

Supply Chain Network Design with Nonlinear Emissions and Cap on Carbon Footprint

by

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Author's Declaration

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

I understand that my thesis may be made electronically available to the public.

Abstract

We consider a green supply chain network design problem with one manufacturing facility, one product, multiple distribution centers, and multiple retailers, and where carbon footprint is capped. We account for cost as well as emissions from storage at the distribution centers and transportation. The latter is done either using electric trucks or diesel trucks. While emissions for electric trucks is linearly dependent on load, emission for diesel trucks is hard to capture. To remedy this, we consider linear, concave, and convex functions of the load transported.

We optimize the location of distribution centers, the allocation of demand, and the transportation modes among diesel and electric trucks. We present a nonlinear mixed-integer model, propose a Lagrangian relaxation to decompose the model by echelon in order to isolate the nonlinearity in one of the subproblems, and devise a Lagrangian heuristic based on the solution of the other subproblem. Through a case study, we evaluate the impact of various emission functions and levels of emission restrictions on the structure of the supply chain, as well as the trade-offs between the utilization of diesel trucks and electric trucks. Our findings reveal that the type of emission function significantly influences the use of diesel versus electric trucks and the distribution of cost components. With a concave function, diesel truck usage slightly increases as the cap on per unit emission increases when electric trucks are cost-efficient and can rise by up to 30% when diesel trucks are the cheaper option. In contrast, a convex function shifts the main cost contribution to transportation emissions, with diesel truck usage decreasing as the emission coefficient increases. The linear function shows mixed trends, aligning with either the concave or convex cases under different conditions. Moreover, extending electric truck range when the emission function is convex heavily favors their utilization in most trips, while under concave emission functions, still diesel trucks are favored over electric ones as the limit on emission loosens.

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Dedication

To my family and loved ones,

For your endless love, support, and encouragement,

This work is dedicated to you.

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Chapter 1

Introduction

The rise in environmental concerns has increased consumer awareness about the carbon footprint of products. Despite the 2022 inflation surge, the sustainable products market in the US constituted 17.3% of purchases. These products displayed a remarkable five-year compound annual growth rate of 9.48%, almost double that of conventionally marketed products [Circana, 2023]. Recognized as a factor impacting consumer choice in today's markets, this trend is underscored by a 2023 report, revealing that roughly two-thirds of US consumers would pay more at the pump for gas that offsets its greenhouse gas emissions [Nouira et al., 2014, PDI Technologies, 2023]. A 2020 McKinsey US consumer sentiment survey indicates that over 60% of respondents are willing to pay more for products with sustainable packaging and are concern regarding the environmental impact of packaging [Feber et al., 2020]. Notably, a recent Forbes report highlights that two-thirds of consumers, spanning all generations, express a willingness to pay a premium for sustainable products, driven primarily by a desire to contribute to environmental conservation [Petro, 2022]. Furthermore, an international survey conducted by Shopify last year found that

two-fifths of consumers say they would pay a higher price for climate-focused products [Sapio Research, 2022].

In response to increased demand for green products, businesses are actively exploring avenues to embed environmental management practices into their operations, seeking a competitive edge [Waltho et al., 2019b]. Leveraging marketing tools like carbon footprint (CF) labels, companies strategically address the growing environmental consciousness among retailers, positioning their products as eco-friendly alternatives [Benjaafar et al., 2012]. CF labels quantify the total emission of carbon dioxide and other greenhouse gases throughout a product’s life cycle [Thøgersen and Nielsen, 2016]. Their primary function is to empower consumers with information about the carbon impact of products, facilitating more sustainable choices [Keramydas et al., 2019, Rondoni and Grasso, 2021]. Consumer reception of CF labels remains positive, as evidenced by widespread approval for their adoption [Li et al., 2017]. According to Deloitte [2023], there is already a growing appetite for products that have a sustainability label. For example, 72% of European citizens endorse footprint labeling, with a notable portion advocating for its mandatory implementation. Studies in Chile reveal consumers’ willingness to pay a premium for products bearing CF labels, with observed premiums of 29% over the average price of milk and 10% over the average price of bread when the CF label is present [Echeverría et al., 2014]. A 2019 survey across seven countries reaffirms strong support for carbon labeling, with percentages ranging from 49% in Sweden to 85% in Italy [The Carbon Trust, 2019]. The commitment to sustainability is embraced by startups such as EcoCart and Carbon Checkout, which focus on calculating and offsetting emission linked to online orders. EcoCart, in collaboration with brands like Walmart Canada, Siete Foods, and Cotopaxi, reports that 60% of e-commerce shoppers utilize its emission offset functionality during online checkouts. Carbon Checkout, cofunded by the European Innovation Council, has forged over 2,000

e-commerce partnerships since its launch in 2015. This trend suggests that retailers and service providers are likely to enhance capabilities for offsetting products or shipments, aiming to strengthen retailer loyalty [Hall, 2022].

With this heightened awareness among consumers as well as the increasing pressures from regulatory bodies, companies are now carefully examining their supply chain processes to reduce carbon emissions given that the supply chain constitutes approximately 60% of total costs and emissions for most manufacturing companies [Hanifan et al., 2012]. Transportation, a critical component of the supply chain, plays a substantial role, contributing 21% to global greenhouse gas (GHG) emissions within the logistics industry. Despite existing policies, transport emissions are expected to increase by almost 20% by 2050 [World Economic Forum, 2021]. As a result, companies are actively investigating strategies to reduce emission, primarily focusing on transportation, which heavily relies on freight trucks. The trucking sector is anticipated to continue expanding, with approximately 65% of freight tonnage projected to be transported by trucks in 2050 [United States Department of Transportation, 2023]. Presently, in the US, nearly seven million medium- and heavy-duty freight trucks are in operation, predominantly equipped with traditional internal combustion engines (ICEs) [McKinsey & Company, 2022, AutoTechInsight, 2022], often fueled by diesel. This extensive fleet contributes to over 25% of total GHG emission [United States Environmental Protection Agency, 2023b].

The structure of the supply chain network holds a significant influence on its environmental impact and the conventional focus on cost reduction and increased responsiveness may not align seamlessly with the objectives of environmental sustainability, which has become a crucial element for organizational success [Waltho et al., 2019b, Hanifan et al., 2012]. Recognizing this shift, numerous studies have integrated environmental considerations into their supply chain network design (SCND), with recent reviews emphasizing

the importance of green practices [Abbasi and Choukolaei, 2023, Waltho et al., 2019b]. However, a notable limitation in existing studies lies in their focus on the total emission of the supply chain, rather than emission per unit, which falls short of resonating with consumers, who often prefer a more tangible per-unit representation, such as eco-labels or CF labels [Elhedhli et al., 2021].

To help address this gap, the current research focuses on emissions per unit, crucial for determining CF labels. While not all emission sources are included, the main ones, namely location and storage of distribution centers (DCs) as well as transportation electrification through the use of electric trucks in lieu of commonly used diesel trucks, are considered. The proposed framework, however, allows for straightforward extensions to include other sources. Specifically, the current work presents the following contributions:

1. We propose a SCND framework that determines the locations of open DCs and their inflows, as well as the assignment of retailers to the open DCs within a two-echelon supply chain. The framework caps per unit emissions incorporate electric trucks alongside commonly used diesel trucks to address consumer environmental concerns and consider different emission functions to represent CO₂-equivalent emissions associated with the conventional diesel trucks.
2. We present a Lagrangian relaxation that decomposes the SCND model into two subproblems. To handle the nonlinearity in the second subproblem caused by the emission functions for conventional diesel trucks, we utilize different approaches based on the type of nonlinearity: for concave emission functions, we leverage the properties that a corner-point optimal solution exists, while for convex emission functions, we employ tangential approximation.
3. We build a case study and use real-world data to validate and test the proposed

methodology and conduct comprehensive numerical experiments and sensitivity analyses to evaluate the impact of different emission functions, level of restriction on per unit emission, and travel range of electric trucks on the design of supply chain networks, overall emission performance, and the trade-off between diesel and electric trucks. We find that, with a concave emission function, diesel truck usage increases as the emission cap loosens, particularly when electric trucks are cost-effective. Conversely, a convex emission function shifts cost contributions to transportation emissions, reducing diesel truck usage as the emission coefficient rises. Extending the electric truck range under a convex function favors electric trucks, whereas, under a concave function, diesel trucks remain preferred as emission limits relax.

The subsequent chapters of this thesis are as follows: Chapter 2 proposes a comprehensive review of studies investigating the correlation between the weight of diesel trucks and their associated emission. Chapter 3 introduces the problem description and outlines the mathematical model of our research. The solution methodology is presented in Chapter 4, with a detailed presentation of numerical experiments in chapter 5. Finally, Chapter 6 concludes our findings. Chapter 7 delves into the extensions of our research.

Chapter 2

Literature Review

Reducing GHG emissions is crucial in SCND due to environmental conservation, increasing customer awareness, and strict carbon policies. Various policies such as carbon tax, carbon cap, and cap-and-trade have been implemented [Abbasi and Choukolaei, 2023], and several studies have integrated these environmental concerns into their SCND [Waltho et al., 2019b]. Rad and Nahavandi [2018] investigated a multi-stage, multi-product SCND problem, considering emissions from both transportation and production. They assessed various truck types based on their environmental impact and customer preferences but did not specify the type of fuel used, such as diesel, electric, or other alternatives. The goal was to minimize supply chain costs, reduce pollution, and enhance customer satisfaction while meeting carbon dioxide restrictions. They used the LP-metric method for solving the problem and provided numerical examples from existing literature. In a similar study, Bortolini et al. [2018] formulated a multi-objective optimization model for a SCND problem by minimizing total costs and environmental impact over the whole network. Zhen et al. [2019] proposed a stochastic bi-objective mixed integer programming (MIP) model to

address uncertain demands in SCND. Their goals were to minimize total CO₂ emissions as well as total cost. They integrated environmental and capacity levels into facility location decisions and employed fixed emission coefficients for transportation. Using a weighted-sum method and Lagrangian relaxation, they demonstrated the model’s validity and efficiency through experimental results. [Yavari and Geraeli \[2019\]](#) designed a resilient supply chain network to minimize total costs and carbon emissions, considering multiple periods and products. They incorporated GHG emissions from facility operations, inventory holding, and transportation. They used an MIP model and a heuristic to address uncertainties. In a recent study, [Kazancoglu et al. \[2022\]](#) developed an MIP model for SCND, considering emissions from facilities and transportation. They proposed two objectives: minimizing total cost and total emissions. They provided a case study and used CPLEX for solving under different parameters.

As evident from the literature, in recent years, there’s been a lack of attention in studies on SCND while considering emissions per unit, despite its importance in determining CF labels. To the best of our knowledge, the most recent studies addressing this important issue were conducted by [Elhedhli et al. \[2021\]](#) and [Nouira et al. \[2016\]](#). The former evaluated the impact of eco-labeling by considering emission-sensitive demand for the final product, showing that higher carbon emissions can reduce customer demand. The emissions from the supply chain’s plant, transportation fleet, and storage were considered. To calculate the carbon footprint, fixed emissions were averaged over throughput, resulting in a nonlinear optimization problem with fractional terms, solved using a mixed-integer second-order cone programming reformulation. Their SCND model optimized facility locations, technology selection, and product flow between echelons to maximize profit. The latter also took into account emission-sensitive demand when designing a forward supply chain, making decisions on supplier selection, production facility locations, production technologies, and

transportation modes (rail, road, air, water), all aimed at maximizing profit.

To effectively establish CF labels, it is crucial to calculate emissions from transportation fleets per unit. This involves evaluating various vehicle types such as diesel and electric trucks, and understanding how emissions vary with payload. Emissions of electric trucks are known to follow a linear function of payload. This correlation arises from the linear relationship between emissions and the energy consumption of their batteries, which, in turn, is linearly correlated with their payload [Davis and Figliozzi, 2013]. However, the nature of this relationship is not quite known for diesel trucks.

The emission and fuel consumption of diesel trucks is significantly influenced by the payload [Clark et al., 2002]. However, current emission inventories for heavy-duty diesel trucks lack sufficient coherent experimental data to accurately describe the effects of payload weight on emission and establish an empirical relationship. Models like the Environmental Protection Agency (EPA) MOBILE [United States Environmental Protection Agency, 2006] and the California Air Resources Board (CARB) EMFAC [California Air Resources Board, 2023] traditionally rely on average fuel economy and engine efficiency factors in their calculations, neglecting the actual impact of truck payload on emission. Only a few researchers have investigated the impact of weight on emissions from heavy-duty vehicles, and one of the earliest studies in this context is presented by Gajendran and Clark [2003]. The study investigated heavy-duty vehicles across varying weight percentages of their gross vehicle weight rating (GVWR). GVWR includes total vehicle weight plus fluids, passengers, and cargo. The results indicated a significant nonlinear impact of weight on emission, emphasizing the need for further research to explore combined effects with real-world factors such as terrain or grade. The Oak Ridge National Laboratory conducted a study between 2006 and 2008 to analyze the impact of vehicle weight, roadway grade, and speed on the fuel efficiency (FE) of Class-8 freight trucks focusing on flat and

mild up-slope terrain. In conclusion, the study demonstrated a nuanced terrain-dependent relationship between vehicle weight and fuel efficiency, emphasizing the non-linear impact on emission [Franzese and Davidson, 2011]. The Department for Environment, Food and Rural Affairs (DEFRA) and the Department for Transport in Great Britain updated emission factors in June 2023, categorizing them based on heavy-duty vehicle’s configuration and weight [Leonardi et al., 2010]. The data shows a linear relationship between freight load and emission factors, with a more pronounced impact on heavier classes. Strimer et al. [2005] conducted a detailed assessment of a 1996 Peterbilt heavy-duty diesel truck’s emission and FE. Different relationships were observed in brake-specific and distance-specific emissions for specific routes, indicating the complexity of the interplay. Additionally, FE exhibited varying patterns, emphasizing the nuanced impact of vehicle weight on real-world driving scenarios. In a study addressing the environmental impact of wood procurement transportation, Palander [2017] examined the effects of increasing truck maximum mass on environmental and operational metrics in the Finnish forest industry. Utilizing data from StoraEnso and national road freight statistics, differentiated by road types, the study indicated that CO_2 emission did not exhibit a proportional change with variations in maximum mass. Delgado et al. [2017] utilized the Autonomie software to assess fuel consumption in two baseline vehicles, representing long-haul and urban freight scenarios. The study covered varying payloads and duty cycles, revealing that the test cycle significantly influenced fuel consumption. Their findings were consistent with the results obtained from VECTO, Europe’s Vehicle Energy Consumption Calculation Tool. In the study by Sandhu et al. [2015], six Roll-off refuse trucks from 2005 to 2012 were examined for fuel use and emission during normal workdays. The results revealed a non-linear adverse impact of weight on fuel consumption and CO_2 emission, aligning with the results obtained from MOVES2010b which indicated similar trends in cycle average fuel use and CO_2 emission.

The study by [Keramydas et al. \[2019\]](#) analyzed twenty-two heavy-duty diesel trucks representing various manufacturers and operational in Hong Kong from 2011 to 2018. The research employed Portable emission Measurement Systems (PEMS) and various sensors to characterize real-world emission and fuel consumption. Notably, loading effects on fuel consumption demonstrated a concave relationship, with increased consumption at higher vehicle loads. As mentioned in the previous chapter, [Elhedhli and Merrick \[2012\]](#) also assessed the effect of weight on the emission of heavy-duty trucks. They conducted a comprehensive study wherein emission data was acquired using the Mobile6 computer program [[United States Environmental Protection Agency, 2006](#)]. Released by the EPA in 2006, the Mobile6 program was introduced as the official model for estimating emissions from cars, trucks, and motorcycles. The study focused on diesel heavy-duty trucks ranging from classes 2b to 8b, utilizing CO_2 -equivalent emission factors to conclude that the emission function of heavy-duty diesel trucks can be modeled as a concave function of their weight.

In light of the above literature, various relationships influenced by various factors including speed, vehicle configuration, driving cycle, and road grade have been documented to describe the payload-emission correlation for heavy-duty diesel trucks. To better understand the relationship, we resort to data from MOVES4.0, EPA’s latest endorsed emission modeling system.

MOVES4.0 provides emission rates for various regulatory classes of vehicles and a diverse set of pollutants through tables that detail emission rates. We focus on diesel trucks (classes 2b to 8b), and their specifications, derived from FHWA, U.S. Census Bureau, and EPA data, are outlined in Table 2.1, where the last two columns project the CO_2 -equivalent emission amounts ($\times 10^{12}$ g) and distances ($\times 10^9$ km) for the year 2040 using MOVES4.0. The calculation of cargo weight involves subtracting the average curb weight from the average gross weight for each regulatory class. The gross weight includes the curb

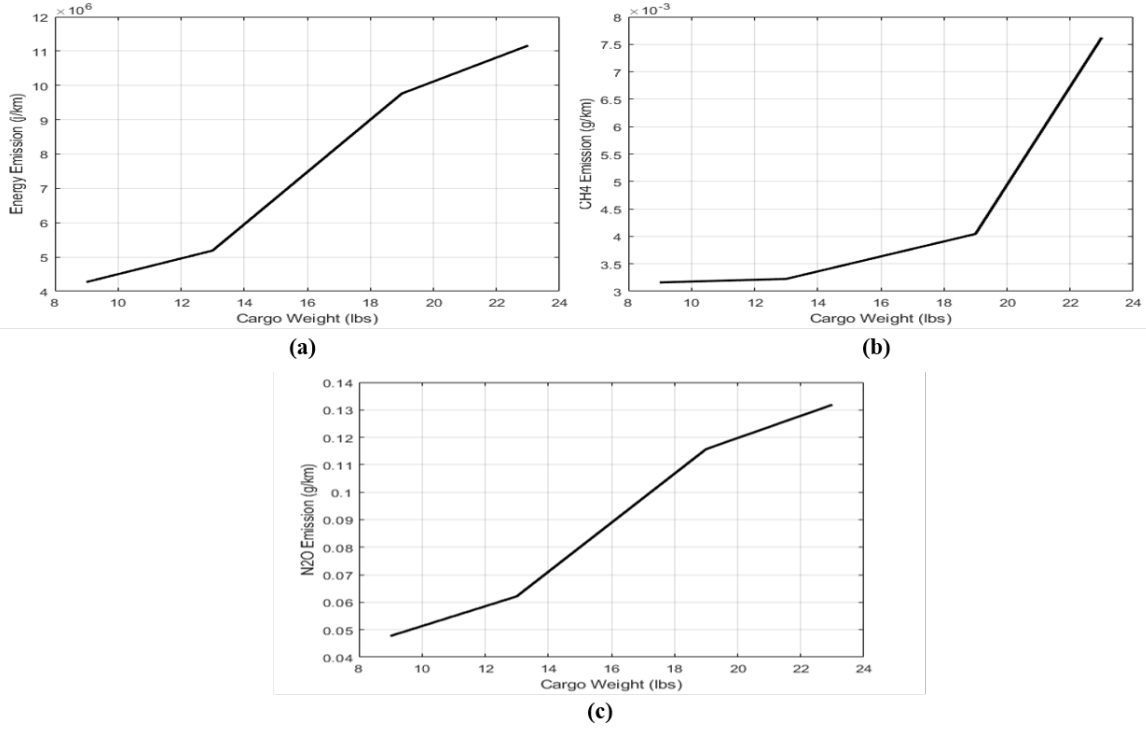


Figure 2.1: Cargo weight vs. energy consumption rate (a), N_2O emission (b), and CH_4 emission rate (c) based on MOVES4.0 for diesel trucks of classes 2b-8b

weight plus cargo weight and passengers. Two distinct approaches are proposed to assess the relationship between truck weight and CO_2 -equivalent emission: first, by examining the payload's connection with emission rates for individual pollutants (atmospheric CO_2 , N_2O , and CH_4), which contribute to the CO_2 -equivalent emission amount; and second, by utilizing aggregated CO_2 -equivalent emission rates from MOVES4.0 for each regulatory class of heavy-duty diesel trucks.

Examining the first approach, it is noteworthy that MOVES4.0 calculates atmospheric CO_2 emission based on total energy consumption rather than storing emission rates directly in the table. Thus, our attention shifts to the energy consumption rates (j/km) for diesel

trucks (classes 2b to 8b) to explore the relationship between atmospheric CO_2 emission and cargo weight. The relationship between energy consumption and cargo weight is illustrated in Figure 2.1(a). MOVES4.0’s CO_2 -equivalent calculation involves atmospheric CO_2 , N_2O , and CH_4 mass emission. In Figure 2.1(b), N_2O emission rates (g/km) for various payloads are outlined. Further, the determination of emission linked to CH_4 is illustrated in Figure 2.1(c). None of the proposed figures show a distinct linear, concave, or convex relationship between the payload and the emission rates. Consequently, as the CO_2 -equivalent emission for diesel trucks of classes 2b-8b are determined by a combination of these functions, the nature of the relationship remains inconclusive. Therefore, the analysis conducted above does not yield a definitive conclusion regarding the correlation between payload and emission.

An alternative approach to establishing the payload-emission relationship involves evaluating the direct CO_2 -equivalent emission from MOVES4.0. Notably, MOVES4.0 introduces a more comprehensive list of vehicles compared to MOBILE6, encompassing gliders—post-2007 heavy-duty vehicles with new chassis but older engines, mainly falling under Class 8 with diesel heavy-duty engines [United States Environmental Protection Agency, 2023c]. In Figure 2.2(a), the relationship between CO_2 -equivalent emissions of diesel trucks and their payload is illustrated, which appears convex. Considering that gliders, not complying with 2007 or 2010 emission standards, exhibit significantly higher emissions than other Class 8 trucks, a refined assessment was conducted. Extracting the contribution of gliders from Figure 2.2(a) resulted in Figure 2.2(b), which shows an "S" shaped payload-emission relationship for the diesel trucks of classes 2b to 8b.

