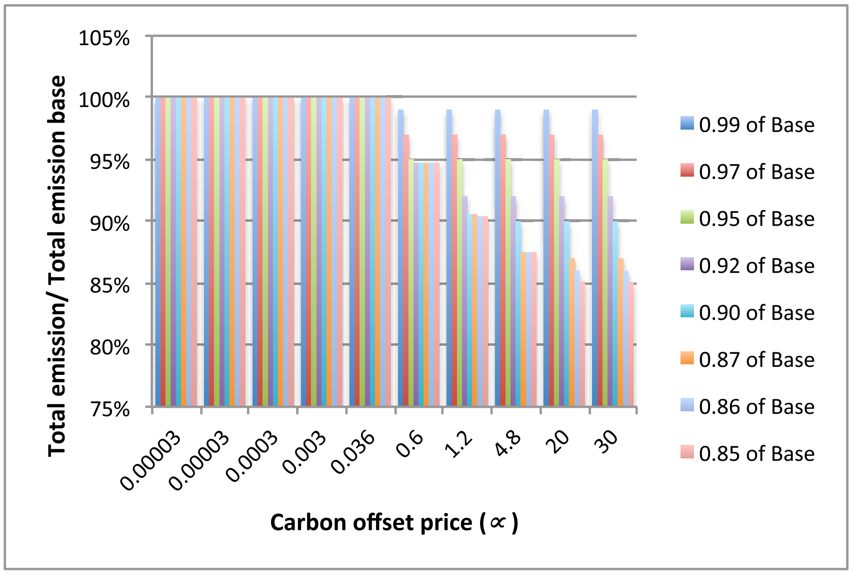

Figure 8 Total emissions of the optimal solutions under Carbon-and-Offset

Figure 8 demonstrates the total emissions in comparison with the base scenario. When the value of ∝ is fixed, the higher the total emission quota are, the higher the total emissions are. For the same amount of free emission quotas, the total emissions of the optimal solutions drop along with the increase of ∝.

6. Results Analysis

In this chapter, we first compare the effects of the four types of environmental policies on GDND in terms of total costs and emissions. Then, we analyze how emission concerns impact the optimal network design from two aspects: warehouse selection and transport mode selection.

6.1 Comparison of Environmental Policies

In this section we compare the four types of environmental polices with each other. We put the results (total costs and emissions of the optimal solutions from Chapter 5) under any two types of environmental policies together to create six graphs. In the following part, these graphs are introduced and discussed.

6.1.1 Strict Emission Cap and Carbon Tax

In Figure 9, the red points represent the results under Strict Emission Cap. The blue line represents the results under Carbon Tax. The red points have better results; they have both lower costs and lower emissions. Thus, it seems that Strict Emission Cap is more effective in reducing emissions while keeping total costs relatively low. However, under Strict Emission Cap, the GDND model sometimes has infeasible solutions. This suggests that Strict Emission Cap has a potential drawback.