Due to the absence of a clear relationship defining the link between CO_2 -equivalent emissions of heavy-duty diesel trucks and their payload, we will consider different functional forms, namely linear, concave, and convex, to represent CO_2 -equivalent emissions as a

Table 2.1: Truck Classification and Characteristics

Class	Gross Weight Range (lb)	Empty Weight Range (lb)	Typical Payload Capacity Max (lb)	Projected CO_2 - equivalent Emission for Year 2040 ($\times 10^{12} g$)	Projected Distance Traveled for Year 2040 ($\times 10^9 km$)
2b	8,501 – 10,000	5,000 – 6,300	3,700	50	152
3	10,001 – 14,000	7,650 – 8,750	5,250		
4	14,001 – 16,000	7,650 – 8,750	7,700		
5	16,001 – 19,500	9,500 – 10,800	8,700		
6	19,501 – 26,000	11,500 – 14,500	14,500	65	85
7	26,001 – 33,000	11,500 – 14,500	18,500		
8a	33,001 – 80,000	20,000 – 34,000	20,000 – 50,000	265	306
8b	33,001 – 80,000	23,500 – 34,000	40,000 – 54,000		

function of payload. The following chapter describes the problem in detail and presents the modeling framework.

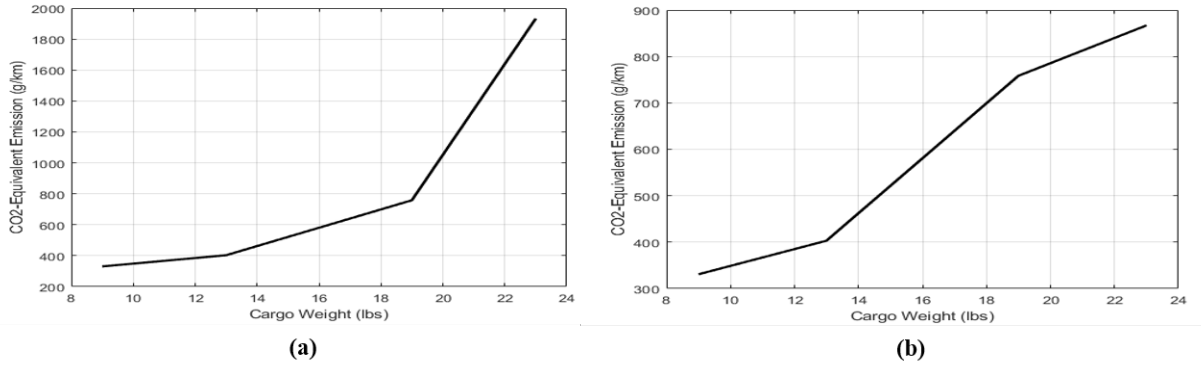


Figure 2.2: Cargo weight vs. CO_2 -equivalent emission rate based on MOVES4.0 for diesel trucks of classes 2b-8b; gliders emission considered (a) and excluded (b)

Table 2.2: Summary of Studies on the Relationship Between the Weight of Diesel Trucks and Their Emission

Study	Vehicle Type	Road Type	Weight	Key Findings	Primary Pollutants	Relationship	Methodology and Specific Aspects
Gajendran and Clark [2003]	Heavy-Duty Vehicles	Varied Terrain	% of GVWR; different vehicles	Correlation between weight and emission; Test weights and terrain considered	NO_x, HC, CO_2	Nonlinear, dependent	West Virginia University testing labs, emission analysis
Franzese and Davidson [2014]	Class-8 Trucks	Freeways	weight of an empty tractor plus payload; similar vehicles	Relationship between weight and fuel efficiency	–	Nonlinear, concave	Real-world study, U.S. Department of Energy Heavy-Truck Duty Cycle, Fuel Efficiency model
Leonardi et al. [2010]	Heavy Goods Vehicles	–	GVWR; different vehicles	Relationship between load and emission factors; GHG emission factors for fleet operations	GHGs (Scope 1, 2, 3)	Linear	Collaboration with transportation companies
Strimer et al. [2005]	Heavy-Duty Diesel Truck	Varied Routes	weight of an empty tractor-trailer plus payload; test weights of a single vehicle	Brake-Specific and Distance-Specific emission	CO_2, NO_x	Nonlinear, varying with routes	Mobile measurement systems, Route selection
Elhedhli and Merrick [2012]	Heavy-Duty Diesel Trucks	–	weight of an empty truck plus payload; different vehicles	Emission modeling as a function of weight; Extension to supply chain network design	CO_2	Concave	Mobile6 computer program, Supply chain network modeling
Palander [2017]	Heavy-Duty Vehicles	Forest Roads and Highways	weight of an empty tractor-trailer plus payload; different vehicles	Impact of increasing truck mass on emission	CO_2	Nonlinear, unspecified	Study on Finnish forest industry, ERP data
Delgado et al. [2017]	Heavy-Duty Freight-Hauling Vehicles	Long Haul, Regional Delivery, Urban	weight of an empty tractor-trailer plus payload; similar vehicles	Payload effect on fuel consumption; Cycle impact on fuel consumption	–	Nonlinear, unspecified	Autonomie software, Comparison with VECTO
Sandhu et al. [2015]	Roll-off Refuse Trucks	Urban, Highway, Trash Collection, Landfill	weight of chassis plus can plus trash; similar vehicles	Impact of weight on fuel use and emission; Real-world data on refuse trucks	HC, CO, CO_2	Nonlinear, unspecified	PEMS for tailpipe emission, Operational aspects study
Keramydas et al. [2019]	Heavy-Duty Diesel Trucks	Urban, Highway, Mixed	% of average payload; similar vehicles	Impact of loading on fuel consumption	NO_x, PM	Nonlinear, unspecified	Testing on Hong Kong road network, PEMS, Euro standards assessment

Chapter 3

Problem Description and Formulation

We consider a two-echelon supply chain with a single manufacturing plant and multiple DCs and retailers. The plant and retailer locations are predetermined, while the determination of the number and location of open DCs, the assignment of retailers to DCs, and the corresponding product shipment quantities from the plant to the DCs and from the DCs to the retailers constitute the decision-making process. The supply chain deals with a single product type within a specified planning period. Goods are transported using two types of trucks: diesel trucks and electric trucks. In line with customer environmental considerations, electric trucks are prioritized for transportation whenever they are available. Their availability is limited by their travel range, which is less extensive than that of diesel trucks. Furthermore, there is a cap on the emissions per unit for each DC-retailer pair. To model this problem, we define $j = 1, \dots, n$ and $i = 1, \dots, m$ corresponding to plant locations, potential DCs, and retailers, respectively. A DC at location j has a known

capacity of v_j , a fixed opening cost of a_j , and a variable capacity-dependent cost $g_j(v_j)$. The cost components for the transportation fleet vary depending on whether diesel or electric trucks are used. The cost c_j^e represents the transportation cost of using electric trucks to send one unit from the plant to DC j , while c_j^d represents the same cost for diesel trucks. Additionally, t_{ij}^e and t_{ij}^d denote the cost coefficients associated with transporting one unit from DC j to retailer i using electric and diesel trucks, respectively. Table 3.1 lists the sets, parameters, and decision variables. The SCND problem is formulated as follows:

$$\begin{aligned}
[\text{EP}] : \min & \sum_{j=1}^n a_j z_j + \sum_{j=1}^n (u'_j c_j^e + (1 - u'_j) c_j^d) y_j + \\
& \sum_{i=1}^m \sum_{j=1}^n (u'_{ij} t_{ij}^e + (1 - u'_{ij}) t_{ij}^d) D_i x_{ij} + \\
& w \left(\sum_{j=1}^n g_j(v_j) z_j + \sum_{j=1}^n (u'_j f_j^e(y_j) + (1 - u'_j) f_j^d(y_j)) + \right. \\
& \left. \sum_{i=1}^m \sum_{j=1}^n (u'_{ij} f_{ij}^e(D_i x_{ij}) + (1 - u'_{ij}) f_{ij}^d(D_i x_{ij})) \right) \\
\text{s.t. } & \sum_{j=1}^n x_{ij} = 1 \quad \forall i \\
& y_j = \sum_{i=1}^m D_i x_{ij} \quad \forall j \\
& y_j \leq T v_j z_j \quad \forall j
\end{aligned}$$

$$[\bar{e} - (u'_j e_j^e + (1 - u'_j) e_j^d)) - (u'_{ij} e_{ij}^e + (1 - u'_{ij}) e_{ij}^d))] \sum_{l=1}^m D_l x_{lj} \geq$$

$$g_j(v_j) z_j - M(1 - x_{ij}) \quad \forall i, j$$

$$y_j \geq 0 \quad \forall j$$

$$z_j, x_{ij} \in \{0, 1\} \quad \forall i, j$$

The first term of the objective function represents the cost associated with opening DCs while the second and third terms capture the transportation costs within the supply chain. To accommodate the differing transportation costs between diesel and electric trucks, we introduce binary parameters u'_j and u'_{ij} , set to 1 if electric trucks are used to transport products between the plant and open DCs, and between open DCs and retailers, respectively (if their range can cover the entire distance from origin to destination and back to the origin), and set to 0 otherwise. In this context, c_j^e and t_{ij}^e represent the per unit transportation cost using electric trucks between the plant and open DCs, and between open DCs and retailers, respectively. Similarly, c_j^d and t_{ij}^d represent the equivalent parameters for diesel trucks.

The remaining three terms in the objective function address the costs associated with CO_2 -equivalent emission from DCs and the transportation of goods between plants and DCs, as well as between DCs and retailers. Within these terms, w represents the conversion factor that could be the carbon market price. The emission functions for the transportation fleet are denoted by $f_j(y_j)$ and $f_{ij}(D_i x_{ij})$. These expressions encompass emissions associated with both diesel and electric trucks. Consequently, using the same

Table 3.1: Notations Table

Parameters	
n	number of potential DC locations.
m	number of retailers.
w	conversion factor for turning emission units into dollars units.
T	number of periods in the planning horizon.
a_j	fixed cost for opening DC j , $j = 1, \dots, n$.
v_j	monthly volumetric capacity of DC j , $j = 1, \dots, n$.
c_j	cost of shipping one unit to DC j from the plant, $j = 1, \dots, n$.
c_j^e	cost of shipping one unit to DC j from the plant using electric trucks, $j = 1, \dots, n$.
c_j^d	cost of shipping one unit to DC j from the plant using diesel trucks, $j = 1, \dots, n$.
t_{ij}	cost of shipping one unit to retailer i from DC j , $i = 1, \dots, m$, $j = 1, \dots, n$.
t_{ij}^e	cost of shipping one unit to retailer i from DC j using electric trucks, $i = 1, \dots, m$, $j = 1, \dots, n$.
t_{ij}^d	cost of shipping one unit to retailer i from DC j using diesel trucks, $i = 1, \dots, m$, $j = 1, \dots, n$.
e_j	emission associated with transporting each unit to DC j from the plant, $j = 1, \dots, n$.
e_j^e	emission associated with transporting each unit to DC j from the plant using electric trucks, $j = 1, \dots, n$.
e_j^d	emission associated with transporting each unit to DC j from the plant using diesel trucks, $j = 1, \dots, n$.
e_{ij}	emission associated with transporting each unit to retailer i from the DC j , $i = 1, \dots, m$, $j = 1, \dots, n$.
e_{ij}^e	emission associated with transporting each unit to retailer i from the DC j using electric trucks, $i = 1, \dots, m$, $j = 1, \dots, n$.
e_{ij}^d	emission associated with transporting each unit to retailer i from the DC j using diesel trucks, $i = 1, \dots, m$, $j = 1, \dots, n$.
$\bar{e}$	upper limit on the amount of emission associated with each unit.
d_j	the travel distance between DC j and the plant, $j = 1, \dots, n$.
d_{ij}	the travel distance between retailer i and DC j , $i = 1, \dots, m$, $j = 1, \dots, n$.
u'_j	1 if $2d_j \leq R$, 0, otherwise, $j = 1, \dots, n$.
u'_{ij}	1 if $2d_{ij} \leq R$, 0, otherwise, $i = 1, \dots, m$, $j = 1, \dots, n$.
D_i	demand of retailer i , $i = 1, \dots, m$.
M	big number.
Decision Variables	
z_j	1 if a DC is located at potential location j , 0, otherwise, $j = 1, \dots, n$.
x_{ij}	1 if retailer i is served by DC j , $i = 1, \dots, m$, $j = 1, \dots, n$.
y_j	units shipped to DC j from the plant, $j = 1, \dots, n$.
q_j	1 if DC j is served by the plant k , 0, otherwise, $k = 1, \dots, p$.
u_j	1 if DC j is served by the plant using electric trucks, 0, otherwise, $j = 1, \dots, n$.
u_{ij}	1 if retailer i is served by DC j using electric trucks, 0, otherwise, $i = 1, \dots, m$, $j = 1, \dots, n$.

binary parameters introduced to denote transportation costs, the emissions generated from transportation within the first and second echelons of the supply chain are expressed as the last two terms of the objective function, respectively. $f_j^e(y_j)$ and $f_{ij}^e(D_ix_{ij})$ represent the emission functions of electric trucks for transportation between the plant and open DCs, and between the open DCs and the retailers, respectively. Similarly, $f_j^d(y_j)$ and $f_{ij}^d(D_ix_{ij})$ denote the emission functions of diesel trucks for transportation between the plant and open DCs, and between the open DCs and the retailers, respectively. We clarify here that functions $f_j^e(y_j)$, $f_{ij}^e(D_ix_{ij})$, $f_j^d(y_j)$, and $f_{ij}^d(D_ix_{ij})$ capture the total emissions for fulfilling the yearly demand. They represent the aggregate emissions using a fleet of either electric or diesel trucks.

Incorporating the closed form of the parameters, problem [EP] is reduced to:

$$\begin{aligned}
[\text{P}] : \quad & \min \sum_{j=1}^n a_j z_j + \sum_{j=1}^n c_j y_j + \sum_{i=1}^m \sum_{j=1}^n t_{ij} D_i x_{ij} \\
& + w \left(\sum_{j=1}^n g_j(v_j) z_j + \sum_{j=1}^n f_j(y_j) + \sum_{i=1}^m \sum_{j=1}^n f_{ij}(D_i x_{ij}) \right)
\end{aligned}$$

$$\text{s.t.} \quad \sum_{j=1}^n x_{ij} = 1 \quad \forall i \tag{3.1}$$

$$y_j = \sum_{i=1}^m D_i x_{ij} \quad \forall j \tag{3.2}$$

$$y_j \leq T v_j z_j \quad \forall j \tag{3.3}$$

$$[\bar{e} - e_j - e_{ij}] \sum_{l=1}^m D_l x_{lj} \geq g_j(v_j) z_j - M(1 - x_{ij}) \quad \forall i, j \quad (3.4)$$

$$y_j \geq 0 \quad \forall j \quad (3.5)$$

$$z_j, x_{ij} \in \{0, 1\} \quad \forall i, j \quad (3.6)$$

In terms of constraints, the first set of constraints establishes assignment rules, ensuring each retailer is allocated to exactly one DC. The flow balance constraints are enforced by constraints (3.2). Constraints

(3.3) enforces the capacity constraints of DCs and ensures that a DC cannot experience inflow or outflow unless it is established. Moreover, Tv_j represents the total inflow of DC j during the entire planning horizon. Here, T is the number of periods in the planning horizon, and v_j is the maximum throughput of DC j in each period. This multiplication accounts for the total annual capacity utilization. To explain this further with an example, if a DC carries at most one month's demand then for a year, it handles 12 times that amount.

In our modeling framework, y_j represents the amount shipped to DC j from the plant over the planning horizon, and D_i represents the yearly demand of retailer i . Thus, the total yearly demand is $\sum_{i=1}^m D_i$. Open DCs are designed to fill up periodically, with their inflow never exceeding the amount needed to satisfy retailer demand for one period. Consequently, the maximum capacity for each open DC j at any time is v_j , sufficient to meet a period's worth of retailer demands. Therefore, it is neither necessary nor cost-efficient to build DCs with capacities equal to $\sum_{i=1}^m D_i$. This explains why the one-period capacity of the DCs is multiplied by the number of periods in the planning horizon.

Constraints (3.4) establish a specified threshold, denoted as $\bar{e}$, representing the maximum acceptable emission per unit for each DC-retailer pair. Here, M serves as a large number introduced into the model. These constraints are added to the model to address consumer concerns related to the quantity of CO_2 -equivalent emission per unit. In this context, the emission level for each unit transported from the plant to retailer i can be determined as follows:

$$e_i = e_j + \frac{g_j(v_j)}{\sum_{l=1}^m D_l x_{lj}} + e_{ij} \quad (3.7)$$

Where e_j represents the per-unit emission from the plant to DC j , the per-unit emission of DC j is denoted by $g_j(v_j) / \sum_{l=1}^m D_l x_{lj}$, and e_{ij} signifies the per-unit emission from DC j to retailer i . The calculated emission, as determined by Equation (3.7), must be constrained to be less than $\bar{e}$ when $x_{ij} = 1$ ($e_i \leq \bar{e}$). The final sets of constraints, (3.5) and (3.6), propose the domains of the variables. Note that we will use formulation [P] to represent the problem, from this point forward.

Note that an alternative way to modeling problem [EP] is to define arcs specific to electric and diesel fleets. Instead of using binary parameters u'_{ij} and u'_j in the objective function to select between vehicle types, we define two sets, A_1 and A_2 , representing the arcs connecting plant(s) to DCs and DCs to retailers, respectively. Each of these sets is divided into two disjoint subsets to account for the arcs that can be covered by electric trucks, given their limited travel range. The remaining arcs will represent those that must be covered by diesel trucks. For instance, consider A_1 . We divide the set A_1 into A_1^e and A_1^d , for electric and diesel trucks, respectively, such that $A_1^e \cap A_1^d = \emptyset$ and $A_1^e \cup A_1^d = A_1$. Similarly, we define A_2^e and A_2^d for the arcs in the second echelon of the supply chain ($A_2^e \cap A_2^d = \emptyset$ and $A_2^e \cup A_2^d = A_2$).

Chapter 4

Solution Methodology

4.1 Concave Emissions for Diesel Trucks

To exploit the echelon structure of the problem, we relax constraints (3.2). To do this, Lagrangian multipliers, μ_j , are used. The term $\sum_{j=1}^n (y_j - \sum_{i=1}^m D_i x_{ij}) \mu_j$ is added to the objective function of the problem, forming the following subproblem:

$$\begin{aligned} [\text{SP}]: \min \quad & \sum_{j=1}^n a_j z_j + \sum_{j=1}^n (c_j - \mu_j) y_j + \sum_{i=1}^m \sum_{j=1}^n (t_{ij} D_i + D_i \mu_j) x_{ij} + \\ & w \left(\sum_{j=1}^n g_j(v_j) z_j + \sum_{j=1}^n f_j(y_j) + \sum_{i=1}^m \sum_{j=1}^n f_{ij}(D_i x_{ij}) \right) \\ \text{s.t} \quad & (3.1), (3.3), (3.4), (3.5), \text{ and } (3.6), \end{aligned}$$

[SP] can be separated by echelon to [SP1] and [SP2]:

$$\begin{aligned}
[\text{SP1}]: \min \quad & \sum_{j=1}^n a_j z_j + \sum_{i=1}^m \sum_{j=1}^n (t_{ij} + \mu_j) D_i x_{ij} + w \left(\sum_{i=1}^m \sum_{j=1}^n f_{ij}(D_i x_{ij}) + \sum_{j=1}^n g_j(v_j) z_j \right) \\
\text{s.t} \quad & (3.1), (3.4), \text{ and } (3.6)
\end{aligned}$$

The assignment of retailers to DCs is determined by the binary variable x_{ij} . Thus, the value of $f_{ij}(D_i x_{ij})$ is dependent on whether x_{ij} is equal to 1 or zero. In this context, $f_{ij}(D_i x_{ij}) = 0$ if x_{ij} is equal to zero, if x_{ij} is equal to 1, $f_{ij}(D_i x_{ij}) = f_{ij}(D_i)$. the objective can be expressed as $\min \sum_{j=1}^n (a_j + w g_j(v_j)) z_j + \sum_{i=1}^m \sum_{j=1}^n (w f_{ij}(D_i) + t_{ij} D_i + D_i \mu_j) x_{ij}$. [SP1], therefore, can be written as the following:

$$\begin{aligned}
[\text{SP1}]: \min \quad & \sum_{j=1}^n (a_j + w g_j(v_j)) z_j + \sum_{i=1}^m \sum_{j=1}^n (w f_{ij}(D_i) + t_{ij} D_i + D_i \mu_j) x_{ij} \\
\text{s.t} \quad & \sum_{j=1}^n x_{ij} = 1 \quad \forall i \\
& \sum_{i=1}^m D_i x_{ij} \leq T v_j z_j \quad \forall j \\
& [\bar{e} - e_j - e_{ij}] \sum_{l=1}^m D_l x_{lj} \geq g_j(v_j) z_j - M(1 - x_{ij}) \quad \forall i, j \\
& z_j, x_{ij} \in \{0, 1\} \quad \forall i, j
\end{aligned}$$

We can solve [SP1] using commercial solvers.