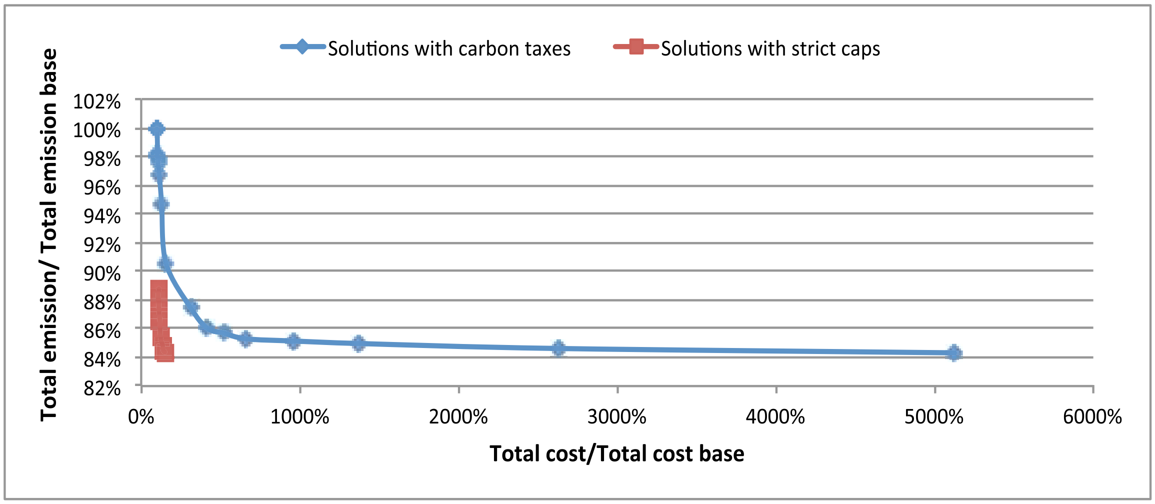

Figure 9 Solution comparison of Strict Emission Cap and Carbon Tax

6.1.2 Strict Emission Cap and Carbon-and-Offset

In Figure 10, the blue line links the results under Strict Emission Cap. The colorful points represent the results under Carbon-and-Offset. It is hard to say which type of policy performs better, considering that the weights of costs and emissions are not certain.

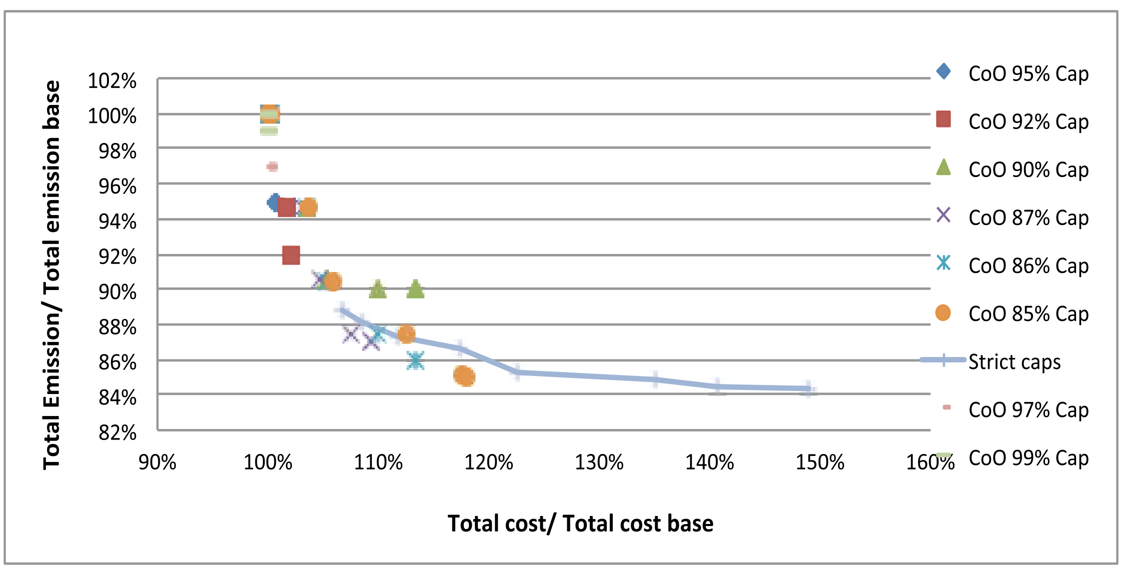

Figure 10 Solution comparison of Strict Emission Cap and Carbon-and-Offset

6.1.3 Strict Emission Cap and Cap-and-Trade

In Figure 11, the blue line links the results under Strict Emission Cap. The points represent the results under Cap-and-Trade. We can see that many results under Cap-and-Trade dominate any results under Strict Emission Cap. However, by referring to Figure 5 in section 5.3.3, one can find that this happens only when p (the price of buying or selling one unit of carbon emission credit) is bigger than 4.8 US Dollar per kg. When p is smaller than 4.8 US Dollar per kg, it is hard to say which policy performs better, considering the weights of costs and emissions are not certain.