The second subproblem is written as:

$$\begin{aligned}
[\text{SP2}]: \min \quad & \sum_{j=1}^n (c_j - \mu_j) y_j + w \sum_{j=1}^n f_j(y_j) \\
\text{s.t} \quad & \text{(3.3) and (3.5)}
\end{aligned}$$

[SP2] can be decomposed by potential DC sites, resulting in n subproblems [SP2j].

$$\begin{aligned}
[\text{SP2j}]: \min \quad & (c_j - \mu_j) y_j + w f_j(y_j) \\
\text{s.t} \quad & y_j \leq T v_j z_j \\
& y_j \geq 0
\end{aligned}$$

Since the case where $z_j = 0$ is straightforward, our primary interest lies in the scenario where $z_j = 1$. Under this specific condition, [SP2j] transitions into a concave knapsack problem when $u_j = 0$ and diesel trucks are employed. In such problems, global optimality is achieved at an extreme point within the feasible domain [Pardalos and Rosen \[1986\]](#). Therefore, we can conclude that [SP2j] attains an optimal solution at such an extreme point, satisfying the constraints $y_j \geq 0$ and $y_j \leq v_j$. This observation implies that under optimality, only one y_j , at most, will take on the value of v_j , while all other y_j will remain at 0. As a result, we can reformulate [SP2j] as follows:

$$\begin{aligned}
[\text{SP2j}]: \min \quad & \left(\frac{w f_j(v_j)}{v_j} + c_j - \mu_j \right) y_j \\
\text{s.t} \quad & y_j \leq T v_j \\
& y_j \geq 0
\end{aligned}$$

which is now a linear knapsack problem. When $u_j = 1$, signifying the utilization of electric trucks, [SP2j] becomes a linear problem, easily solvable using a commercial solver.

According to all mentioned above, the solutions to the subproblems yield a lower bound:

$$LB = [SP1(\mu)] + \sum_{j=1}^n [SP2j(\mu)]$$

The best Lagrangian lower bound, LB^* , is:

$$LB^* = \max_{\mu} \left([SP1(\mu)] + \sum_{j=1}^n [SP2j(\mu)] \right)$$

that can be found by solving:

$$\begin{aligned} \max_{\mu} \left\{ \min_{h \in I_y} \sum_{j=1}^n (a_j + wg_j(v_j)) z_j^h + \sum_{i=1}^m \sum_{j=1}^n (wf_{ij}(D_i) + t_{ij}D_i + D_i\mu_j) x_{ij}^h \right. \\ \left. + \sum_{j=1}^n \min_{h_j \in I_{x_j}} (c_j - \mu_j) y_j^{h_j} + wf_j(y_j^{h_j}) \right\} \end{aligned}$$

where I_y represents the index set of feasible integer points within the set:

$$\begin{aligned} \{(x_{ij}^h, z_j^h) : \sum_{j=1}^n x_{ij}^h = 1; \sum_{i=1}^m D_i x_{ij}^h \leq Tv_j z_j^h; [\bar{e} - e_j - e_{ij}] \sum_{l=1}^m D_l x_{lj}^h \geq g_j(v_j) z_j^h - M(1 - x_{ij}^h); \\ x_{ij}^h, z_j^h \in \{0, 1\}, \forall i, j\} \end{aligned}$$

and I_{x_j} denotes the index set of extreme points within the set:

$$\{(y_j^{h_j}) : y_j^{h_j} \leq Tv_j; y_j^{h_j} \geq 0\}$$

We can then reformulate the above as the Lagrangian master problem:

$$\begin{aligned}
[\text{LMP}]: \max \quad & \theta_0 + \sum_{j=1}^n \theta_j \\
\text{s.t.} \quad & \theta_0 - \sum_{j=1}^n \sum_{i=1}^m D_i x_{ij}^h \mu_j \leq \sum_{j=1}^n (a_j + w g_j(v_j)) z_j^h + \sum_{j=1}^n \sum_{i=1}^m (w f_{ij}(D_i) + t_{ij} D_i) x_{ij}^h \\
& h \in I_y \\
& \theta_j + y_j^{h_j} \mu_j \leq f_j(y_j^{h_j}) + c_j y_j^{h_j} \quad h_j \in I_{xj}, \quad \forall j
\end{aligned}$$

The problem [LMP] can be treated as a linear programming problem. The sets $\bar{I}_y \subseteq I_y$ and $\bar{I}_{xj} \subseteq I_{xj}$ represent a relaxation of [LMP]. We utilize an initial set of Lagrangian multipliers, denoted as μ , to address both [SP1] and [SP2] and generate $n + 1$ cuts in the following format:

$$\begin{aligned}
\theta_0 - \sum_{j=1}^n \sum_{i=1}^n D_i x_{ij}^{\bar{a}} \mu_j &\leq \sum_{j=1}^n (a_j + w g_j(v_j)) z_j^{\bar{a}} + \sum_{i=1}^m \sum_{j=1}^n (w f_{ij}(D_i) + t_{ij} D_i) x_{ij}^{\bar{a}} \\
\theta_j + y_j^{\bar{b}_j} \mu_j &\leq w f_j(y_j^{\bar{b}_j}) + c_j y_j^{\bar{b}_j} \quad \forall j
\end{aligned}$$

The index sets $I_y \subseteq \{\bar{a}\}$ and $I_{xj} \subseteq \{\bar{b}_j\}$ are updated at each iteration.

4.2 Convex Emissions for Diesel Trucks

To solve the problem [P] with a convex payload-emission relationship assumed for diesel trucks, two approaches are proposed: a direct linearization approach and a Lagrangian

approach similar to the previous section.

4.2.1 Direct Linearization Approach

Considering the fact that x_{ij} is a binary variable, we can write the term $\sum_{j=1}^n f_{ij}(D_i x_{ij})$ in the objective function of [P] as $\sum_{j=1}^n f_{ij}(D_i) x_{ij}$. In this way the only nonlinear component of the objective function will be $\sum_{j=1}^n f_j(y_j)$. According to the work presented by [Elhedhli \[2005\]](#), a linearization approach can be employed for this nonlinear term. In this regard we introduce $f_j(y_j) = a_j y_j^b$, $b \geq 1$ to represent the emission function of diesel trucks. As a convex function, y_j^b can be written as the maximum of a set of tangent piece-wise linear functions. Consider non-negative points y_j^h indexed by set H , then,

$$y_j^b = \max_{h \in H} \{b(y_j^h)^{b-1}(y_j - y_j^h) + (y_j^h)^b\} \quad (4.1)$$

Therefore [P] can be reformulated as the following:

$$\begin{aligned} [\text{P}(H)]: \min \quad & \sum_{j=1}^n (a_j + w g_j(v_j)) z_j + \sum_{j=1}^n \sum_{i=1}^m (w f(D_i) + t_{ij} D_i) x_{ij} + \\ & \sum_{j=1}^n w \max_{h \in H} (b(y_j^h)^{b-1}(y_j - y_j^h) + (y_j^h)^b) + \sum_{j=1}^n c_j y_j \\ \text{s.t.} \quad & (3.1) - (3.6) \end{aligned}$$

which is equivalent to:

$$\begin{aligned}
[\text{P}(H)]: \min \quad & \sum_{j=1}^n (a_j + wg_j(v_j))z_j + \sum_{j=1}^n \sum_{i=1}^m (wf(D_i) + t_{ij}D_i)x_{ij} + \\
& \sum_{j=1}^n wa_j\eta_j + \sum_{j=1}^n c_jy_j \\
\text{s.t.} \quad & (3.1) - (3.6) \\
& \eta_j \geq b(y_j^h)^{b-1}(y_j - y_j^h) + (y_j^h)^b \quad h \in H, \quad \forall j
\end{aligned}$$

This leads to a linear mixed integer problem featuring one additional continuous variable and a substantial number of constraints. Employing a cutting plane (constraint generation) approach proves effective in managing these numerous constraints. The process begins with an initial set and progressively includes more constraints as needed. At the q -th iteration, a finite set of the last constraints is generated at points y_j^h , where h belongs to the subset H^q of H . This leads to the formation of $[\text{P}(H^q)]$, serving as a relaxation of $[\text{P}(H)]$. Consequently, its optimal objective yields a lower bound (LB^q) for $[\text{P}(H)]$ and, equivalently, for $[\text{P}]$. Additionally, the solution of $[\text{P}(H^q)]$, denoted as $(\bar{x}^q, \bar{y}^q, \bar{z}^q, \bar{\eta}^q)$, provides a feasible solution $(\bar{x}^q, \bar{y}^q, \bar{z}^q)$ for $[\text{P}]$. Therefore, the expression $\sum_{j=1}^n (a_j + wg_j(v_j))\bar{z}_j + \sum_{j=1}^n \sum_{i=1}^m (wf(D_i) + t_{ij}D_i)\bar{x}_{ij} + \sum_{j=1}^n wa_j\bar{y}_j^b + \sum_{j=1}^n c_j\bar{y}_j$ acts as an upper bound (UB^q) for $[\text{P}]$. At the q -th iteration, LB^q is set to the best lower bound, while the best upper bound is determined as $\min\{\text{UB}, \text{UB}^q\}$. If LB equals UB , then $\bar{y}^q$ represents an optimal solution to $[\text{P}]$. Otherwise, a new candidate point is introduced to generate additional cuts in the second constraint.

4.2.2 LR-based Approach

This section introduces the LR-based approach developed to address problem $[\text{P}]$, considering a convex relationship between the weight of cargo and the emission of diesel trucks.

The initial steps to exploit the echelon structure of the problem using LR is the same as the concave case forming the following subproblems:

$$\begin{aligned}
[\text{SP1}]: \min \quad & \sum_{j=1}^n (a_j + wg_j(v_j))z_j + \sum_{i=1}^m \sum_{j=1}^n (wf_{ij}(D_i) + t_{ij}D_i + D_i\mu_j) x_{ij} \\
\text{s.t} \quad & \sum_{j=1}^n x_{ij} = 1 \quad \forall i \\
& \sum_{i=1}^m D_i x_{ij} \leq Tv_j z_j \quad \forall j \\
& [\bar{e} - e_j - e_{ij}] \sum_{l=1}^m D_l x_{lj} \geq g_j(v_j)z_j - M(1 - x_{ij}) \quad \forall i, j \\
& z_j, x_{ij} \in \{0, 1\} \quad \forall i, j
\end{aligned}$$

and the second subproblem which can be decomposed by potential DC sites, resulting in n subproblems [SP2j]:

$$\begin{aligned}
[\text{SP2j}]: \min \quad & (c_j - \mu_j)y_j + wf_j(y_j) \\
\text{s.t} \quad & y_{jk} \leq Tv_j z_j \\
& y_j \geq 0
\end{aligned}$$

Since the case where $z_j = 0$ is straightforward, our primary interest lies in the scenario where $z_j = 1$. This condition transforms [SP2j] into a convex knapsack problem.

By employing the same approach detailed in section 4.2.1, [SPj2] can be written as:

$$\begin{aligned}
[\text{SP2j}(H)]: \min \quad & (c_j - \mu_j)y_j + wa_j \max_{h \in H} (b(y_j^h)^{b-1}(y_j - y_j^h) + (y_j^h)^b) \\
\text{s.t} \quad & y_j \leq Tv_j \\
& y_j \geq 0
\end{aligned}$$

which is equivalent to:

$$\begin{aligned}
[\text{SP2j}(H)]: \quad & \min \quad (c_j - \mu_j)y_j + wa_j\eta_j \\
\text{s.t} \quad & y_j \leq Tv_j \\
& \eta_j \geq b(y_j^h)^{b-1}(y_j - y_j^h) + (y_j^h)^b \quad h \in H, \quad y_j \geq 0
\end{aligned}$$

At iteration q , a finite set of the second constraints is generated at points y_j^h , $h \in H^q \subset H$. $[\text{SP2j}(H^q)]$ thus serves as a relaxation of $[\text{SP2j}(H)]$. Consequently, its optimal objective provides a lower bound (LB^q) to $[\text{SP2j}(H)]$ and equivalently to $[\text{SP2j}]$. Furthermore, the solution of $[\text{SP2j}(H^q)]$, denoted by $(\bar{y}^q, \bar{\eta}^q)$, offers a feasible solution $(\bar{y}^q)$ to $[\text{SP2j}]$. Hence, $(c_j - \mu_j)\bar{y}_j + wa_j(\bar{y}_j)^b$ serves as an upper bound (UB^q) to $[\text{SP2j}]$. At iteration q , the best lower bound is assigned to LB^q , while the best upper bound is set to $\min\{\text{UB}, \text{UB}^q\}$. If LB equals UB , then $\bar{y}^q$ represents an optimal solution to $[\text{SP2j}]$. If not, a new candidate point is introduced to generate additional cuts in the second constraint. The convergence of the algorithm follows from [Elhedhli \[2005\]](#).

It is important to highlight that this approach is specifically tailored for scenarios involving diesel trucks transporting units between the plant and DCs. Conversely, the utilization of electric trucks is more straightforward, as $[\text{SP2j}]$ is a linear program in that case.

$$LB = [\text{SP1}(\mu)] + \sum_{j=1}^n [\text{SP2j}(\mu)]$$

The best Lagrangian lower bound, LB^* , is:

$$LB^* = \max_{\mu} \left([\text{SP1}(\mu)] + \sum_{j=1}^n [\text{SP2j}(\mu)] \right)$$

which is equivalent to:

$$\max_{\mu} \left\{ \min_{h \in I_y} \sum_{j=1}^n (a_j + w g_j(v_j)) z_j^h + \sum_{i=1}^m \sum_{j=1}^n (w f_{ij}(D_i) + t_{ij} D_i + D_i \mu_j) x_{ij}^h \right. \\ \left. + \sum_{j=1}^n \min_{h_j \in I_{x_j}} (c_j - \mu_j) y_j^{h_j} + w f_j(y_j^{h_j}) \right\}$$

where I_y represents the index set of feasible integer points of the set:

$$\{(x_{ij}^h, z_j^h) : \sum_{j=1}^n x_{ij}^h = 1; \sum_{i=1}^m D_i x_{ij}^h \leq T v_j z_j^h; [\bar{e} - e_{0j} - e_{ij}] \sum_{l=1}^m D_l x_{lj}^h \geq g_j(v_j) z_j^h - M(1 - x_{ij}^h); \\ x_{ij}^h, z_j^h \in \{0, 1\}, \forall i, j\}$$

and I_{x_j} denotes the index set of extreme points of the set:

$$\{(y_j^{h_j}) : y_j^{h_j} \leq T v_j; y_j^{h_j} \geq 0\}$$

The corresponding Lagrangian master problem is:

$$\begin{aligned}
\text{[LMP]: } \max \quad & \theta_0 + \sum_{j=1}^n \theta_j \\
\text{s.t.} \quad & \theta_0 - \sum_{j=1}^n \sum_{i=1}^m D_i x_{ij}^h \mu_j \leq \sum_{j=1}^n (a_j + w g_j(v_j)) z_j^h + \sum_{j=1}^n \sum_{i=1}^m (w f_{ij}(D_i) + t_{ij} D_i) x_{ij}^h \\
& h \in I_y \\
& \theta_j + y_j^{h_j} \mu_j \leq w f_j(y_j^{h_j}) + c_j y_j^{h_j} \quad h_j \in I_{xj}, \quad \forall j
\end{aligned}$$

The sets $\bar{I}_y \subseteq I_y$ and $\bar{I}_{xj} \subseteq I_{xj}$ represent a relaxation of [LMP]. We utilize an initial set of Lagrangian multipliers, denoted as μ , to solve both [SP1] and [SP2] and generate $n + 1$ cuts in the following format:

$$\theta_0 - \sum_{j=1}^n \sum_{i=1}^n D_i x_{ij}^{\bar{a}} \mu_j \leq \sum_{j=1}^n (a_j + w g_j(v_j)) z_j^{\bar{a}} + \sum_{i=1}^m \sum_{j=1}^n w (f_{ij}(D_i) + t_{ij} D_i) x_{ij}^{\bar{a}}$$

$$\theta_j + y_j^{\bar{b}_j} \mu_j \leq w f_j(y_j^{\bar{b}_j}) + c_j y_j^{\bar{b}_j} \quad \forall j$$

The index sets $I_y \subseteq \{\bar{a}\}$ and $I_{xj} \subseteq \{\bar{b}_j\}$ are updated at each iteration. It is important to mention that if the emission of diesel trucks is a linear function of the weight of their payload, either of the approaches presented for both concave and convex cases can be applied to solve [P].

4.3 LR Heuristic

To generate feasible solutions, we employed a primal heuristic based on [Elhedhli and Merick \[2012\]](#)'s work. In the initial subproblem [SP1], we establish retailer assignments (x_{ij}^h) and operational statuses of DCs (z_j^h). We then determine retailer demand quantities (y_j). Notably, the deterministic nature of demand simplifies the problem into a continuous flow transportation problem, [TP], ensuring feasible solutions.

$$\begin{aligned}
\text{[TP]: min} \quad & \sum_{j=1}^n (a_j + g_j(v_j)) z_j^h + \sum_{j=1}^n \sum_{i=1}^m (f(D_i) + t_{ij} D_i) x_{ij}^h + \sum_{j=1}^n f(y_j) + \sum_{j=1}^n c_j y_j \\
\text{s.t.} \quad & y_j = \sum_{i=1}^m D_i x_{ij}^h \quad \forall j, \\
& y_j \geq 0 \quad \forall j
\end{aligned}$$

The first and second terms within [TP] are fixed constants, reducing the objective function to just two terms. Given the concave nature of [TP], an optimal solution exists at an extreme point. This suggests that each DC will have a unique supplier (single-sourced by one plant). As a result, the optimal unit flow from a plant to a DC will precisely match the DC's demand or be zero. This reduces [TP] to an assignment problem:

$$\begin{aligned}
\text{[TP2]: min} \quad & C + \sum_{j=1}^n (f(\sum_{i=1}^m D_i x_{ij}^h) + c_j (\sum_{i=1}^m D_i x_{ij}^h)) q_j \\
\text{s.t.} \quad & (\sum_{i=1}^m D_i x_{ij}^h) q_j = \sum_{i=1}^m D_i x_{ij}^h \quad \forall j \\
& q_j \in \{0, 1\} \quad \forall j
\end{aligned}$$

In the context of this problem, q_j is set to one when the plant supplies DC j , and it is set to zero otherwise.

Chapter 5

Numerical Experiments

To assess the effectiveness of the proposed framework, we constructed a case study for a Canadian prepared meats producer in the province of Ontario, Canada. We assumed a single plant located in Brampton that produces one product. Table 5.1 displays the monthly demand for each city (retailer) for the product based on the population size of each city. The cost structure for each DC j comprises a fixed annual cost of 22 and a variable cost linked to volume, calculated as $1.3 \cdot v_j^{0.68}$ inspired by [Saif and Elhedhli \[2016\]](#), both in thousands of dollars. Additionally, each DC contributes a fixed annual emission of 30 tonnes of CO₂-equivalent and a concave volume-dependent emission function of $5 \cdot v_j^{0.76}$ tonnes of CO₂-equivalent. Moreover, to calculate the volumetric capacity of the DCs,

Table 5.1: Average Monthly Demand

i	City	Demand	i	City	Demand	i	City	Demand	i	City	Demand
1	Toronto	3928	2	Ottawa	1326	3	Mississauga	1102	4	Brampton	781
5	Hamilton	786	6	London	570	7	Markham	444	8	Vaughan	477
9	Kitchener	352	10	Windsor	360	11	Burlington	229	12	Sudbury	273
13	Oshawa	226	14	Barrie	202	15	St. Catharines	182	16	Cambridge	219
17	Kingston	197	18	Guelph	167	19	Pickering	106	20	Waterloo	147

initially, an average capacity was calculated by dividing the sum of the demand at all retailer nodes, for one month ($T = 12$), by 4. Then, the averaged value is either multiplied by 0.8, 1.2, or 2. The capacities obtained are subsequently randomly assigned to the DCs.

For transportation between plants and DCs, as well as DCs and retailers, we utilize trucks of regulatory class 8 which can accommodate 1230 units of the product. An example of an electric truck suitable for our purposes is the eCascadia by Freightliner, a widely used electric truck in North America [Freightliner, 2023].

Regarding the emissions associated with electric trucks, it is important to note that MOVES4.0 does not directly report the tailpipe emissions of these types of vehicles. However, the emission of electric trucks is directly dependent on their electricity consumption [United States Environmental Protection Agency, 2022]. Therefore, we utilized the energy rates (kWh/km) provided by MOVES4.0 to estimate the emissions associated with transporting units using an electric truck. To delve into more detail, we acquired energy consumption rates for electric trucks of class 8 for the years 2030, 2035, and 2040 from MOVES4.0. These rates were averaged to obtain an estimation of the energy consumption rate for these trucks over the next 15 years. Subsequently, we divided this rate by the truck’s capacity (1230 units) to derive the energy consumption (kWh) per distance traveled (km) and per unit. Finally, to account for the excess emission of a cold transportation fleet compared to the regular one [Leonardi et al., 2010, News, 2015], as MOVES4.0 does not consider emission related to refrigerated transportation fleet, we multiplied the obtained emission rates by a factor.

Therefore, the CO₂-equivalent emission of electric trucks, particularly during transportation between the plant and DCs, are calculated using the following linear function: $f_j^e(y_j) = ERE \times E \times y_j \times d_j$, where $f_j^e(y_j) = 0$ if $y_j = 0$. In this equation, ERE represents the energy consumption rate (kWh/km.unit) associated with an electric truck of class 8,

and E represents the electricity consumption CO₂-equivalent intensity in (g/kWh). Similarly, the emission associated with the transportation of goods between DCs and retailers is computed by replacing y_j with $D_i x_{ij}$ and d_j with d_{ij} . Details regarding the calculation of the CO₂-equivalent emission of transporting goods using a diesel truck belonging to class 8 will be discussed in the following sections.

To compute the transportation costs for diesel trucks of class 8, we start by extracting fuel consumption rates (l/km) for the years 2030, 2035, and 2040 from MOVES4.0. Subsequently, we calculate the average of these rates and divide the result by the number of units that the truck can accommodate. This yields the diesel consumption (l) per km traveled and per unit. We then multiply this figure by the average diesel fuel price. For electric trucks, a similar process is undertaken using data from MOVES4.0 and using transportation electricity prices. In line with emission rates, the derived shipping cost rates are adjusted by a multiplier to reflect the impact of employing refrigerated transportation fleets on fuel consumption (both diesel and electricity) and overall transportation expenses. Table 5.2 provides a comprehensive summary of the parameters gathered from various sources.