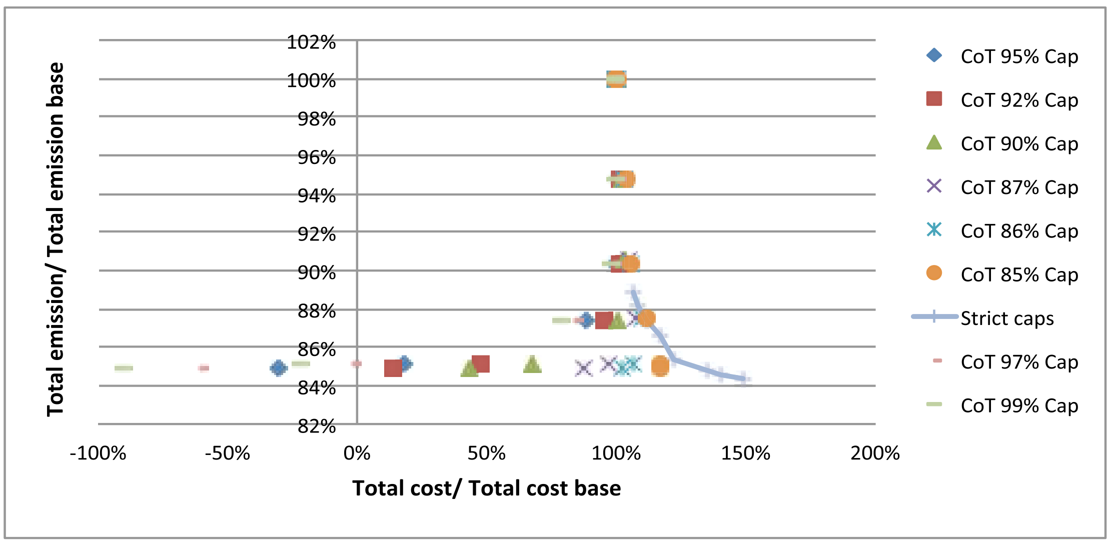

Figure 11 Solution comparison of Strict Emission Cap and Cap-and-Trade

6.1.4 Carbon Tax and Cap-and-Trade

In Figure 12, the blue line links the results under Carbon Tax. The points represent the results under Cap-and-Trade. The results under Cap-and-Trade dominate any results under Carbon Tax. Thus, it seems that Cap-and-Trade performs better than Carbon Tax.

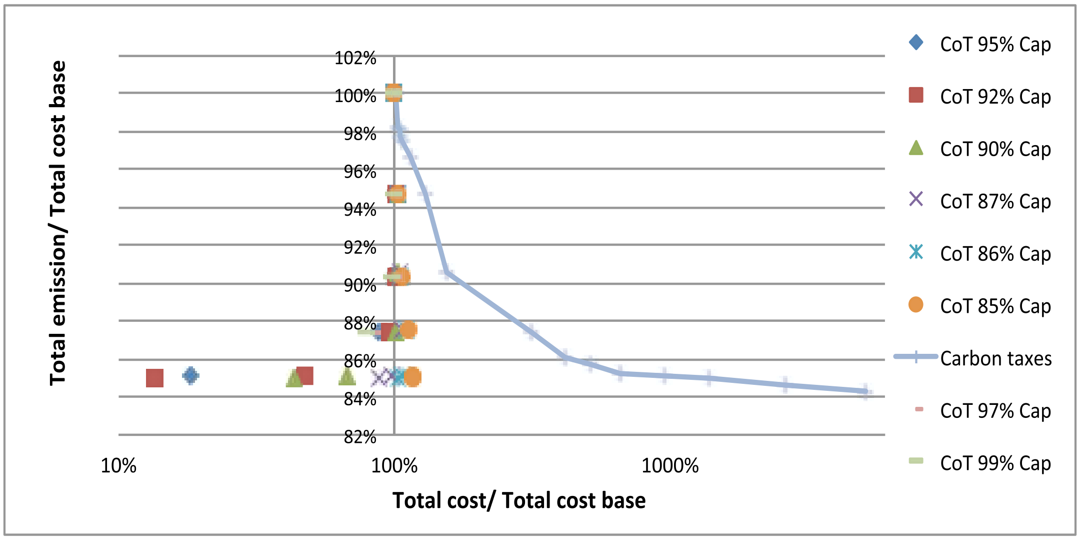

Figure 12 Solution comparison of Carbon Tax and Cap-and-Trade

6.1.5 Carbon Tax and Carbon-and-Offset

In Figure 13, the blue line links the results under Carbon Tax. The points represent the results under Carbon-and-Offset. Here the results under Carbon-and-Offset dominate any results under Carbon Tax. Thus, it seems that Carbon-and-Offset performs better Carbon Tax.