As discussed in Chapter 2, we explore three types of emission functions (concave, convex, and linear) for diesel trucks based on the type of payload-emission link considered. The following sections present the numerical results obtained by applying the model discussed in Chapter 3. Each scenario corresponds to a specific emission function for diesel trucks.

It is important to highlight that we explored two main scenarios for each type of emission function. One that assumes electric trucks are more cost-effective than diesel trucks, and vice versa.

Table 5.2: Summary of reported values and sources for the parameters

Parameter	Reported Value	Source
Class 8 truck capacity	1230 (unit)	Estimated based on the data by Saif and Elhedhli [2016]
Electric truck range (R)	370 (km)	Freightliner [2023]
Electric trucks energy consumption rate (ERE)	0.007 (kWh/km.unit)	MOVES4.0
Electricity consumption CO_2 -equivalent intensity in Ontario (E)	30 (g/kWh)	Canada's Greenhouse Gas Offset Credit System [2023]
Electric truck CO_2 -equivalent emission rate	2 (g/km.unit)	MOVES4.0
Diesel truck CO_2 -equivalent emission rate (ERD)	20 (g/km.unit)	MOVES4.0
Diesel truck fuel consumption	0.0002 (l/km.unit)	MOVES4.0

5.1 Concave Emission Function for Diesel Trucks

In this section, we evaluate both the performance of the framework and the design of the supply chain for the concave case. We assume a general concave function of the form $y = ax^b$, where $b < 1$, y denotes CO_2 -equivalent emission, and x represents the cargo weight of the diesel trucks. To estimate the value of a , we utilized MOVES4.0 to obtain the CO_2 -equivalent emission rates associated with diesel trucks of class 8 for the years 2030, 2035, and 2040. After averaging these rates, we divided by the number of units that can fit in a fully loaded diesel truck of class 8, which, as previously stated, equals 1230 units. The resulting value provides the amount of emission per distance traveled (km) and per unit, denoted as ERD . The value is then scaled by a factor to accommodate the refrigerated transportation fleet and to compensate for the effect of using a concave emission function in comparison with a convex one which is explained in the following section.

Therefore, the CO_2 -equivalent emission of diesel trucks, specifically during transportation between the plant and DCs, are computed using the following concave function: $f_j^d(y_j) = ERD \times y_j^b \times d_j$ where $f_j^d(y_j) = 0$ if $y_j = 0$, and $b < 1$. Similarly, the emission associated with the transportation of goods between DCs and retailers is computed

by replacing y_j by $D_i x_{ij}$, and d_j by d_{ij} .

5.1.1 Scenario 1: Electric Trucks are more Cost-Efficient than Diesel Trucks

While the transition to electric trucks may initially present challenges such as higher up-front costs and the need for investment in charging infrastructure [ACT News, Year], studies indicate that electric trucks will outperform diesel trucks in terms of cost efficiency in the near future. This is mainly driven by advancements in technology and sustainability efforts [News, 2022]. To reflect this, in this section, we considered smaller cost coefficients for electric trucks compared to their diesel counterparts. Our analysis focuses on evaluating the impact of various values of b and $\bar{e}$, on the model's framework and across different problem scales. We create three distinct problem sizes, detailed in Table 5.3, by adjusting the parameters associated with n and m . Each problem instance is evaluated under specific b and $\bar{e}$ settings outlined in the first column of the table.

Subsequent columns in the table illustrate the distribution of costs among the emission cost of opening DCs (DCER), the operating cost of opening DCs (DCCR), the transportation cost (TRCR), and emission-related expenses incurred in inter-echelon goods transport (TRER) expressed as a percentage of the total cost (tot) in thousands of dollars. The table also depicts the total emissions from the open DCs in tonnes of CO_2 -equivalent (DCE), the total cost of opening DCs in thousands of dollars (DCC), the total cost of the transportation fleet in thousands of dollars (TRC), and the total emissions of the transportation fleet in tonnes of CO_2 -equivalent. Moreover, the table presents the percentage of the unit-distance transported via diesel trucks to the total unit-distance transported (DTR). Additionally, it includes the number of iterations needed to reach the Lagrangian bound (Iters), and the

Table 5.3: Sensitivity analysis: concave emission function; $R = 370$ km; electric trucks more cost-efficient than diesel trucks

Problem	Cost(%, %, %, %, thousands dollars)									Time (%, %, %, %, s)							
n, m, b	DCER	DCCR	TRCR	TRER	TOT	DCE*	DCC**	TRC**	TRE*	DTR	Iters.	HQ1	SP1	SP2	Hue	MP	tTOT
$\bar{e} = 0.050$																	
10,20,0.2	56.97	30.11	12.81	0.1	1937.97	3680.37	583.45	248.29	6.45	38.51	4	0.000	93.50	1.34	0.73	4.43	20.96
10,20,0.5	56.64	29.94	12.74	0.6	1938.41	3659.72	580.36	246.95	38.77	31.85	12	0.002	94.18	1.32	0.70	3.79	53.07
10,20,0.7	54.91	30.57	11.32	3.20	1949.04	3567.39	595.82	220.63	207.90	38.51	4	0.001	93.45	1.43	0.80	4.29	18.45
15,40,0.2	55.66	29.30	14.91	0.1	3117.26	5783.70	913.25	464.90	13.33	39.27	5	0.015	96.68	0.60	0.24	2.47	103.74
15,40,0.5	55.30	29.11	14.82	0.8	3137.76	5783.70	913.25	464.90	81.67	39.27	5	0.020	97.20	0.50	0.20	2.10	136.32
15,40,0.7	53.37	28.09	14.49	4.05	3251.33	5784.12	913.30	471.12	438.93	34.09	6	0.012	96.80	0.41	0.24	2.54	211.12
20,100,0.2	55.10	27.12	17.63	0.2	6574.87	12075.93	1783.07	1159.03	33.30	38.89	6	0.006	98.84	0.25	0.05	0.86	328.29
20,100,0.5	54.68	26.91	17.49	0.9	6625.79	12075.67	1783.07	1159.03	203.03	38.87	6	0.007	98.88	0.22	0.05	0.85	320.47
20,100,0.7	52.66	25.92	16.86	4.56	6879.55	12075.90	1783.17	1159.89	1045.69	30.32	4	0.005	98.83	0.26	0.05	0.86	215.05
Min	52.66	25.92	12.74	0.1	1937.97	3680.37	583.45	248.29	30.32	6.45	4	0.000	93.45	0.22	0.05	0.85	18.45
Max	56.97	30.11	17.63	4.56	6879.55	12075.93	1783.17	1159.89	1045.69	39.27	12	0.020	98.88	1.43	0.80	4.43	328.29
Mean	55.26	28.51	14.95	1.26	3934.67	5373.88	820.73	466.23	172.42	36.62	5.78	0.008	96.48	0.70	0.34	2.47	156.39
$\bar{e} = 0.055$																	
10,20,0.2	55.73	30.07	14.09	0.1	1796.56	3680.37	583.45	248.29	7.10	52.99	5	0.000	94.23	1.52	0.67	3.57	25.43
10,20,0.5	55.38	29.88	14.00	0.7	1808.22	337.63	540.27	253.20	42.19	52.10	4	0.000	93.95	1.39	0.70	3.94	25.09
10,20,0.7	53.52	28.88	13.54	4.06	1796.56	3205.06	518.85	243.25	243.13	52.10	9	0.000	93.77	1.52	0.65	4.06	36.20
15,40,0.2	55.66	29.30	14.91	0.1	3117.14	5783.70	913.25	464.79	13.30	39.32	5	0.002	96.83	0.60	0.27	2.30	102.52
15,40,0.5	55.30	29.11	14.81	0.8	3137.65	5783.70	913.25	464.79	81.67	39.32	5	0.030	97.06	0.55	0.23	2.16	132.42
15,40,0.7	53.43	28.12	14.31	4.13	3247.21	5783.28	913.12	464.68	447.30	39.32	7	0.000	96.96	0.44	0.22	2.38	190.53
20,100,0.2	55.14	27.14	17.58	0.2	6570.76	12075.93	1783.07	1154.83	33.60	38.17	6	0.000	98.85	0.24	0.05	0.86	311.50
20,100,0.5	54.72	26.93	17.44	0.9	6621.09	12075.93	1783.07	1154.83	201.37	38.17	6	0.007	98.78	0.29	0.06	0.87	307.10
20,100,0.7	52.66	25.92	16.86	4.56	6879.53	12075.87	1783.17	1159.89	1045.68	30.33	4	0.000	98.91	0.25	0.05	0.79	230.150
Min	52.66	25.92	14.00	0.1	1796.56	3659.39	580.36	220.63	6.45	30.33	4	0.000	93.77	0.24	0.05	0.79	25.09
Max	55.73	30.07	17.58	4.56	6879.53	12.75.93	1783.17	1159.89	1045.63	52.99	9	0.030	98.91	1.52	0.70	4.06	311.50
Mean	54.86	28.50	15.34	1.28	3886.08	6755.72	1081.28	623.17	235.04	42.42	5.67	0.004	96.59	0.76	0.32	2.33	151.22
$\bar{e} = 0.070$																	
10,20,0.2	46.71	53.29	13.95	0.09	1793.42	3337.67	540.27	250.12	5.77	53.29	4	0.000	93.87	1.22	0.65	4.23	24.85
10,20,0.5	55.48	29.93	13.86	0.7	1804.94	3337.63	540.27	250.12	44.17	53.29	4	0.000	94.75	1.12	0.65	3.47	31.55
10,20,0.7	53.64	28.94	13.40	4.03	1793.42	3206.63	519.02	240.32	240.92	53.29	9	0.000	94.54	1.28	0.69	3.49	38.58
15,40,0.2	55.67	29.30	14.90	0.1	3116.89	5843.70	913.25	464.55	13.27	39.42	5	0.000	97.02	0.61	0.23	2.14	98.31
15,40,0.5	55.30	29.11	14.81	0.8	3137.39	5783.70	913.25	464.55	81.63	39.42	5	0.000	96.83	0.58	0.24	2.34	140.61
15,40,0.7	53.45	28.13	14.33	4.09	3246.53	5784.23	913.25	465.23	442.47	37.78	7	0.000	97.12	0.36	0.18	2.33	161.53
20,100,0.2	55.14	27.14	17.58	0.2	6570.76	12075.93	1783.07	1159.03	33.30	38.17	6	0.006	98.75	0.29	0.08	0.89	302.55
20,100,0.5	54.72	26.93	17.44	0.9	6621.09	12075.93	1783.07	1154.83	201.37	38.17	6	0.007	98.78	0.29	0.06	0.87	307.10
20,100,0.7	52.66	25.92	16.86	4.56	6879.44	12075.71	1783.15	1159.87	1045.67	30.33	4	0.000	98.96	0.26	0.04	0.74	241.67
Min	46.71	25.92	13.86	0.09	1793.42	337.63	519.02	240.32	5.77	30.33	4	0.000	93.87	0.21	0.04	0.74	24.85
Max	55.83	53.29	17.58	4.56	6879.44	12075.93	1783.15	1159.03	1045.67	53.29	9	0.007	98.98	1.28	0.69	4.23	356.39
Mean	53.94	31.47	15.42	1.03	3884.87	7057.90	1076.51	623.18	234.29	42.57	5.56	0.001	96.76	0.66	0.31	2.27	155.12

*Values reported in tonnes of CO₂-equivalent.

**Values reported in thousands of dollars.

heuristic’s quality (HQ1) calculated as:

$$\text{HQ1} = 100 \times \frac{\text{heuristic solution} - \text{Lagrangian bound}}{\text{Lagrangian bound}}$$

Furthermore, columns 10, 11, 12, and 13 provide the percentage time taken by each function contributing to the solution algorithm, with the total run time of the algorithm (tTOT) placed in the last column in seconds. By analyzing the data presented in the table, it is evident that the emission cost associated with opening DCs is the most significant factor in the total cost in almost all of the cases, followed by the cost of establishing and operating these DCs.

The unit-distance covered by diesel trucks as captured by DTR increases on average from 36.62% to 42.57% when $\bar{e} = 0.050$ and $\bar{e} = 0.070$, respectively. Moreover, a closer analysis of the model’s results uncovers that changes in diesel truck usage are primarily driven by alterations in the inflow of open DCs. These adjustments are aimed at minimizing the total costs while ensuring that emission levels per unit remain under $\bar{e}$. Consequently, depending on the setup of the supply chain, particularly the open DCs, the model might opt for higher diesel truck utilization when emission limits per unit are more relaxed. Conversely, it could reduce reliance on diesel trucks if the transportation costs outweigh the savings from adjusting assignments between DCs and plants, as well as between retailers and DCs. In specific scenarios, such as the case where $b = 0.7$, the unit-distance traveled by diesel trucks remains constant from $\bar{e} = 0.050$ to $\bar{e} = 0.055$. However, the observed increase in DTR results from reduced electric truck usage due to revised retailer assignments across the same two open DCs. This adjustment was made possible by allowing one DC’s per-unit emissions to exceed $\bar{e} = 0.050$ while keeping them below $\bar{e} = 0.055$, thus reducing its inflow while increasing that of the other DC. This strategic alteration not only decreased total

transportation costs and emissions but also led to an overall reduction in the total cost. A consistent trend observed is the decline in diesel truck usage as the parameter b increases.

The details of the SCND under three different values of $\bar{e}$, with b held constant at 0.5, are outlined in Figures 5.1 - 5.3. The figures utilize distinct symbols to represent retailers and open DCs, with the plant located at location ID 4. Green arrows denote the use of electric trucks, while red arrows indicate diesel truck usage. Open DCs, along with three values denoting their monthly capacity, inflow, and total yearly emission, are displayed to the left of the map. DCs highlighted in green are serviced by electric trucks from the plant, while those highlighted in red utilize diesel trucks for their supply needs. Following this, the retailers allocated to each DC, along with the per-unit DC-retailer emission, are indicated adjacent to the location IDs of the corresponding retailer. For instance, referring to Figure 5.1, under the scenario in which the upper limit on the per unit emission is equal to 0.050 tonnes of CO_2 -equivalent; three DCs are open at locations 8, 13, and 18 corresponding to the cities of Vaughan, Oshawa, and Guelph, respectively. The one in Guelph has a capacity of 6075 units per month, with 5079 units allocated among the assigned retailers monthly. It emits a total of 1456 metric tonnes of CO_2 -equivalent annually. Retailers 1, 6, 10, and 18 are assigned to this DC, emitting a per-unit emission of 0.024 metric tonnes for the first three and 0.046 for the last retailer. The data provided beneath the map in each figure includes the value of $\bar{e}$, the total cost of the supply chain in thousands of dollars, the contribution of diesel trucks to the transportation of goods within the echelons, and the utilization of the DCs, denoted by DCU and calculated as the inflow value of each DC over its capacity and averaging these values across all open DCs. The proportional breakdown of each cost component to the total cost of the supply chain is also depicted in the same manner as Table 5.3.

It is clear that although the costs associated with the open DCs remain constant,

the model strategically adjusts the placement and inflow of each open DC, as well as the utilization of diesel trucks, to minimize the total cost while respecting the per-unit emission constraint. When comparing Figure 5.2 and Figure 5.3, with a per-unit emission allowance of 0.070 tonnes, the model chooses to open DC 18 instead of DC 9, while keeping DCs 3 and 13 open in both cases. This change, along with adjustments in retailer assignments to the open DCs, increases both transportation costs and emissions. However, it also causes some DC-retailer pairs to exceed the per-unit emission limit of 0.055 tonnes. Additionally, DTR increases slightly as the unit-distance traveled by diesel trucks rises, while the unit-distance traveled by electric trucks decreases significantly compared to the scenario with $\bar{e} = 0.055$.

5.1.2 Scenario 2: Diesel Trucks are more Cost-Efficient than Electric Trucks

In this section, we assume that the transportation costs for electric trucks are higher than those for diesel trucks. By employing binary the parameters u_j and u_{ij} , which dictate the use of electric trucks for round trips within R , we demonstrate our willingness to incur higher costs and use electric trucks whenever available to minimize emissions. This scenario can also accommodate the reality that there are still businesses for which using electric trucks is not yet cheaper than diesel trucks as the improvement in electric truck cost efficiency has not yet occurred in these sectors. With this premise, we conducted a series of experiments similar to Section 5.1.1. As a result, we observed a larger effective range for $\bar{e}$ as the model responded to variations in $\bar{e}$ from 50 to 100. Table 5.4 summarizes our findings.

As evident from the table, the emission cost associated with opening DCs emerges as

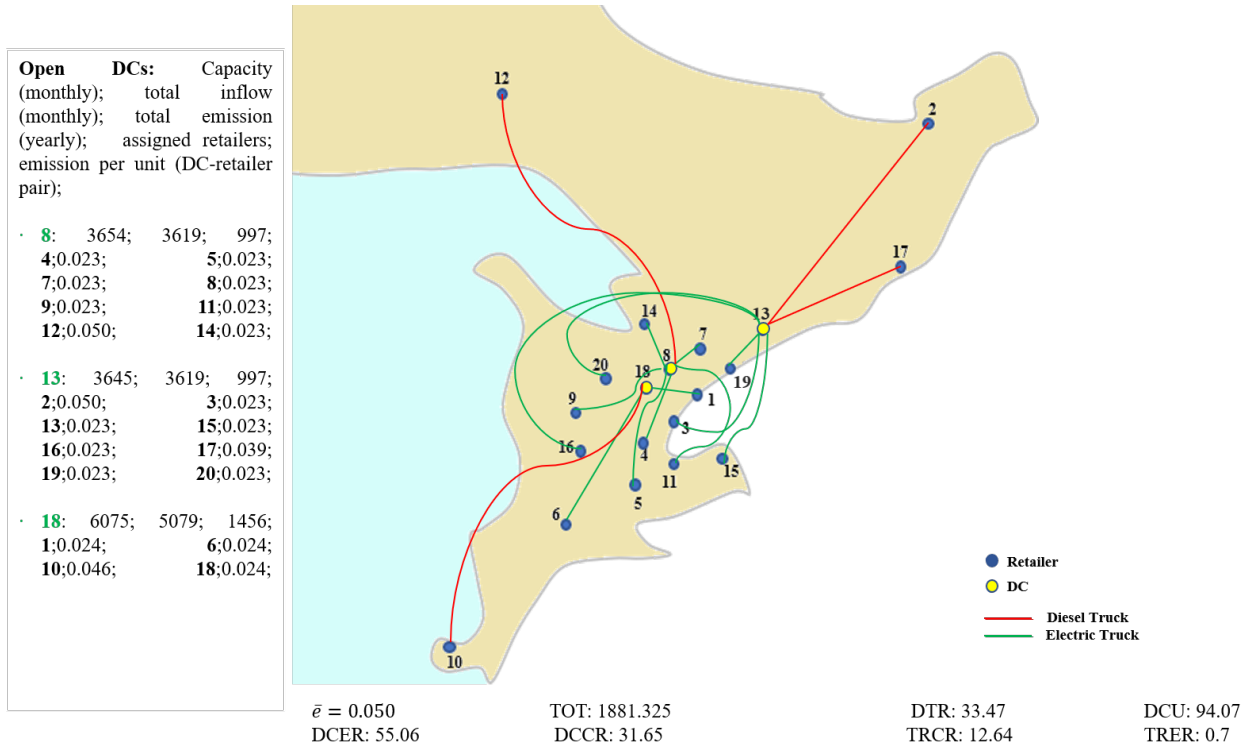


Figure 5.1: SCND: concave emission function; electric trucks more cost efficient than diesel trucks; $\bar{e} = 0.050$; $R = 370$ km

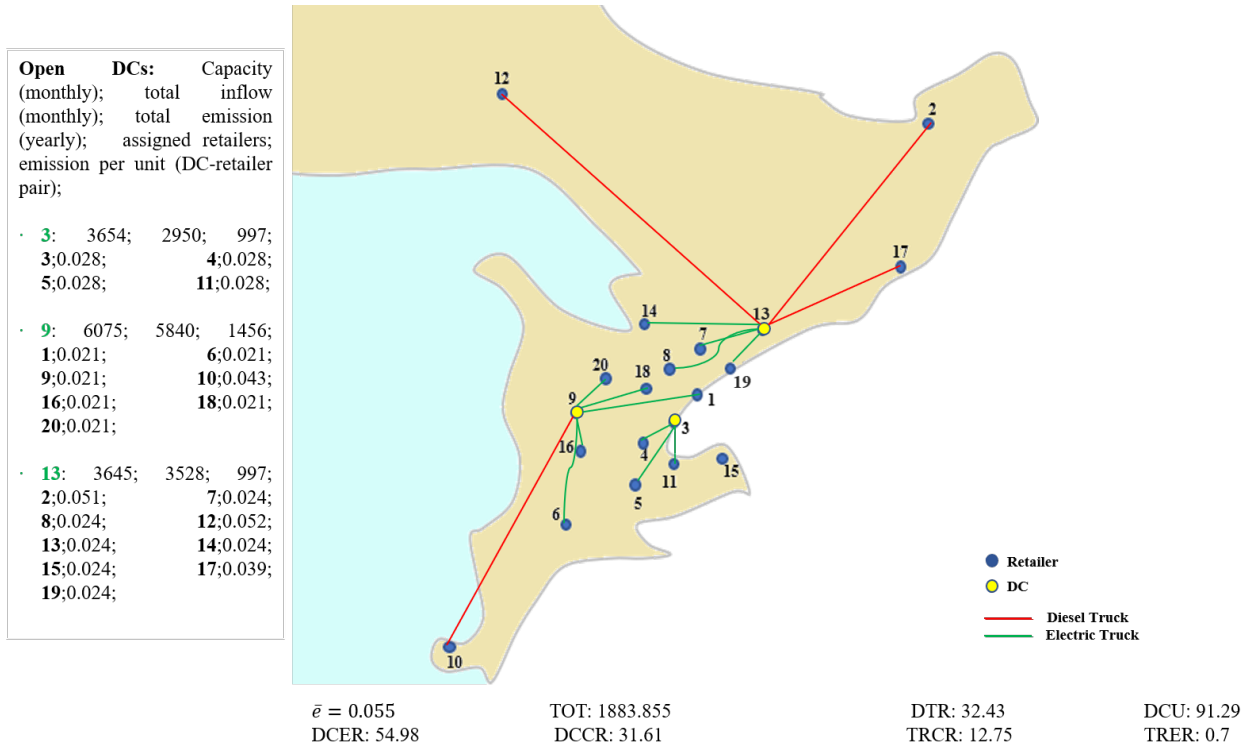


Figure 5.2: SCND: concave emission function; electric trucks more cost efficient than diesel trucks; $\bar{e} = 0.055$; $R = 370$ km