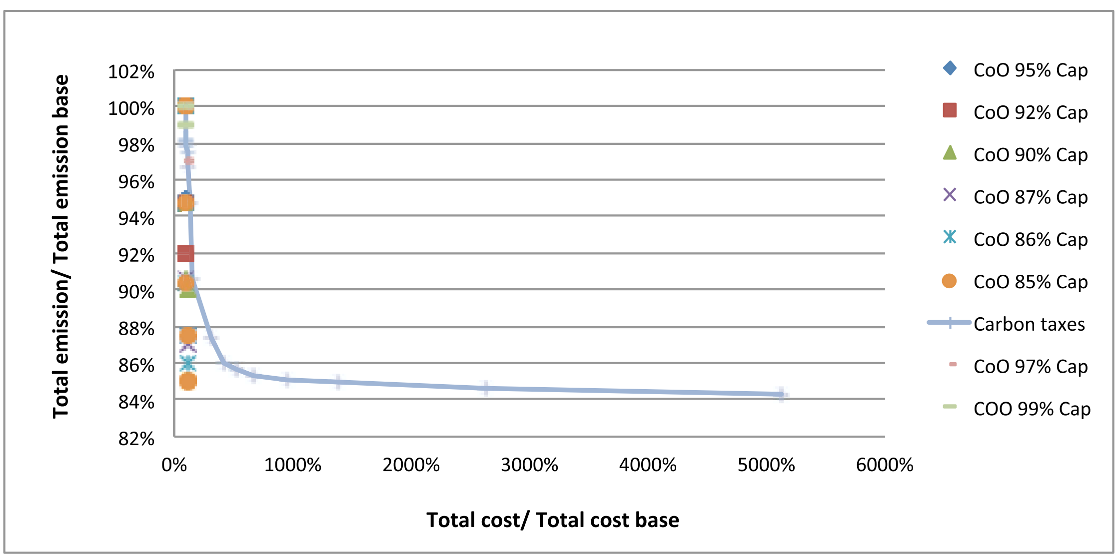

Figure 13 Solution comparison of Carbon Tax and Carbon-and-Offset

6.1.6 Cap-and-Trade and Carbon-and-Offset

In Figure 14, the line links the results under Carbon-and-Offset. The points represent the results under Cap-and-Trade. The points are all at the left side of the lines. This indicates that the point-represented results have both lower costs and lower emissions than the results linked by the lines. Thus, Cap-and-Trade performs better than Carbon-and-Offset.