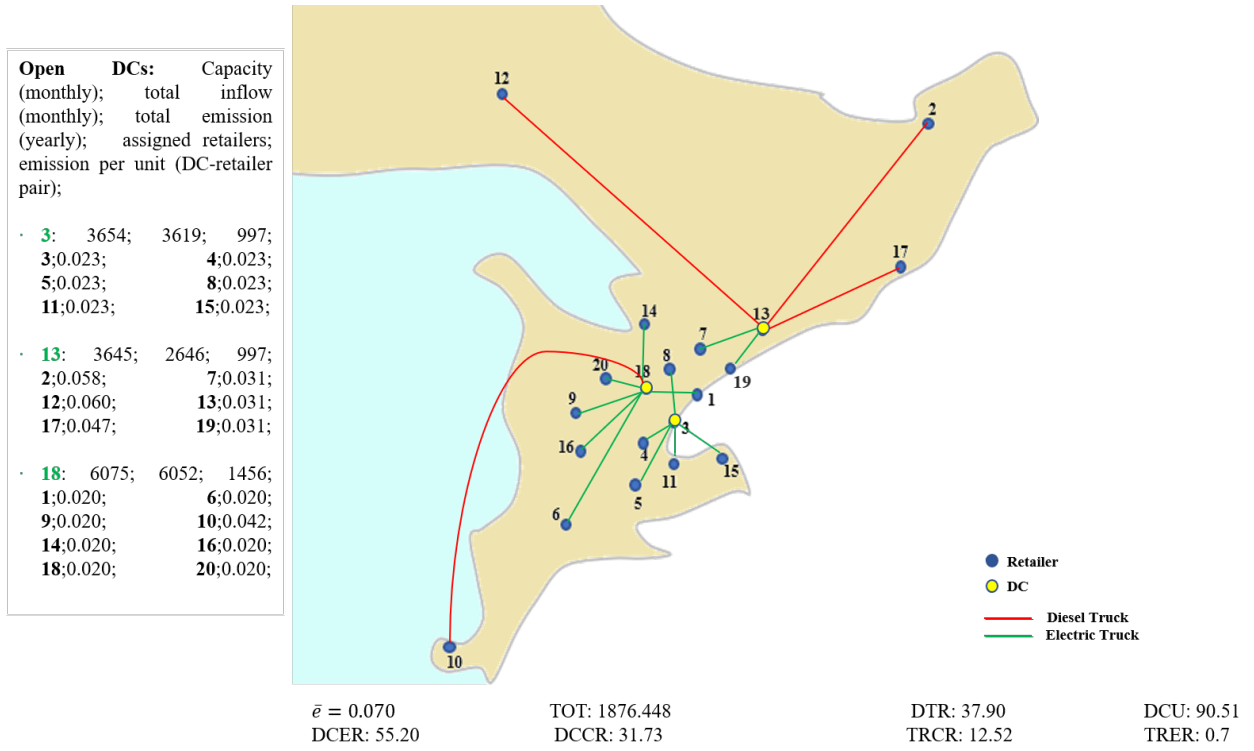


Figure 5.3: SCND: concave emission function; electric trucks more cost efficient than diesel trucks; $\bar{e} = 0.070$; $R = 3700$ km

Table 5.4: Sensitivity analysis: concave emission function; $R = 370$ km; diesel trucks more cost efficient than electric trucks

Problem	Cost(% , % , % , % , thousands dollars)									Time (% , % , % , % , s)								
n, m, b	DCER	DCCR	TRCR	TRER	TOT	DCE	DCC	TRC	TRE	DTR	Iters.	HQ1	SP1	SP2	Hue	MP	tTOT	
$\bar{e} = 0.050$																		
10,20,0.2	52.60	29.97	17.35	0.07	2081.90	3650.26	623.95	361.21	4.86	59.29	3	0.000	93.25	1.39	0.66	4.70	15.04	
10,20,0.5	52.28	29.79	17.24	0.60	2094.69	3650.35	624.01	361.12	41.89	59.29	3	0.000	93.50	1.16	0.59	4.74	26.83	
10,20,0.7	50.65	28.89	16.70	3.79	2126.27	3589.85	614.28	355.09	268.62	59.29	3	0.000	86.18	1.30	0.68	11.85	26.98	
15,40,0.2	52.78	29.69	17.44	0.09	3701.18	6511.61	1098.88	645.49	11.10	61.96	9	0.000	96.68	0.40	0.22	2.71	238.76	
15,40,0.5	52.42	29.49	17.32	0.77	3726.65	6511.70	1098.98	645.46	95.65	61.95	8	0.000	96.86	0.41	0.27	2.46	243.84	
15,40,0.7	50.61	28.47	16.73	4.19	3860.13	6512.04	1098.98	645.80	539.13	55.83	10	0.000	97.09	0.38	0.21	2.32	275.66	
20,100,0.2	51.66	26.45	21.79	0.10	7956.60	13701.27	2104.52	1733.74	26.52	61.62	10	0.000	99.01	0.06	0.04	0.88	1960.67	
20,100,0.5	51.23	26.23	21.62	0.92	8022.45	13699.67	2104.29	1734.45	246.02	61.55	10	0.000	98.96	0.07	0.04	0.93	2014.33	
20,100,0.7	45.00	22.73	27.63	4.64	8369.06	12394.59	1902.29	2312.37	1294.41	51.49	10	0.000	99.05	0.07	0.04	0.85	2042.89	
Min	45.00	22.73	16.70	0.01	2081.902	3589.85	614.28	355.09	4.86	51.49	3	0.000	86.18	0.06	0.04	0.85	15.04	
Max	52.78	29.97	27.63	4.64	8369.064	13701.27	2104.52	2312.37	1294.41	61.96	10	0.000	99.05	1.39	0.68	11.85	2042.89	
Mean	51.03	27.97	19.31	1.62	4248.639	7802.37	1252.24	977.19	280.91	59.81	7.33	0.000	95.62	0.58	0.31	3.49	760.56	
$\bar{e} = 0.070$																		
10,20,0.2	52.53	28.41	18.97	0.09	1878.96	3290.06	533.81	356.44	5.64	61.01	5	0.000	94.22	1.29	0.73	3.76	15.04	
10,20,0.5	52.16	28.21	18.84	0.70	1892.16	3289.84	533.78	356.48	44.15	61.01	5	0.000	94.45	1.23	0.69	3.63	27.07	
10,20,0.7	50.29	27.20	18.16	4.35	1962.59	3289.96	533.82	356.41	284.58	61.01	5	0.000	94.43	1.23	0.64	3.67	16.68	
15,40,0.2	55.42	30.29	14.12	0.16	3329.69	6151.05	1008.56	470.15	17.76	92.59	10	0.000	97.29	0.37	0.21	2.13	175.47	
15,40,0.5	54.37	29.72	13.96	1.96	3394.47	6152.50	1008.84	473.87	221.77	92.06	7	0.000	97.24	0.40	0.20	2.14	180.19	
15,40,0.7	46.19	24.37	24.41	5.03	3702.65	5700.85	902.34	903.82	620.81	57.27	10	0.000	97.05	0.42	0.21	2.32	220.27	
20,100,0.2	52.03	26.29	21.50	0.02	7237.62	12552.45	1902.77	1556.09	4.83	89.96	11	0.000	99.07	0.06	0.04	0.83	2463.69	
20,100,0.5	50.89	25.71	21.08	2.33	7400.01	12552.88	1902.54	1559.92	574.73	89.68	13	0.001	99.19	0.05	0.03	0.72	2890.41	
20,100,0.7	46.78	23.63	20.42	9.17	8046.96	12547.89	1901.50	1643.19	2459.60	82.78	7	0.000	99.18	0.05	0.03	0.73	1607.52	
Min	46.19	23.63	18.16	0.02	1878.959	3289.84	533.78	356.41	4.83	57.27	5	0.000	94.22	0.05	0.03	0.72	15.04	
Max	52.53	28.41	25.67	9.17	8046.959	12552.88	1902.77	1643.19	2459.60	89.96	13	0.001	99.19	1.29	0.73	3.76	2890.41	
Mean	49.74	26.10	21.61	2.53	4354.460	7280.83	1136.44	852.93	470.43	68.58	7.78	0.000	96.90	0.57	0.31	2.21	844.04	
$\bar{e} = 0.100$																		
10,20,0.2	56.28	30.44	13.07	0.23	1753.81	3290.15	533.86	229.22	13.45	97.33	5	0.000	93.48	1.32	0.75	4.42	37.23	
10,20,0.5	54.79	29.63	12.86	2.72	1801.39	3289.94	479.71	231.66	163.33	96.96	4	0.000	94.46	1.25	0.68	3.62	23.56	
10,20,0.7	50.29	27.20	18.16	4.35	1962.59	3329.86	533.82	356.41	284.58	61.01	5	0.000	94.43	1.23	0.64	3.67	16.68	
15,40,0.2	56.22	29.66	13.87	0.35	3042.19	5701.06	902.31	421.95	35.49	99.28	5	0.000	97.13	0.38	0.22	2.26	112.70	
15,40,0.5	54.23	28.61	13.51	3.64	3152.41	5698.51	901.90	425.89	382.49	98.75	6	0.000	97.23	0.42	0.23	2.12	137.39	
15,40,0.7	46.25	24.40	16.92	12.44	3691.28	5690.72	883.10	624.56	1530.65	92.44	14	0.002	97.12	0.41	0.23	2.24	309.82	
20,100,0.2	55.92	27.58	16.23	0.26	6384.84	11901.34	1760.94	1036.26	55.34	99.19	9	0.000	98.96	0.07	0.04	0.93	1751.58	
20,100,0.5	53.89	26.58	15.78	3.75	6625.85	11902.24	1761.15	1045.56	828.23	99.01	8	0.001	98.81	0.07	0.04	1.07	1611.96	
20,100,0.7	47.46	23.98	15.38	13.19	7922.19	12532.90	1899.74	1218.43	3483.12	93.41	10	0.002	99.27	0.04	0.03	0.65	2841.42	
Min	46.25	23.63	12.86	0.23	1036.408	3289.94	479.71	229.22	13.45	61.01	4	0.000	93.48	0.04	0.03	0.65	16.68	
Max	56.28	30.44	20.42	13.19	8046.959	12532.90	1899.74	1218.43	3483.12	99.28	14	0.002	99.27	1.32	0.75	4.42	2841.42	
Mean	52.21	27.17	15.62	5.01	3903.507	7037.41	1072.95	621.10	745.59	92.02	7.30	0.001	97.01	0.52	0.29	2.17	844.99	

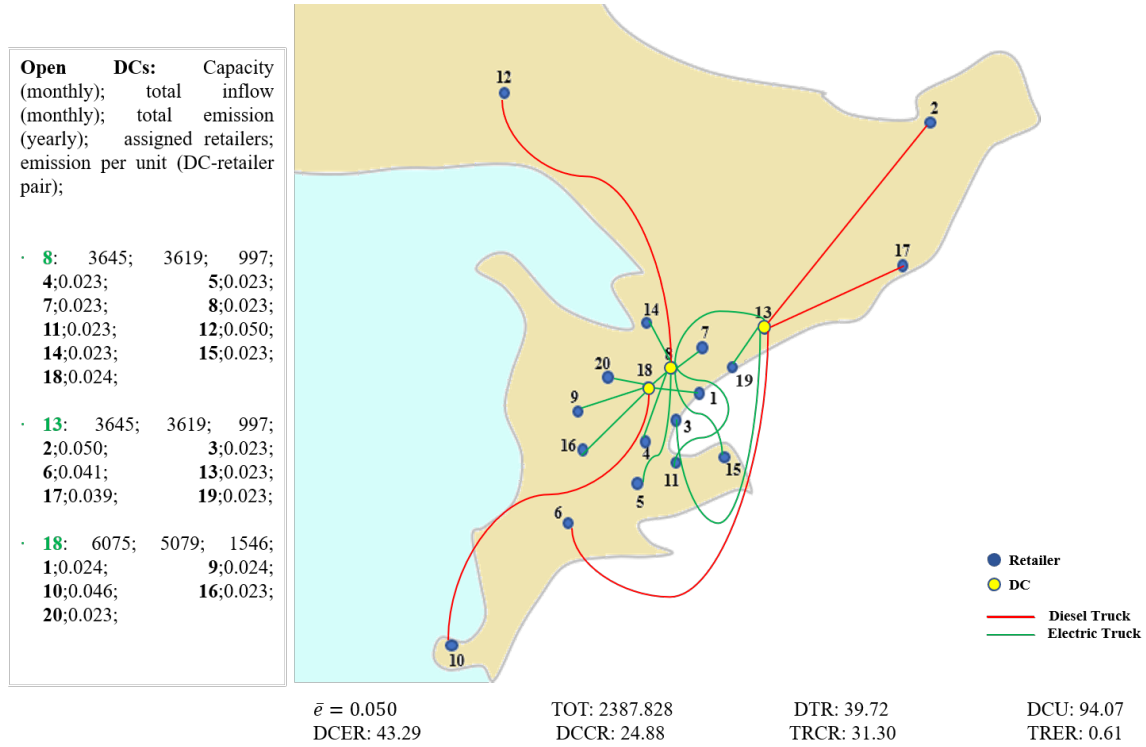


Figure 5.4: SCND: concave emission function; $\bar{e} = 0.050$; $R = 370$ km; diesel trucks more cost efficient than electric trucks

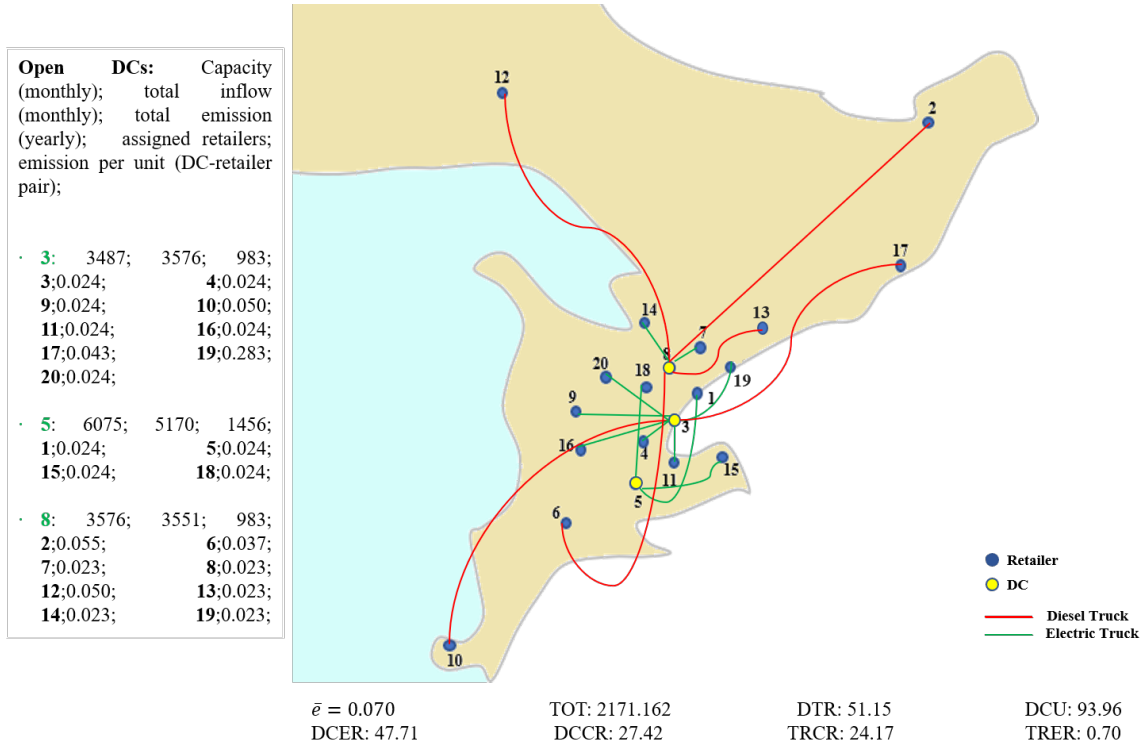


Figure 5.5: SCND: concave emission function; $\bar{e} = 0.070$; $R = 370$ km; diesel trucks more cost efficient than electric trucks

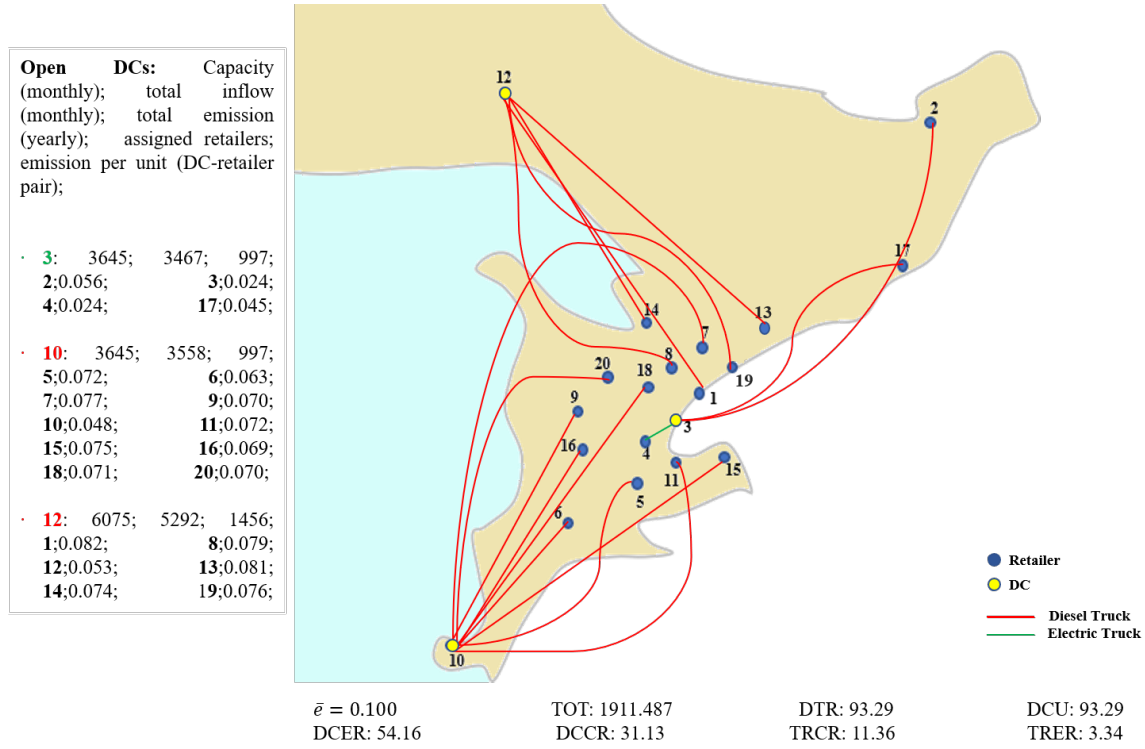


Figure 5.6: SCND: concave emission function; $\bar{e} = 0.100$; $R = 370$ km; diesel trucks more cost efficient than electric trucks

the primary contributor to the total cost of the supply chain across all analyzed scenarios, followed by the emission cost/ transportation cost. The impact of increasing the restriction on the per unit emission for each DC-retailer pair is also apparent from the table, as it leads to an increase in the total cost. As the constraint on per unit emission decreases, considering that diesel trucks are less costly but emit more, DTR also increases. In other words, as the value of $\bar{e}$ rises, the model tends to favor more diesel trucks which also results in increasing values of TRER. By analyzing DTR under each $\bar{e}$ scenario independently, it's noticeable that when $b = 0.7$, the DTR is lower compared to other values of b . This is attributed to the reduced concavity of the emission function for diesel trucks as also observed in Table 5.3.

We then evaluated the supply chain design across various values of $\bar{e}$, with b held constant at 0.5 (Figures 5.4 - 5.6). It is evident from the figures that imposing a stricter constraint on the per-unit emission leads to an increase in the total cost of the supply chain. Electric trucks emit less emission but are more costly for transporting goods within the echelons compared to diesel trucks. Thus, when the constraint on $\bar{e}$ becomes less strict, the model favors more diesel trucks over electric trucks. This is also attributed to the concave emission function characteristic of diesel trucks. Consequently, transporting more units via diesel trucks results in a proportionally smaller increase in emissions compared to the reduction in transportation costs. This results in decreasing values for TRCR and increasing values for TRER over the presented scenarios. Moreover, a comparison between Figure 5.4 and Figure 5.6 reveals a significant increase in DTR from 39.66 to 98.75.