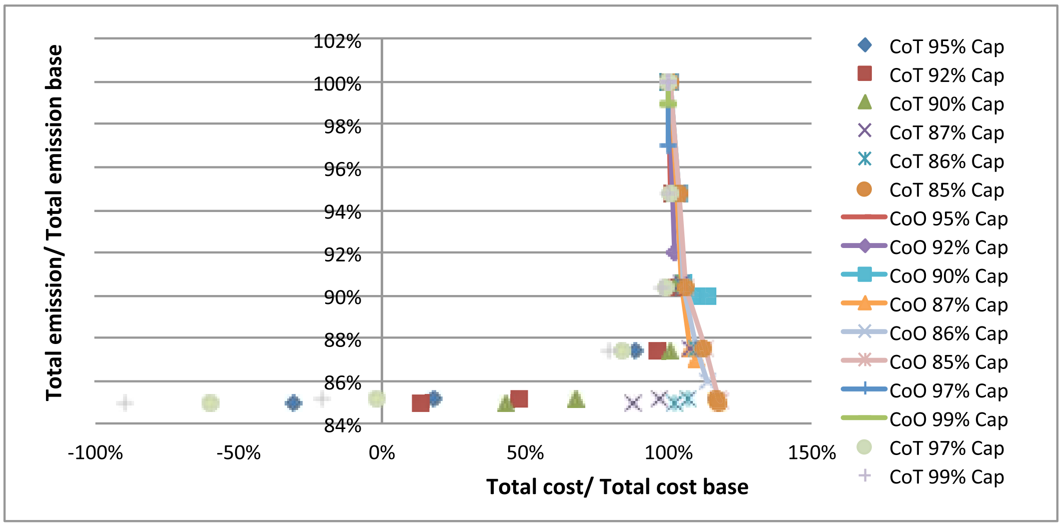

Figure 14 Solution comparison of Cap-and-Trade and Carbon-and-Offset

6.2 Warehouse Selection

It is generally believed that the more warehouses a network contains, the more fixed costs a company will incur. It is also believed that the more warehouses a network has, the lower the transport costs will be. However, in BD's distribution network design, no matter whether there is an environmental policy or not, the optimal solutions always select as many warehouses as possible. One may think that because the transport costs are overwhelming in BD's distribution network, the best solutions always sacrifice warehouse fixed costs. This is not the reason. In the following part, we use part of warehouse-related input data to explore the reason.

Table 14 includes part of warehouse-related input data. We can see that the fixed cost for using a warehouse is zero (see column 2). This is because BD uses a 3PL for its warehouse service. Though the 3PL does not charge fixed costs for warehouse usage, it does impose a fixed cost for assigning a new category of product to some of the warehouses (see column 4). As selecting more warehouses does not impact fixed facility costs, the optimal solutions always choose as many warehouses as possible, in order to reduce travel distances. This suggests that increasing the number of warehouses does not always increase fixed facility costs when a 3PL is used.

Table 14 Part of an input file for warehouse related input data (reported values are not real but have been scaled to protect confidentiality)

Warehouses	Fixed Cost per Warehouse	Product	Fixed Cost	Handling Unit Cost	Storage Unit Cost
Memphis	0	Product 1	24506.1	0.0	0.3
Memphis	0	Product 2	24506.1	0.0	0.3
Memphis	0	Product 3	24506.1	0.0	0.3
Memphis	0	Product 4	24506.1	0.0	0.3
Memphis	0	Product 5	24506.1	0.0	0.3
Memphis	0	Product 6	24506.1	0.0	0.3
Burnaby	0	Product 4	0.0	0.1	0.3
Burnaby	0	Product 7	0.0	0.1	0.3
Burnaby	0	Product 6	0.0	0.1	0.3
Burnaby	0	Product 8	0.0	0.1	0.3
Burnaby	0	Product 9	0.0	0.1	0.3
Burnaby	0	Product 10	0.0	0.1	0.3
Los Angeles	0	Product 11	24506.1	0.0	0.3
Los Angeles	0	Product 6	24506.1	0.0	0.3
Los Angeles	0	Product 12	24506.1	0.0	0.3
Los Angeles	0	Product 13	24506.1	0.0	0.3
Los Angeles	0	Product 14	24506.1	0.0	0.3
Los Angeles	0	Product 2	24506.1	0.0	0.3
Los Angeles	0	Product 15	24506.1	0.0	0.3
Los Angeles	0	Product 16	24506.1	0.0	0.3
Denver	0	Product 4	24506.1	0.1	0.3
Denver	0	Product 11	24506.1	0.1	0.3
Denver	0	Product 7	24506.1	0.1	0.3
Denver	0	Product 12	24506.1	0.1	0.3
Denver	0	Product 6	24506.1	0.1	0.3
Denver	0	Product 8	24506.1	0.1	0.3

6.3 Transport Mode Selection

Some authors claimed that environmental policies were powerful enough to trigger transport mode switching to slower modes. Other authors questioned this effect, and thought that emission related costs were too small to induce big changes. The observation from the case study of this thesis provides a new angle to perceive this question.

In the current network, between BD's single plant and five warehouses, most of the products are shipped by road transport, while the rest is done by rail transport. In GeDND and GDND, the transport mode between the plant and the five warehouses is set as a variable, and two transport modes (road and rail transport) can be selected from. However, all optimal solutions select only rail transport (the slow mode), no matter whether there is an environmental policy or not. Therefore, it is hard to interpret the role that the environmental policies play.

7. Conclusions and Further Research

In this thesis, we explore how CO_2 emissions impact optimal distribution network designs. We first introduce the GeDND model, which has no emission consideration. This model is then extended to address four types of environmental policies: Carbon Tax, Strict Emission Cap, Cap-and-Trade and Carbon-and-Offset. Corresponding to each type of environmental policy, a GDND model is developed.