Scenario 2.1: The Range of Electric Trucks is Extended

In this section, we focused on the effect of increasing the range of electric trucks on the design of the supply chain. In this regard, the transportation range for these trucks was extended to 800 km. An example of such a vehicle is Tesla Semi [Tesla, 2024]. With the extension of the electric trucks' range to 800 km, it becomes evident that lower emissions per unit become attainable for each DC-retailer pair. In the previous scenario, the minimum value of $\bar{e}$ for a feasible model stood at 0.050 tonnes of CO₂-equivalent. However, with $R = 800$, the model can achieve a reduced minimum value of 0.025 tonnes for $\bar{e}$. Figures 5.7 - 5.11 summarize our findings.

5.2 Convex Emission Function for Diesel Trucks

In this section, we assume a convex emission function for diesel trucks by considering a general convex function represented by $y = ax^b$, where $b > 1$, y signifies CO₂-equivalent emission, and x denotes cargo weight. We adopt the same methodology outlined in Section 5.1.1 to compute the value of a . However, to accommodate the impact of employing a convex emission function, a distinct correction factor is applied to calibrate the value of a . Similar to the concave case, a series of experiments are conducted which are detailed in the following sections.

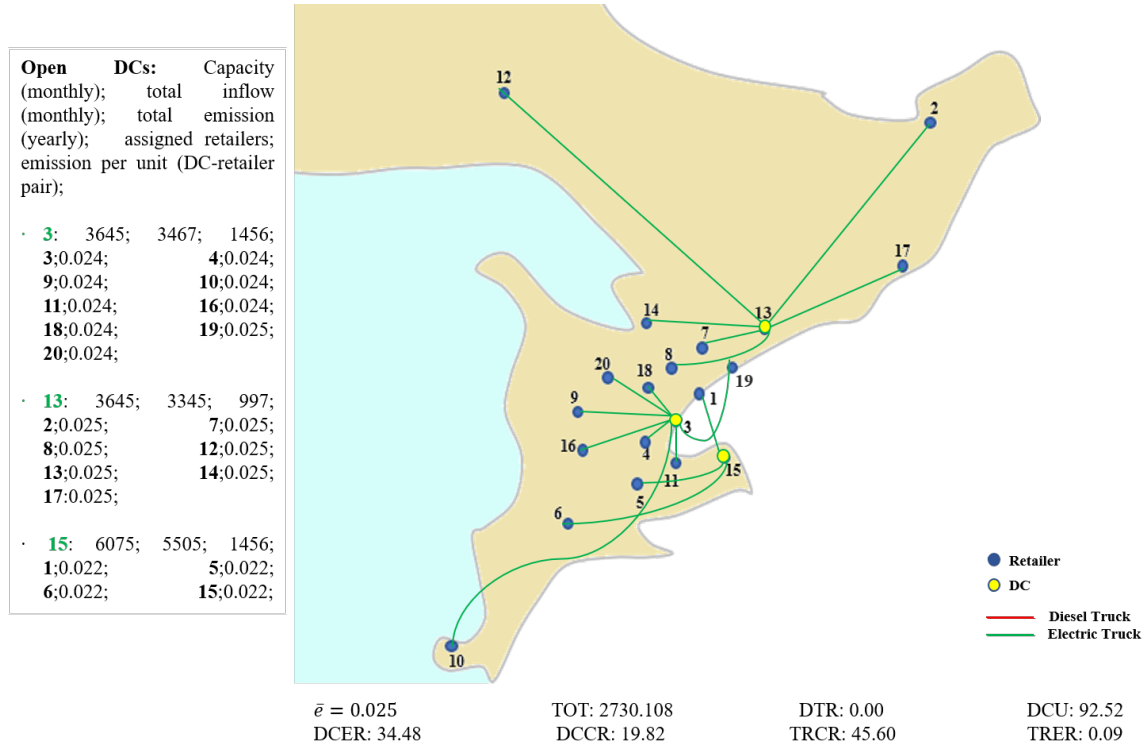


Figure 5.7: SCND: concave emission function; $\bar{e} = 0.025$; $R = 800$ km; diesel trucks more cost efficient than electric trucks

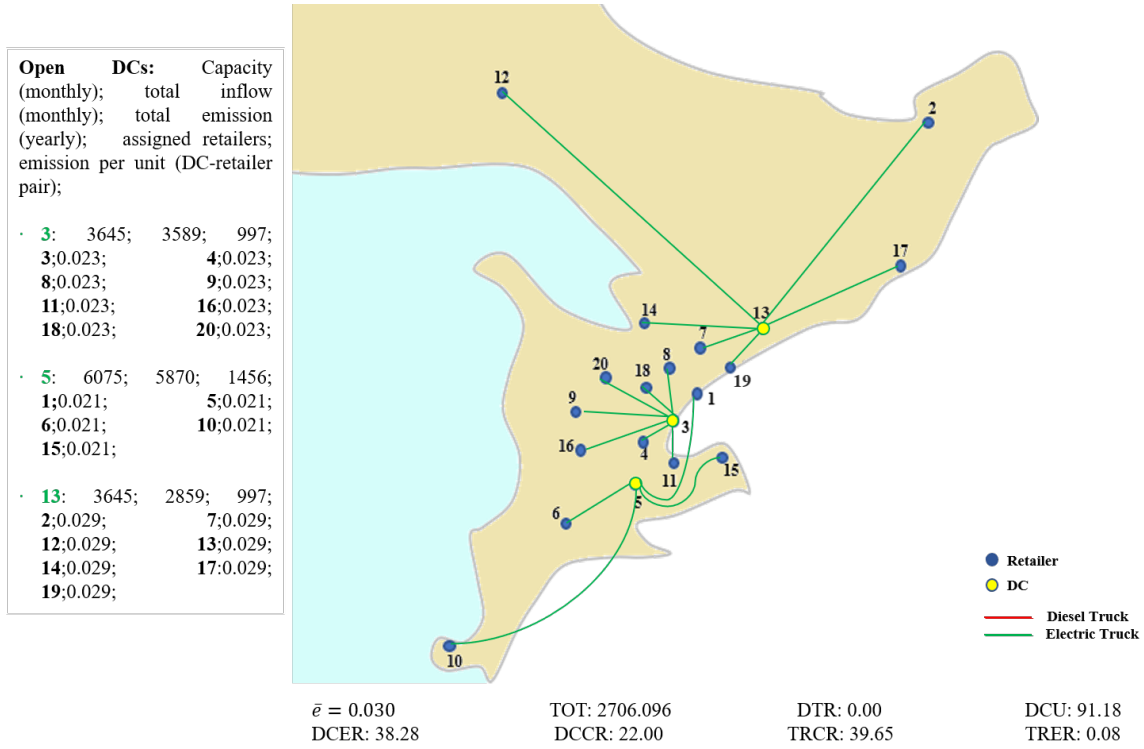


Figure 5.8: SCND: concave emission function; $\bar{e} = 0.030$; $R = 800$ km; diesel trucks more cost efficient than electric trucks

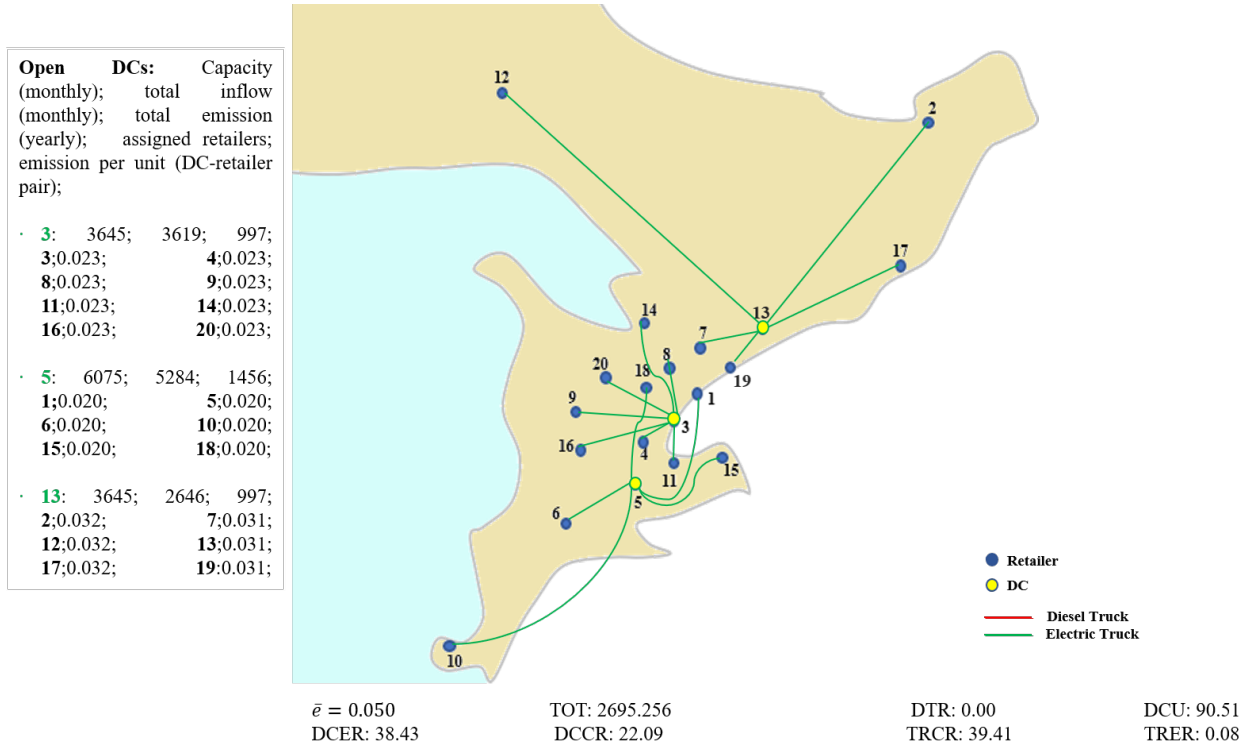


Figure 5.9: SCND: concave emission function; $\bar{e} = 0.050$; $R = 800$ km; diesel trucks more cost efficient than electric trucks

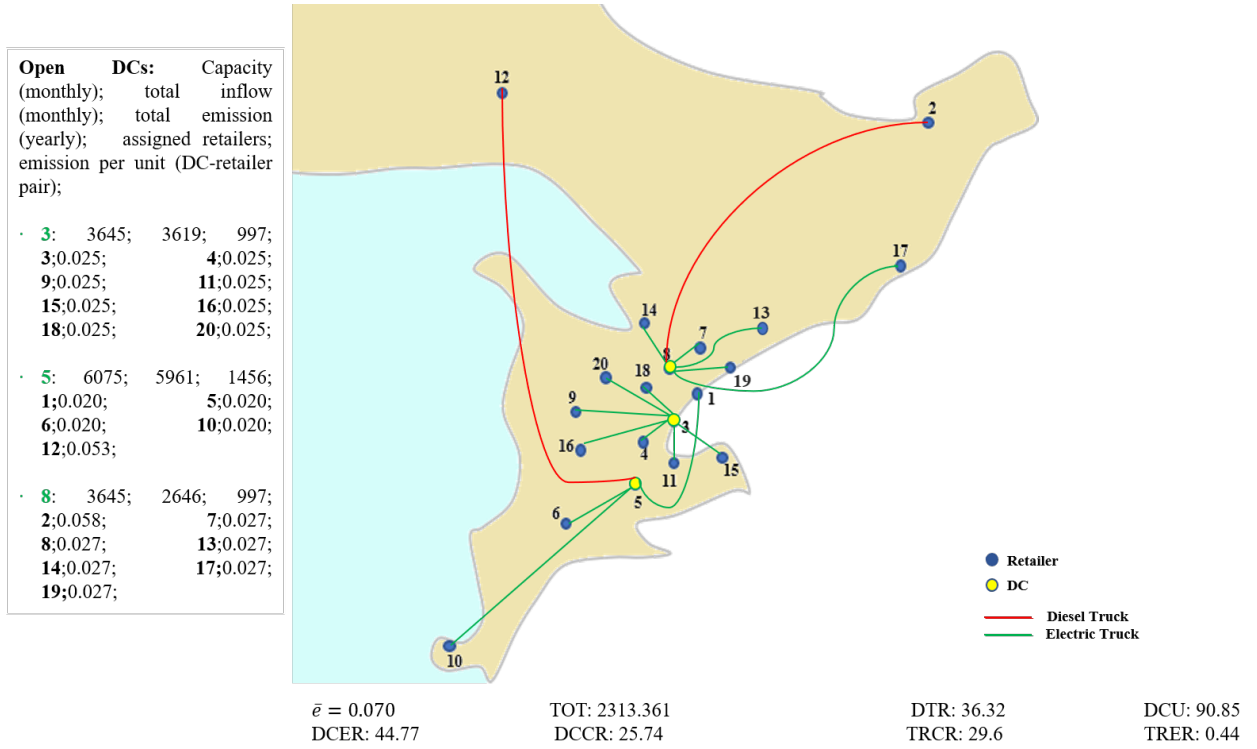


Figure 5.10: SCND: concave emission function; $\bar{e} = 0.070$; $R = 800$ km; diesel trucks more cost efficient than electric trucks

5.2.1 Scenario 1: Electric Trucks are more Cost-Efficient than Diesel Trucks

In this section, we conducted a set of experiments similar to that of section 5.1.1 in which the cost coefficients for electric trucks are smaller compared to diesel trucks. Table 5.5 summarizes our findings. In this table, three additional columns, namely OPT, HQ2, and tOPT, are included. OPT and tOPT display the value obtained from solving the problem using the direct linearization approach presented in Section 4.2.1 and its respective run time in seconds. Column HQ2 indicates the quality of the heuristic solution in comparison to the optimal solution, calculated as follows:

$$\text{HQ2} = 100 \times \frac{\text{heuristic solution} - \text{Optimal Solution}}{\text{Optimal Solution}}$$

Based on this table, except for when $b = 1.2$, the emission cost linked with the transportation fleet outweighs other cost components in the supply chain. Additionally, the DTR decreases as b increases. However, different variations in DTR values can be observed when the per-unit emission limit is raised. For instance, in the medium-sized problem where $b = 1.5$, transitioning from $\bar{e} = 0.055$ to $\bar{e} = 0.070$ results in opening the same DCs (DCs 3, 13, and 18 corresponding to Mississauga, Oshawa, and Guelph, respectively). With the permission to emit more than 0.055 tonnes, there's a rearrangement in the assignment of retailers and the inflow of open DCs. Although this rearrangement results in an increase per unit emission of some of the DC-retailer pairs, a decrease in the total fleet cost is obtained. In this updated setup, while the unit distance covered by diesel trucks remains unchanged, that of electric trucks decreases, contributing to an overall reduction in costs.

On the other hand, for the small-sized problem with $b = 1.7$, the open DCs shifted from $\bar{e} = 0.055$ to $\bar{e} = 0.070$, while maintaining the cost associated with opening DCs constant. This adjustment, coupled with changes in plant-DC and DC-retailer assignments, enabled the model to achieve reduced costs and emissions for the transportation fleet. This was achieved by allowing larger per-unit emission values for certain pairs. Furthermore, the new SCND was obtained by employing fewer diesel trucks and more electric ones, resulting in a decrease in DTR, which was the primary factor behind the reduction in transportation fleet/overall costs.

Figures 5.12-5.14 provide detailed insights into the SCND under various values of $\bar{e}$ while fixing b at 1.5. Comparing the first two figures, it is apparent that the model opens different DCs while maintaining the same total emission and operating cost for the open DCs in both scenarios. However, by adjusting the plant-DC and DC-retailer pairs, the total unit-distance covered by both diesel and electric trucks is reduced, resulting in lower transportation emissions and costs. In contrast, comparing the last two figures, when $\bar{e} = 0.070$, the model opts to open different DCs compared to the other scenario, leading to different costs and emissions for the open DCs. By opening DCs 5, 9, and 17 corresponding to Hamilton, Kitchener, and Kingston, respectively, the total cost and total emission of the open DCs increase, along with the contribution of DCs' per-unit emission for some retailers compared to the previous scenarios (for instance, retailer 2 the only retailer assigned to DC 17). However, since the reduction achieved in transportation costs and emissions outweighs the increase in DC costs with per unit emissions below $\bar{e} = 0.070$, the model selects this new SCND.

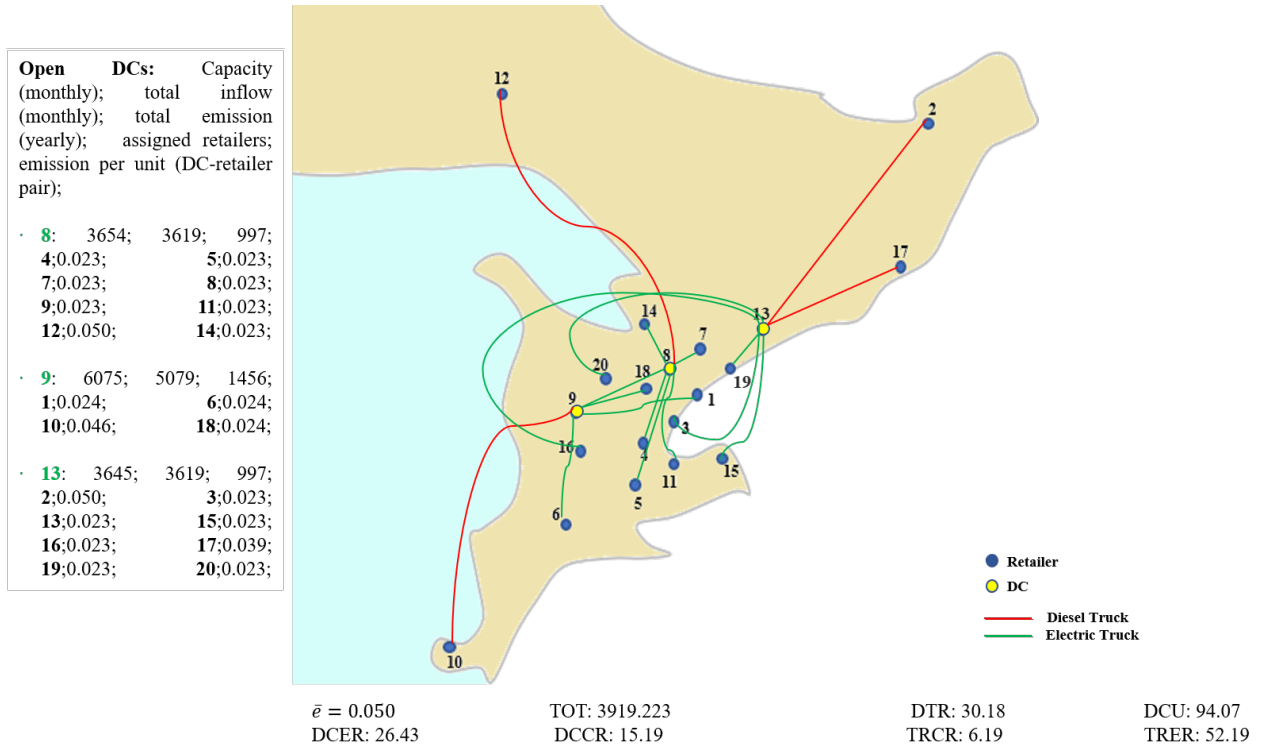


Figure 5.12: SCND: convex emission function; electric trucks more cost efficient than diesel trucks; $\bar{e} = 0.050$; $R = 370$ km

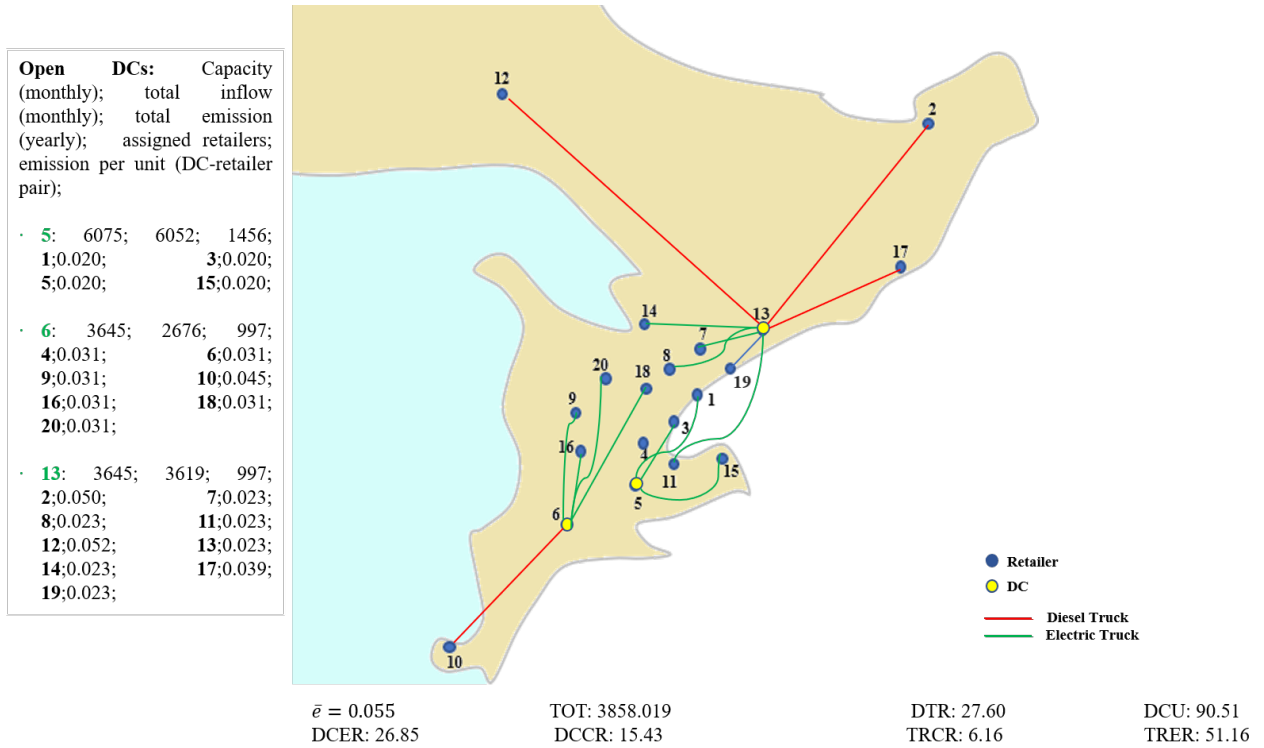


Figure 5.13: SCND: convex emission function; electric trucks more cost efficient than diesel trucks; $\bar{e} = 0.055$; $R = 370$ km