Accurately estimating emissions is extremely important for the GDND. We adopt the CEME model, a microscopic second-by-second fuel consumption model, to estimate the road transport emissions. We use the ton-mile model, the most common method, to estimate the rail transport emissions. Based on these two models, we compute the values of an emission parameter, which are used in GDND to calculate the total network emissions. This parameter considers specific arcs, planning periods and vehicle types. This helps capture the changes of emissions and emission costs among different network designs.

A case study on optimizing the distribution network of an energy company is implemented. CPLEX is used to solve the GeDND and GDND models to optimality, where the optimality gap was set to 1%. Using the optimal solution of the GeDND problem as the basis for comparison, it is found that: (1) under Strict Emission Cap, when the emission caps are loose, there are good chances to reduce 11% of emissions while causing an increase of only 7% in total costs. When the emission caps are very strict, an emission reduction of 16% causes an increase of 45% in total costs; (2) under Carbon Tax, generally, the rate of emission reduction is always lower than the rate of cost increase. For example, an emission reduction of 17% causes an increase of 213% in total costs; (3) under Cap-and-Trade, when the prices of carbon credits are very high, 15% of emissions could be reduced, and this could either lead to a cost increase if the free emission quotas are low, or a cost decrease if the free emission quotas are high; (4) under Carbon-and-Offset, when the prices of carbon offsets are very high, more than 10% of emission could be reduced. However, contrary to Cap-and-Trade, Carbon-and-Offset never leads to a cost decrease, even if the free emission quotas are very big.

In the considered case we found that: (1) Carbon Tax produces the worst results. For any optimal solution under Carbon Tax, one can always find a better one under other policies; (2) Cap-and-Trade performs better than Carbon-and-Offset. This is because under Cap-and-Trade, companies can sell their unused emission quotas, while under Carbon-and-Offset, companies can never profit from their unused quotas; (3) between Carbon-and-Offset and Strict Emission Cap, it is hard to say which one performs better, because neither consistently produces better results than the other; (4) when the price of buying or selling emission credits is very high, the optimal solutions under Cap-and-Trade dominate those under Strict Emission Cap. When the price of buying or selling emission credits is low, it is hard to say which type performs better.

From the perspective of strategic decision-making, it is found that CO_2 emissions do not impact warehouse selection in this case; whether there is an environmental policy or not, all the optimal solutions choose as many warehouses as possible. This is because BD uses a 3PL for its warehouse service, and the 3PL does not impose fixed facility usage costs. Also, it is found that whenever possible, the optimal solutions choose the cheaper transport mode, no matter whether an environmental policy is in place or not. However, the emission considerations impact the assignment of products to warehouses.

Both warehouse and transport mode selection impact the total emission of a supply chain network. Future research could explore which of the two has a more significant impact. Future research could also consider various average truckloads instead of a single average truckload that has been used in the case study. Companies often experience large demand fluctuations. When demands are low, to keep the same shipping frequency, the average payloads drop. Future research could explore when it is more beneficial to use a smaller truck when the average payload drops. In this thesis, only CO_2 emissions are considered. Other GHGs could be included in the future as well as more types of transport modes.

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Appendix 1:

The assumptions on the trucks used in BD's current distribution networks are as follows:

1.Night cab long-haul trucks

According to EPA & NHTSA (2011), regional-haul trucks are used only for routes that are less than 500 miles. In BD's distribution network, many arcs have a distance of more than 500 miles. Thus, we assume that the BD uses long-haul trucks. For long-haul trucks, a sleeping cab usually is included.

2. The trucks burn diesel

According to EPA (2009), more and more trucks are burning diesel these years. By 2009, around 74% of trucks used diesel fuel in the US (see Table 15), we thus assume that the trucks burn diesel fuel.