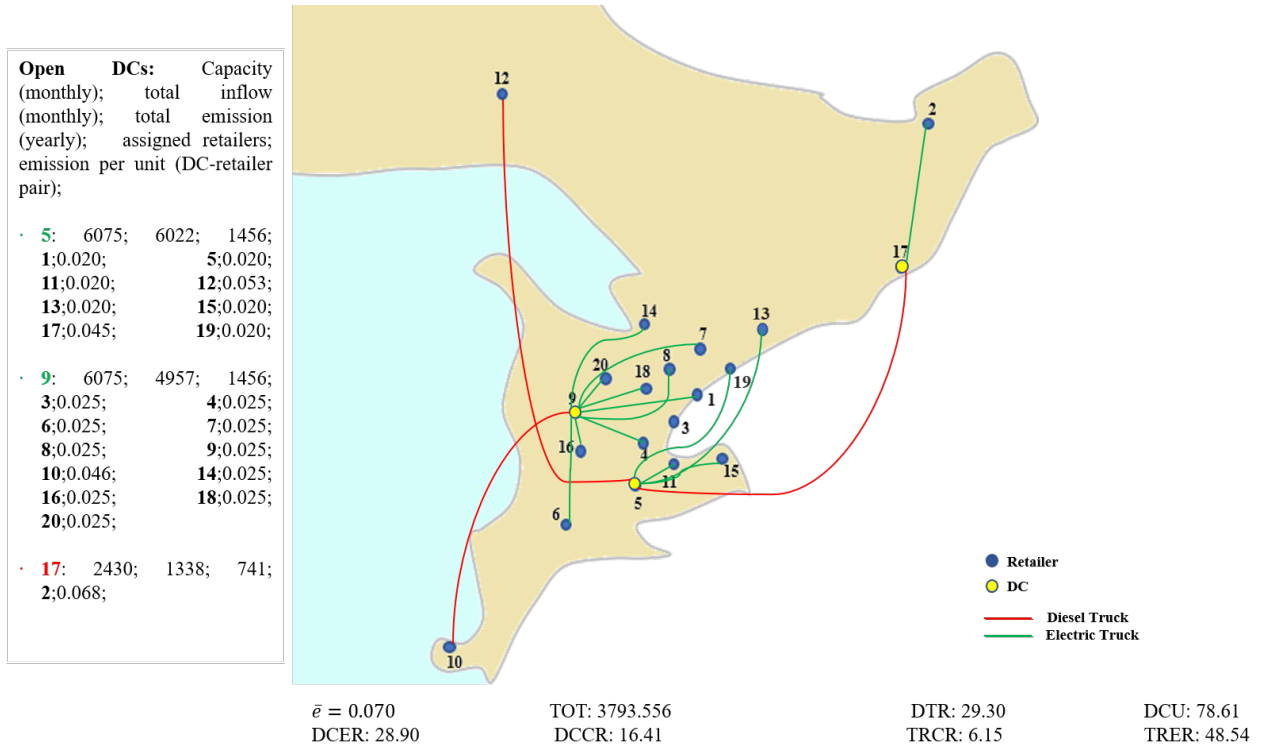


Figure 5.14: SCND: convex emission function; electric trucks more cost efficient than diesel trucks; $\bar{e} = 0.070$; $R = 370$ km

Table 5.5: Sensitivity analysis: convex emission function; R = 370 km; electric trucks more cost-efficient than diesel trucks

Problem	Cost(%, %, %, %, thousands dollars)										Time(%, %, %, %, s, s)									
n, m, b	DCER	DCCR	TRCR	TRER	TOT	OPT	DCE	DCC	TRC	TRE	DTR	Iters.	HQ1	HQ2	SP1	SP2	Hue	MP	tTOT	tOPT
$\bar{\epsilon} = 0.050$																				
10,20,1.2	53.32	28.18	11.99	6.51	2070.55	2066.31	3680.06	583.48	248.26	449.31	38.51	11	0.002	0.002	95.17	2.36	0.37	2.03	66.11	1.76
10,20,1.5	30.13	16.49	5.68	47.69	4551.91	4048.15	4571.63	750.61	258.09	7236.02	32.06	12	0.125	0.124	95.84	2.13	0.40	1.60	44.53	1.64
10,20,1.7	6.98	3.69	1.57	87.76	15821.43	15821.43	3681.12	583.81	24.83	46282.96	31.85	11	0.000	0.000	96.48	2.19	0.25	1.07	73.32	1.66
15,40,1.2	51.54	27.13	14.10	7.23	3366.24	3366.24	5783.20	913.26	474.64	811.26	27.82	11	0.000	0.000	97.62	1.03	0.14	1.20	139.71	11.59
15,40,1.5	26.45	15.63	12.79	45.14	4466.60	4100.99	3938.05	698.13	571.28	6720.74	26.03	28	0.089	0.089	96.35	1.77	0.28	1.59	335.43	3.18
15,40,1.7	6.40	3.49	1.55	88.57	29278.14	29277.89	6246.00	1021.81	453.81	86438.83	25.81	10	0.000	0.000	98.75	0.54	0.07	0.61	705.19	6.03
20,100,1.2	50.51	24.86	16.17	8.47	7173.09	7173.09	12077.09	1783.23	1159.89	2025.20	39.33	19	0.000	0.000	96.33	1.28	0.03	2.36	3625.29	73.01
20,100,1.5	5.34	2.50	2.53	86.63	73125.00	72626.96	13016.25	1828.13	1850.06	211160.63	38.61	21	0.008	0.007	98.59	0.64	0.08	0.69	2365.23	50.27
20,100,1.7	53.33	26.87	1.54	90.44	72118.30	71678.78	128202.30	19378.19	1110.62	217412.64	31.90	17	0.006	0.006	97.10	1.17	0.15	1.54	2333.70	45.00
Min	5.34	2.50	1.54	6.51	2070.55	2066.31	3680.06	583.48	24.83	449.31	26	10	0.000	0.000	95.17	0.54	0.03	0.61	44.53	1.64
Max	53.33	28.18	16.17	90.44	73125.00	72626.96	128202.30	19378.19	1850.06	217412.64	39	28	0.125	0.124	98.75	2.36	0.40	2.36	3625.29	73.01
Mean	31.56	16.54	7.55	52.05	23552.36	23351.09	20132.86	3060.07	683.50	64281.95	32.44	15.56	0.026	0.026	96.91	1.46	0.20	1.41	1076.50	21.57
$\bar{\epsilon} = 0.055$																				
10,20,1.2	53.44	28.24	12.01	6.31	2060.30	2060.30	3670.08	581.83	247.44	433.35	31.93	11	0.000	0.000	95.08	2.41	0.46	1.98	42.49	1.64
10,20,1.5	27.28	14.41	6.13	52.18	4048.00	4048.00	3680.98	583.32	248.14	7040.82	31.93	10	0.000	0.000	91.43	4.73	0.70	3.12	23.50	1.32
10,20,1.7	7.90	4.40	1.50	86.20	15704.98	15704.98	4135.64	691.02	235.57	45125.64	31.83	8	0.000	0.000	89.61	6.42	0.68	3.20	15.53	1.43
15,40,1.2	51.54	27.13	14.10	7.23	3366.24	3366.24	5783.20	913.26	474.64	811.26	31.82	11	0.000	0.000	98.15	0.84	0.10	0.89	173.61	6.19
15,40,1.5	26.98	15.94	10.75	46.33	4378.94	4097.31	3938.13	698.00	470.74	6762.54	30.29	27	0.070	0.069	96.53	1.73	0.29	1.43	334.50	3.90
15,40,1.7	6.40	3.49	1.55	88.57	29277.89	29277.89	6245.95	1021.80	453.81	86438.09	28.81	14	0.000	0.000	99.48	0.21	0.03	0.28	130.22	5.99
20,100,1.2	50.51	24.86	16.17	8.47	7173.09	7173.09	12077.09	1783.23	1159.89	2025.20	32.33	19	0.000	0.000	98.20	0.59	0.02	1.19	3625.29	73.01
20,100,1.5	5.26	2.65	2.83	89.26	72626.96	72626.96	12733.93	1924.61	2055.34	216089.42	31.94	21	0.000	0.000	98.28	0.80	0.09	0.83	3025.21	74.49
20,100,1.7	5.33	2.69	1.54	90.44	72109.69	71679.62	12811.49	1939.75	1110.49	217386.68	31.80	25	0.007	0.006	97.92	1.02	0.10	0.96	2000.62	48.25
Min	5.26	2.65	1.50	6.31	2060.30	2060.30	3670.08	581.83	235.57	433.35	28.81	8	0.000	0.000	89.61	0.21	0.02	0.68	15.53	1.32
Max	53.44	28.24	16.17	90.44	72626.96	72626.96	12811.49	1939.75	2055.34	217386.68	32.33	27	0.070	0.069	99.48	6.42	0.70	3.20	3625.29	74.49
Mean	26.07	13.76	7.40	52.78	23416.23	23337.15	7230.72	1126.31	717.34	64679.22	31.41	16.22	0.009	0.009	96.08	2.08	0.27	1.59	1041.22	24.02
$\bar{\epsilon} = 0.070$																				
10,20,1.2	51.70	27.90	12.92	7.49	1936.68	1936.68	3337.55	540.33	250.22	483.52	53.29	9	0.000	0.000	92.89	3.18	0.66	3.25	23.16	1.33
10,20,1.5	27.28	14.41	6.13	52.18	4048.00	4048.00	3680.98	583.32	248.14	7040.82	31.93	10	0.000	0.000	91.43	4.73	0.70	3.12	23.50	1.32
10,20,1.7	6.98	3.69	1.58	87.75	15821.39	15700.77	3681.11	583.81	249.98	46277.57	30.86	9	0.008	0.008	89.57	5.58	0.88	3.96	18.09	2.39
15,40,1.2	51.54	27.13	14.10	7.23	3366.24	3366.24	5783.20	913.26	474.64	811.26	31.82	11	0.000	0.000	98.15	0.84	0.10	0.89	173.61	6.19
15,40,1.5	25.61	14.72	8.74	50.93	4044.59	4041.67	3450.24	594.93	353.24	6861.41	37.69	9	0.000	0.000	91.87	3.73	0.63	3.74	45.52	2.55
15,40,1.7	6.40	3.49	1.55	88.57	29278.01	29278.01	6245.98	1021.80	453.81	86438.45	28.78	13	0.000	0.000	98.66	0.66	0.07	0.61	295.35	8.40
20,100,1.2	50.51	24.86	16.17	8.47	7173.09	7173.09	12077.09	1783.23	1159.89	2025.20	39.33	19	0.000	0.000	96.33	1.28	0.03	2.36	3625.29	73.01
20,100,1.5	5.34	2.50	2.53	86.63	73125.00	72626.96	13016.25	1828.13	1850.06	211160.63	38.61	21	0.008	0.007	98.59	0.64	0.08	0.69	2365.23	50.27
20,100,1.7	53.33	26.87	1.54	90.44	72118.30	71678.78	128202.30	19378.19	1110.62	217412.64	31.90	17	0.006	0.006	97.10	1.17	0.15	1.54	2333.70	45.00
Min	5.26	2.65	1.54	7.23	1936.68	1936.68	3337.55	540.33	248.14	483.52	28.78	8	0.000	0.000	89.57	0.45	0.06	0.50	11.69	1.29
Max	51.70	27.90	16.17	90.44	75979.81	72626.96	128202.30	19378.19	1850.06	217412.64	53.29	21	0.060	0.060	98.99	5.96	0.88	3.96	3136.02	85.23
Mean	25.62	13.50	7.28	53.59	23808.31	23316.72	19941.63	3025.22	683.40	64279.06	34.83	12.89	0.008	0.008	94.91	2.59	0.36	2.12	997.93	23.17

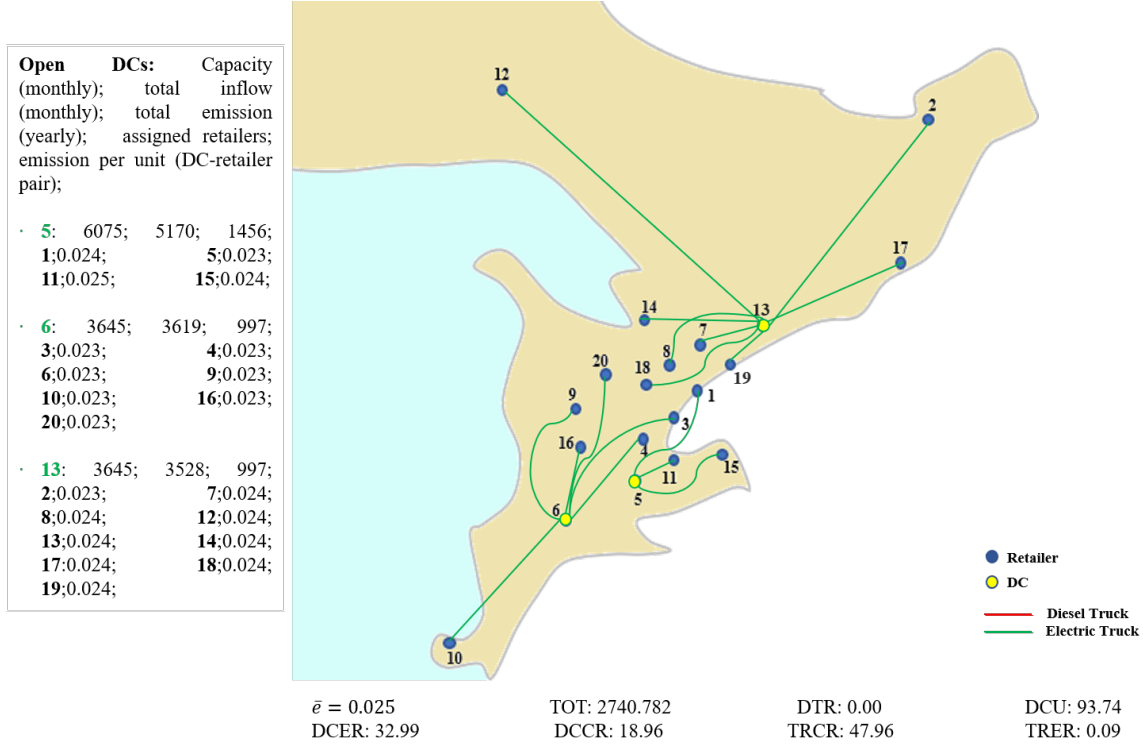


Figure 5.15: SCND: convex emission function; $\bar{e} = 0.025$; $R = 800$ km; diesel trucks more cost efficient than electric trucks

5.2.2 Scenario 2: Diesel Trucks are more Cost-Efficient than Electric Trucks

In this section, we undertake a similar analysis to Section 5.2.1, while considering diesel trucks to be more cost-efficient than electric trucks. In contrary to the concave case, the emission of the open DCs does not dominate the total cost for all values of b . As indicated in Table 5.6, when b increases from 1.2 to 1.5, the dominant component shifts to the emission cost associated with the transportation fleet, reaching approximately 80% of the total cost when $b = 1.7$. Regarding the variation in DTR, unlike the concave scenario, diesel trucks are not consistently favored over electric trucks as $\bar{e}$ increases. To elaborate,

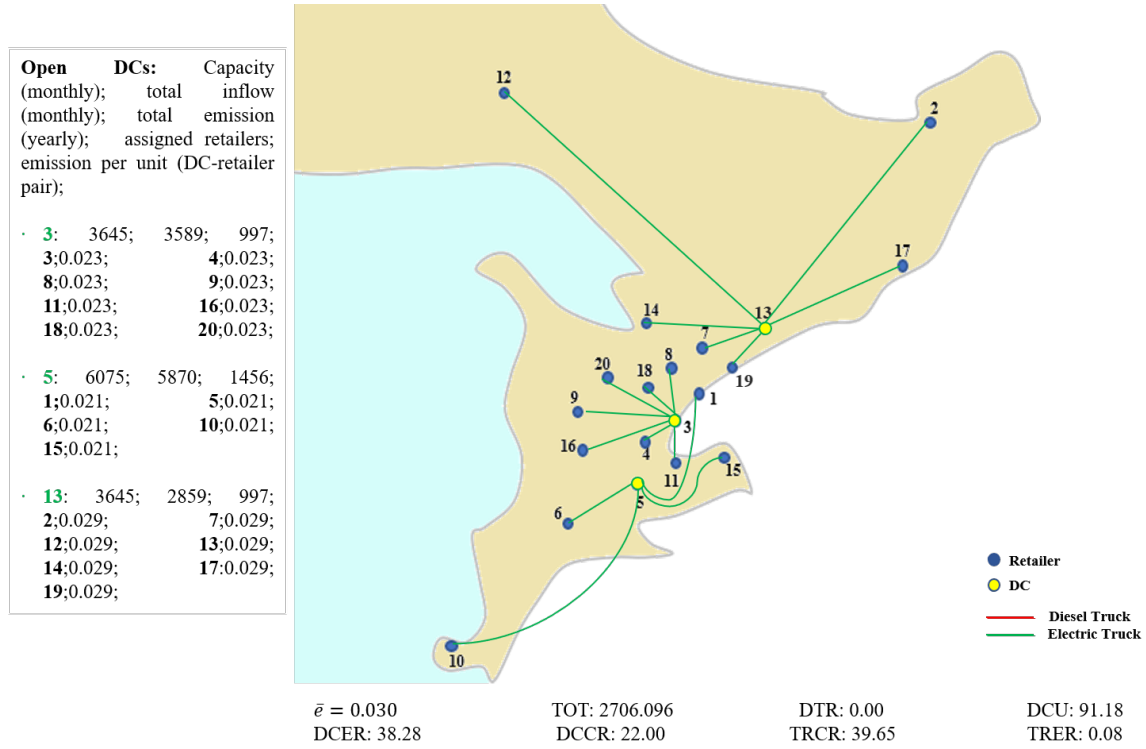


Figure 5.16: SCND: convex emission function; $\bar{e} = 0.030$; $R = 800$ km; diesel trucks more cost efficient than electric trucks

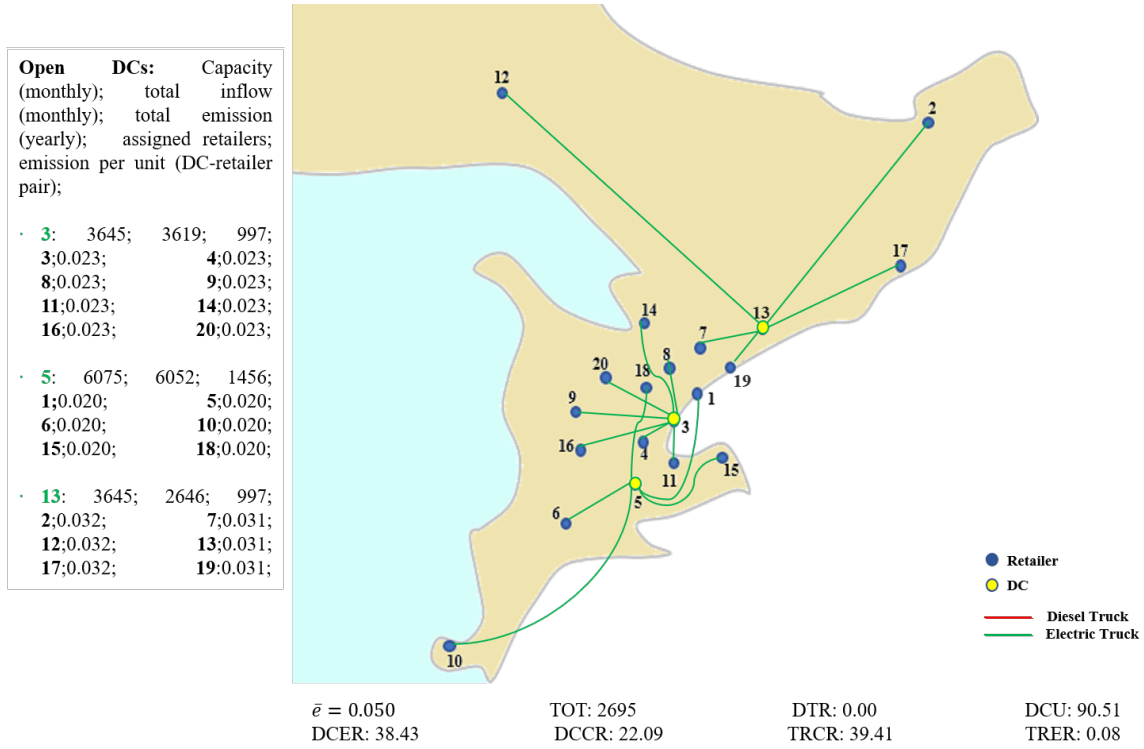


Figure 5.17: SCND: convex emission function; $\bar{e} = 0.050$; $R = 800$ km; diesel trucks more cost efficient than electric trucks

Table 5.6: Sensitivity analysis: convex emission function; $R = 370$ km; diesel trucks more cost efficient than electric trucks