Table 15 Fuel factions of trucks since 2002 (EPA, 2009)

	Single Unit Short Haul		Single Unit Long Haul		Motor Home	
Model Year	gasoline	diesel	gasoline	diesel	gasoline	diesel
2002	0.2631	0.7369	0.0627	0.9373	0.2237	0.7763
2003	0.2924	0.7076	0.2924	0.7076	0.2924	0.7076
2004	0.2869	0.7131	0.2869	0.7131	0.2869	0.7131
2005	0.2809	0.7191	0.2809	0.7191	0.2809	0.7191
2006	0.2758	0.7242	0.2758	0.7242	0.2758	0.7242
2007	0.2710	0.7290	0.2710	0.7290	0.2710	0.7290
2008	0.2674	0.7326	0.2674	0.7326	0.2674	0.7326
2009	0.2642	0.7358	0.2642	0.7358	0.2642	0.7358
2010	0.2620	0.7380	0.2620	0.7380	0.2620	0.7380
2011	0.2602	0.7399	0.2602	0.7399	0.2602	0.7399
2012	0.2589	0.7411	0.2589	0.7411	0.2589	0.7411
2013	0.2579	0.7421	0.2579	0.7421	0.2579	0.7421
2014	0.2572	0.7428	0.2572	0.7428	0.2572	0.7428
2015	0.2566	0.7434	0.2566	0.7434	0.2566	0.7434
2016	0.2562	0.7438	0.2562	0.7438	0.2562	0.7438
2017	0.2560	0.7440	0.2560	0.7440	0.2560	0.7440
2018	0.2560	0.7440	0.2560	0.7440	0.2560	0.7440
2019	0.2561	0.7439	0.2561	0.7439	0.2561	0.7439
2020	0.2563	0.7437	0.2563	0.7437	0.2563	0.7437
2021	0.2565	0.7435	0.2565	0.7435	0.2565	0.7435
2022	0.2569	0.7431	0.2569	0.7431	0.2569	0.7431
2023	0.2573	0.7427	0.2573	0.7427	0.2573	0.7427
2024	0.2578	0.7422	0.2578	0.7422	0.2578	0.7422
2025	0.2586	0.7414	0.2586	0.7414	0.2586	0.7414
2026	0.2591	0.7409	0.2591	0.7409	0.2591	0.7409
2027	0.2594	0.7406	0.2594	0.7406	0.2594	0.7406
2028	0.2602	0.7398	0.2602	0.7398	0.2602	0.7398
2029	0.2608	0.7392	0.2608	0.7392	0.2608	0.7392
2030	0.2613	0.7387	0.2613	0.7387	0.2613	0.7387
2031 and Newer	0.1532	0.8468	0.1532	0.8468	0.1532	0.8468

3. Class 8 trucks

EPA & NHTSA (2015) provides the average vehicle weight and payload of the various classes of trucks in the US. According to it, a truck that carries more than 25,000lbs of products belongs to the category of Class 8.

We learned from BD that the average payload in BD's current distribution network is 23,470 USG, which has a weight of around 51,751lbs. We thus assume that BD is using Class 8 trucks.

4. DD15L Detroit engine

The 2013 Vehicle Technologies Market Report by Oak Ridge National Laboratory (2014) indicates that half of the trucks produced in the US in 2012 were from Freightliner and Western Star. This report also indicates that most of the truck engines from these two companies were provided either by Cummins or by Detroit. As the information for Detroit engines is easier to find, we assume that Detroit engines are used.

5. Engine displacement

The baseline engine for the Class 8 trucks is the Heavy-Duty Diesel engine with 15 liters of displacement (EPA & NHTSA, 2015). The DD15L Detroit engine has 14.8 liters of displacement (Detroit, 2015), close to the baseline of 15 liters of displacement. We thus assume that DD15L Detroit engines are used, and the engine displacement is 14.8 liters.

6. Coefficient of aerodynamics drag

It is hard to find out whether the trucks in BD's current distribution network have high roof, middle roof or low roof, so we choose the middle one. For Class 8 trucks with middle roof, the coefficient of aerodynamics drag is 0.87 (see Table 16). This is the default value in GEM, which is an official emission calculation tool targeting heavy-duty vehicle emission calculation.

Table 16 GEM Input for the Class 7 and 8 tractor standard setting (EPA & NHTSA, 2011)

	CLASS 7			CLASS 8					
	Day Cab			Day Cab			Sleeper Cab		
	Low Roof	Mid Roof	High Roof	Low Roof	Mid Roof	High Roof	Low Roof	Mid Roof	High Roof
Aerodynamics (Cd)									
Baseline	0.77	0.87	0.73	0.77	0.87	0.73	0.77	0.87	0.70
Steer Tires (Crr kg/metric ton)									
Baseline	7.8	7.8	7.8	7.8	7.8	7.8	7.8	7.8	7.8
Drive Tires (Crr kg/metric ton)									
Baseline	8.2	8.2	8.2	8.2	8.2	8.2	8.2	8.2	8.2
Weight Reduction (lb)									
Baseline	0	0	0	0	0	0	0	0	0
Extended Idle Reduction (gram CO_2/ton-mile reduction)									
Baseline	N/A	N/A	N/A	N/A	N/A	N/A	0	0	0
Vehicle Speed Limiter									
Baseline	--	--	--	--	--	--	--	--	--
Engine									
Baseline	2010 MY 11L Engine	2010 MY 11L Engine	2010 MY 11L Engine	2010 MY 15L Engine	2010 MY 15L Engine	2010 MY 15L Engine	2010 MY 15L Engine	2010 MY 15L Engine	2010 MY 15L Engine

7. Cab frontal area

Table 17 indicates that if the coefficient of aerodynamics drag is 0.87, the frontal area of a mid-roof sleeper cabs must be bigger than 5.6 m^2. As a result, we assume that the front area of the trucks is 0.56 m^2.

Table 17 Frontal area and coefficient of aerodynamics drag of different trucks with different roofs (EPA & NHTSA, 2011)

	CLASS 7		CLASS 8			
	Day Cab		Day Cab		Sleeper Cab	
	Low Roof	Mid Roof	Low Roof	Mid Roof	Low Roof	Mid Roof
Aerodynamic Test Results (CdA in m^2)						
Bin I	≥ 5.1	≥ 5.6	≥ 5.1	≥ 5.6	≥ 5.1	≥ 5.6
Bin II	≤ 5.0	≤ 5.5	≤ 5.0	≤ 5.5	≤ 5.0	≤ 5.5
Aerodynamic Input to GEM (Cd)						
Bin I	0.77	0.87	0.77	0.87	0.77	0.87
Bin II	0.71	0.82	0.71	0.82	0.71	0.82

8. Vehicle average speed

EPA & NHTSA (2011) states that for night cabs, 86% of time they keep a speed of 65 mph, and 9% of time they keep a speed of 55 mph. For the last 5% of time, the speed is transient; it could be higher than 65 mph, lower than 55 mph, or between them. We assume that the average of the transient speeds is 60 mph. Then, we obtain the average speed of the whole trips: 62.35 miles per hour.

9. Engine speed

For a typical on-highway tractor-trailer application of 80,000lb or less, to get a maximum fuel economy at 65 mph, an engine speed of 1350 $\mathrm{rev/s}$ is recommended (Detroit, 2015). The average vehicle speed of BD trucks is assumed to be 62.35 mph, very close to 65 mph. Thus, we assume that the engine speed is 1350 $\mathrm{rev/s}$.

10. Value of f_{co2}

According to EPA (2014), the CO_2 emission of burning one USG of diesel fuel is 10.21 kg. One USG of diesel fuel equals to 3.785 liters. Thus, $f_{co2} = 2.70\,\mathrm{kg}\,/\,\mathrm{liter}$.

Appendix 2:

EPA & NHTSA (2011) estimate that from 2010 to 2018, the fuel efficiency of the diesel and gasoline vehicles will increase 15% and 10%, respectively. The numbers are based on the agencies' assessment of the feasibility of incorporating new technologies in the 2010-2018 model years. From this, we learned that the annual improvement of engine efficiency for diesel trucks is 3.75%. Thus, the values of emission reduction coefficient ϖ^t, which suggest the improvement of engine efficiency in period *t* when compared with current period 0, are given in Table 18.

Table 18 The values for emission reduction coefficient ϖ^t

ϖ^1	1
ϖ^2	0.9625
ϖ^3	0.92640625
ϖ^4	0.891666016
ϖ^5	0.85822854
ϖ^6	0.82604497
ϖ^7	0.795068283
ϖ^8	0.765253223
ϖ^9	0.736556227
ϖ^{10}	0.708935368