Problem	Cost(% , %, % , %, thousands dollars)										Time (% , %, % , %, s, s)									
n, m, b	DCER	DCCR	TRCR	TRER	TOT	OPT	DCE	DCC	TRC	TRE	DTR	Iters.	HQ1	HQ2	SP1	SP2	Hue	MP	tTOT	tOPT
$\bar{\epsilon} = 0.050$																				
10,20,1.2	49.09	27.90	16.24	6.77	2263.06	2263.06	3703.12	631.39	367.52	510.70	49.93	9	0.000	0.000	96.82	1.37	0.30	1.49	105.88	2.82
10,20,1.5	24.41	12.90	15.70	46.96	4522.42	4339.86	3679.74	583.39	710.02	7079.09	49.17	10	0.060	0.042	99.47	0.23	0.05	0.25	887.04	3.88
10,20,1.7	7.68	4.28	4.27	83.75	16357.91	16357.91	4187.62	700.12	698.48	45665.83	37.75	7	0.000	0.000	97.99	0.98	0.17	0.85	143.32	3.74
15,40,1.2	41.85	22.39	27.81	7.37	4148.66	4148.66	5787.38	928.88	1153.74	1019.19	47.39	9	0.000	0.000	94.95	2.52	0.24	2.29	63.85	13.30
15,40,1.5	24.56	11.84	15.28	51.32	8077.01	8077.01	6612.38	956.32	1234.17	13817.07	40.56	7	0.000	0.000	94.79	2.53	0.29	2.39	49.57	22.99
15,40,1.7	5.57	3.06	8.20	83.18	30917.12	30682.40	5740.28	946.06	2535.20	85722.87	22.66	10	0.020	0.008	96.08	1.70	0.20	2.03	71.82	15.25
20,100,1.2	40.45	21.71	31.39	6.45	8836.42	8836.42	11914.44	1918.39	2773.75	1899.83	40.61	6	0.000	0.000	99.11	0.29	0.05	0.55	1068.25	230.52
20,100,1.5	20.92	10.08	15.80	53.21	18980.02	18623.72	13235.40	1913.19	2998.84	33664.23	35.85	8	0.050	0.019	95.46	1.53	0.24	2.77	1125.37	187.63
20,100,1.7	4.71	2.04	9.02	84.23	80159.00	74341.11	12584.96	1635.24	7230.34	225059.75	21.85	15	0.082	0.078	94.36	3.33	0.28	2.03	3254.26	141.32
Min	4.71	2.04	2.76	6.45	2263.06	2263.06	3679.74	583.39	367.52	510.70	21.85	6	0.000	0.000	94.36	0.23	0.05	0.25	49.57	2.82
Max	49.09	27.90	31.39	86.59	80159.00	74341.11	13235.40	1918.39	7230.34	225059.75	49.93	15	0.082	0.078	99.47	3.33	0.30	2.77	3254.26	230.52
Mean	24.26	12.86	15.80	47.34	19362.40	18630.02	7493.92	1134.78	2189.12	46048.73	38.42	9	0.021	0.013	96.56	1.61	0.20	1.63	752.15	69.05
$\bar{\epsilon} = 0.055$																				
10,20,1.2	49.89	28.36	14.97	6.79	2226.57	2085.62	3702.79	631.46	333.32	503.95	55.27	12	0.075	0.068	91.85	3.53	0.82	3.76	52.64	2.67
10,20,1.5	26.09	14.83	8.74	50.35	4339.86	4280.07	3774.23	643.60	379.30	7283.73	54.66	12	0.014	0.014	93.50	2.67	0.61	3.16	60.33	3.90
10,20,1.7	6.79	3.86	2.76	86.59	16172.49	16172.49	3660.37	624.26	446.36	46679.20	53.15	7	0.000	0.000	91.75	3.95	0.72	3.55	34.52	3.81
15,40,1.2	43.36	23.80	24.32	8.52	4003.93	4003.93	5787.01	952.94	973.76	1137.12	54.30	9	0.000	0.000	95.03	2.49	0.30	2.18	63.27	14.99
15,40,1.5	24.56	11.84	15.28	51.32	8038.36	8038.36	6580.74	951.74	1228.26	13750.96	40.56	7	0.000	0.000	95.02	2.52	0.28	2.18	50.39	29.88
15,40,1.7	6.56	3.80	4.80	84.85	30632.15	30632.15	6698.23	1164.02	1470.34	86637.92	34.04	8	0.000	0.000	95.93	1.81	0.28	1.97	56.24	28.00
20,100,1.2	41.67	22.37	27.29	8.68	8731.01	8731.01	12127.37	1953.13	2382.69	2526.17	51.69	17	0.000	0.000	97.12	1.46	0.11	1.31	1064.35	472.24
20,100,1.5	20.60	10.02	15.36	54.02	18715.24	18501.50	12851.13	1875.27	2874.66	33699.90	40.36	8	0.030	0.012	94.12	3.52	0.25	2.11	2598.65	519.90
20,100,1.7	5.72	2.59	5.07	86.22	74572.31	74328.22	14218.45	1931.42	3780.82	214320.81	27.35	13	0.005	0.003	94.15	2.35	0.43	3.08	4205.36	344.60
Min	5.72	2.59	4.27	6.79	2226.57	2085.62	3660.37	624.26	333.32	503.95	27.35	7	0.000	0.000	91.75	1.46	0.11	1.31	34.52	2.67
Max	49.89	28.36	27.29	86.22	74572.31	74328.22	12851.13	643.60	2874.66	214320.81	55.27	17	0.075	0.068	97.12	3.95	0.82	3.76	4205.36	519.90
Mean	25.13	13.54	13.34	48.28	28500.19	27262.15	6926.23	633.11	1008.41	46604.98	45.71	10	0.013	0.011	94.27	2.70	0.42	2.59	909.53	157.78
$\bar{\epsilon} = 0.070$																				
10,20,1.2	48.39	26.11	17.62	7.89	2069.44	2069.44	3338.01	540.33	364.64	544.26	60.76	11	0.000	0.000	92.18	3.20	0.73	3.85	46.38	2.64
10,20,1.5	25.60	14.56	9.86	50.00	4258.06	4258.06	3633.54	619.97	419.84	7096.76	37.04	10	0.000	0.000	98.05	0.78	0.19	0.97	406.12	3.56
10,20,1.7	7.68	4.28	4.27	83.78	16159.62	16159.62	4136.86	691.63	690.02	45128.44	37.03	14	0.000	0.000	91.46	3.85	0.85	3.80	34.52	3.71
15,40,1.2	43.36	23.80	24.32	8.52	4003.93	4003.93	5787.01	952.93	973.76	1137.12	54.30	19	0.000	0.000	93.76	3.84	0.29	2.11	136.08	14.08
15,40,1.5	24.56	11.84	15.28	51.32	8038.36	8038.36	6580.74	951.74	1228.26	13750.96	40.56	16	0.000	0.000	95.10	2.93	0.19	1.17	136.81	30.71
15,40,1.7	6.54	3.64	4.96	84.86	30624.48	30624.48	6676.14	1114.73	1518.97	86626.43	33.28	7	0.000	0.000	93.87	3.33	0.38	2.41	48.30	35.46
20,100,1.2	41.67	22.37	27.29	8.68	8731.01	8731.01	12127.37	1953.13	2382.69	2526.17	51.69	17	0.000	0.000	97.22	1.25	0.12	1.25	1057.56	498.70
20,100,1.5	21.33	9.61	15.42	53.64	18715.24	18501.50	13306.53	1798.53	2885.89	33462.84	37.28	15	0.080	0.012	95.47	2.64	0.37	1.52	3265.12	633.23
20,100,1.7	6.11	3.21	5.08	85.61	74572.31	74328.22	15187.89	2393.77	3788.27	212804.51	26.85	19	0.005	0.003	96.46	1.65	0.21	1.68	5236.69	570.68
Min	6.11	3.21	4.27	7.89	2069.44	2069.44	3338.01	619.97	364.64	7096.76	26.85	7	0.000	0.000	91.46	0.78	0.12	0.97	34.52	2.64
Max	41.67	26.11	27.29	85.61	74572.31	74328.22	15187.89	1114.73	3788.27	86626.43	60.76	19	0.080	0.068	98.05	3.85	0.85	3.85	5236.69	633.23
Mean	23.04	13.27	13.79	48.26	27306.49	27255.62	9619.33	895.48	2079.05	46861.60	41.22	14	0.012	0.006	94.84	2.61	0.37	2.08	1151.95	199.196

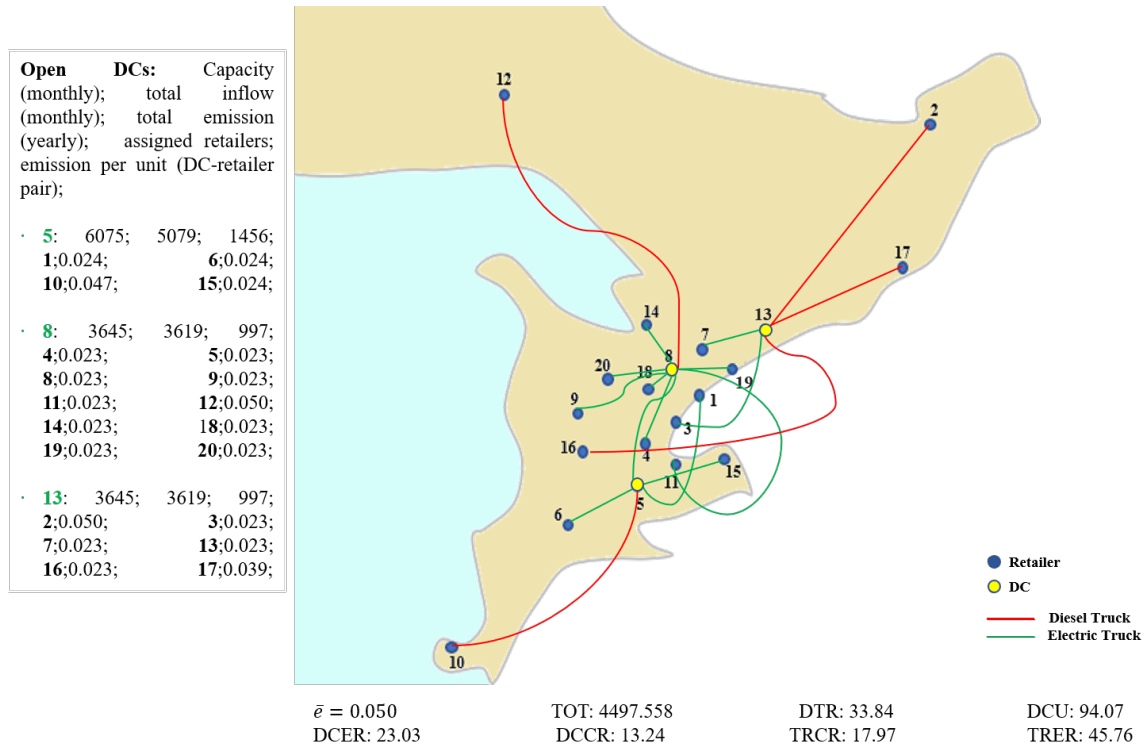


Figure 5.18: SCND: convex emission function; $\bar{e} = 0.050$; $R = 370$ km; diesel trucks more cost efficient than electric trucks

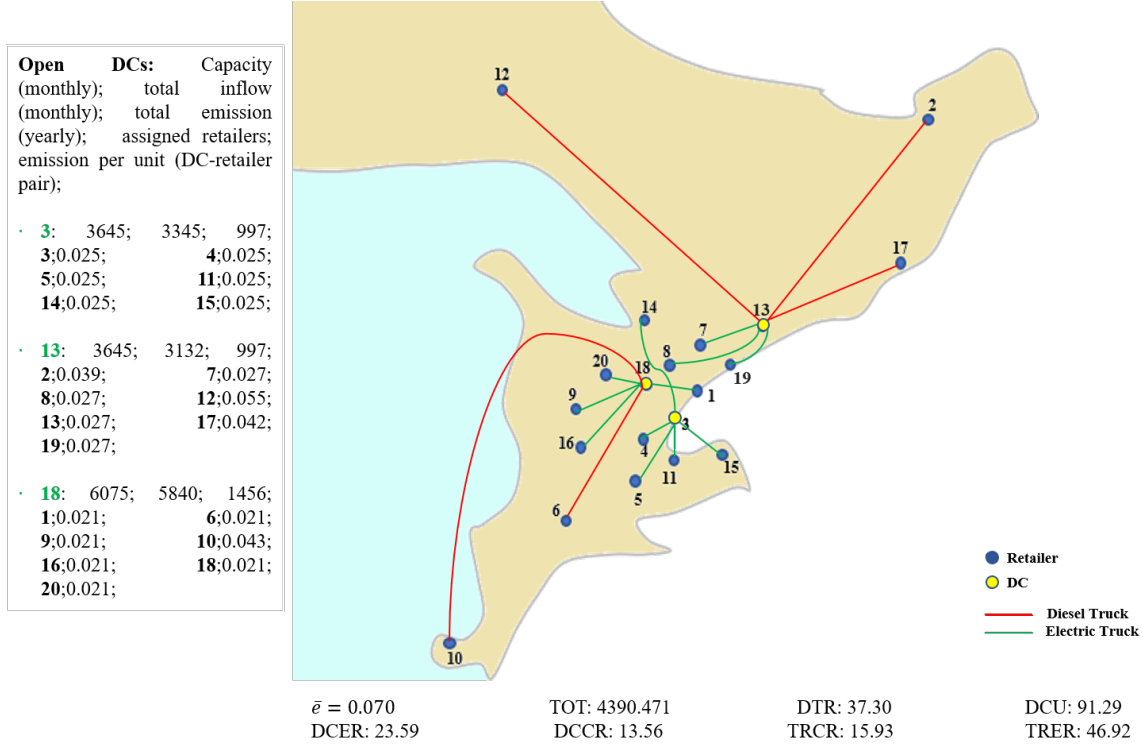


Figure 5.19: SCND: convex emission function; $\bar{e} = 0.070$; $R = 370$ km; diesel trucks more cost efficient than electric trucks

while a similar trend to the concave case is observed, with a notably smaller increase at each increment compared to the concave scenario, when $b = 1.2$, an increase in DTR from $\bar{e} = 0.050$ to $\bar{e} = 0.070$ is followed by a decrease from $\bar{e} = 0.070$ to $\bar{e} = 0.100$ when $b = 1.5$ and $b = 1.7$.

A more detailed look into the model output reveals that this is attributed to the convex nature of the emission function which results in the significant contribution of TRER to the total cost when $b = 1.5$ and $b = 1.7$. The model aims to minimize the emission cost of the transportation fleet to reduce the overall cost of the supply chain. Achieving this entails reassessing the open DCs while also considering the restrictions imposed on

per-unit emission. When $\bar{e} = 0.100$, the model gains more flexibility in selecting which DCs to open. For instance, let us compare the SCND details for the small problem size and $b = 1.7$ when $\bar{e} = 0.070$ with the case where $\bar{e} = 0.100$. In both scenarios, the model opens three DCs: DCs 1, 4, and 7 corresponding to Toronto, Brampton, Markham, respectively, for the former, and DCs 6, 4, and 7 corresponding to London, Brampton, Markham, respectively, for the latter. DC 6 is larger than DC 1, and the arrangement of 6, 4, 7 provides a more dispersed distribution, allowing for the utilization of short-ranged electric trucks with significantly lower emissions compared to diesel trucks. However, when comparing the DCU of these cases, the scenario with $\bar{e} = 0.070$ yields $DCU = 86.81$, whereas $DCU = 78.16$ is reported for $\bar{e} = 0.100$, primarily due to the lower utilization of DC 6, which stands at 37%, significantly less than that of DC 1 in the $\bar{e} = 0.070$ case (85%), while the other two DCs show more similar utilization rates in both scenarios. Thus, the model reduces TRER by increasing the per-unit emission of certain DC-retailer pairs, achievable only by raising $\bar{e}$ from 0.070 to 0.100. This decision leads to heightened open and emission costs for DCs. Nevertheless, because the reduction in transportation emission costs surpasses the increase in these cost elements, an overall decrease in the total supply chain cost is observed.

Figures 5.18-5.20 depict the supply chain design under varying values of $\bar{e}$ while keeping b fixed at 1.5. The figures exhibit a pattern similar to that observed in the concave case concerning DCU . However, there is a subtle increase in DTR as $\bar{e}$ rises, in contrast to the significant increase observed in the concave case. This highlights the disparities in the model output when utilizing a concave emission function for diesel trucks compared to a convex one.

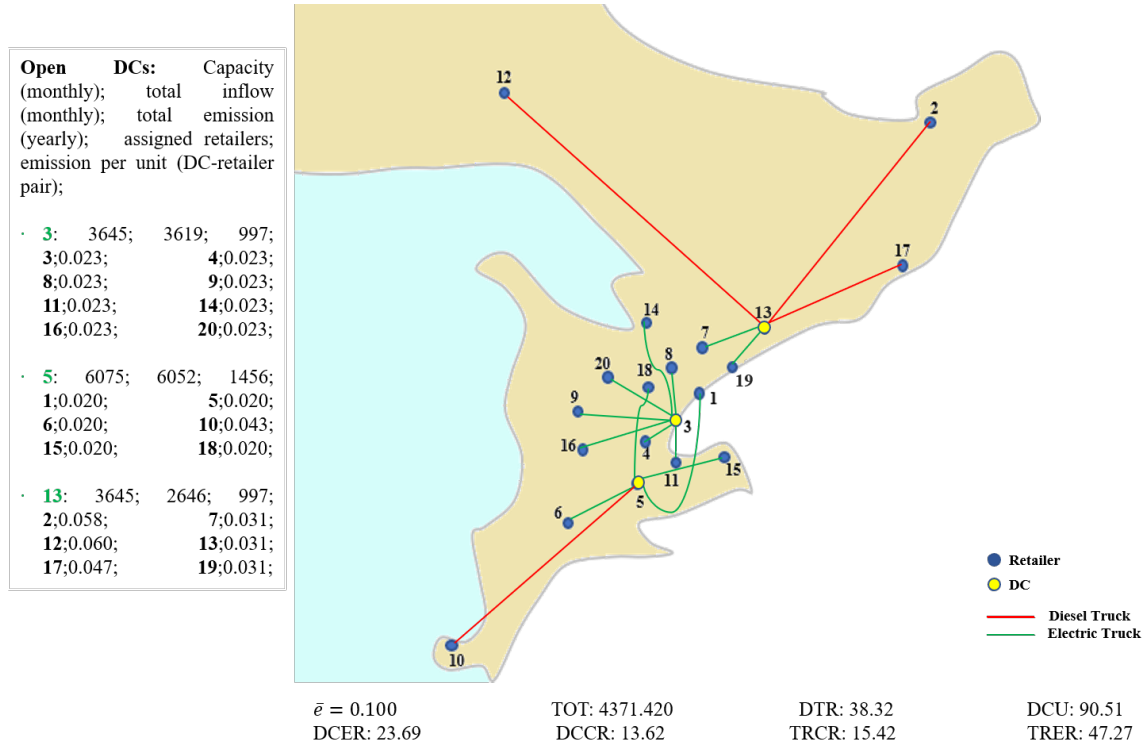


Figure 5.20: SCND: convex emission function; $\bar{e} = 0.100$; $R = 370$ km; diesel trucks more cost efficient than electric trucks

Scenario 2.1: The Range of Electric Trucks is Extended

In this section, we replicate the analysis conducted in Section 5.1.2. Figures 5.15-5.17 summarize our findings. As evident from the figures, when the range of electric trucks is extended and the emission function of diesel trucks is convex instead of concave, the model designs the supply chain in a manner where electric trucks are utilized to cover almost all trips.

5.3 Linear Emission Function for Diesel Trucks

In this section, similar to the convex and concave cases, a series of experiments assuming a linear emission function for diesel trucks are conducted which are detailed in the following subsections.

5.3.1 Scenario 1: Electric Trucks are more Cost-Efficient than Diesel Trucks

In this section, we carried out a series of experiments resembling those detailed in section 5.1.1, wherein the cost coefficient for electric trucks is lower than that for diesel trucks. The findings are outlined in Table 5.7. Similar to the findings in Table 5.3, the primary cost driver in the supply chain remains the emissions associated with opening DCs, followed by the DCs' operating costs and transportation expenses. As depicted in Tables 5.5 and 5.3, varied trends for DTR are observed as $\bar{e}$ is increased. For the small-sized problems, the proportion of diesel trucks involved in total transportation diminishes. When $\bar{e} = 0.050$ compared to $\bar{e} = 0.055$, identical DCs are open, resulting in consistent cost components for

DC emissions and operating expenses. However, considering unit-distance transportation, electric trucks are utilized more compared to diesel trucks, resulting in a lower unit-distance traveled by diesel trucks compared to when $\bar{e} = 0.050$. This shift in truck utilization led to a decrease in DTR. Consequently, there was a reduction in both transportation costs and emissions, contributing to an overall decrease in the total cost. It is important to highlight that this was achieved by allowing an additional 0.005 tones of emission per unit and adjusting the per unit emission for certain DC-retailer pairs. By increasing $\bar{e}$ to 0.070, different DCs are opened, contributing to reduced emissions and opening costs. Consequently, the unit-distance metrics for both types of trucks have increased, resulting in an increase in transportation costs and emissions and a decrease in DTR. However, since the cost reduction in DCs outweighs the increase in transportation costs, an overall reduction is observed in the total cost of the supply chain. For the larger-scale problem, comparing the case where $\bar{e} = 0.050$ with $\bar{e} = 0.055$, reveals consistent DC operation. Nonetheless, the second case shows a slight decrease in the unit-distance of electric trucks, while that of diesel trucks remains constant. Consequently, DTR increases slightly, but the overall cost decreases due to slight reductions in transportation expenses and emissions.

Figures 5.21 and 5.22 depict the design of the supply chain under two different values of $\bar{e}$. It is worth noting that the output did not change for larger values of $\bar{e}$. Although different DCs are open under each scenario, the cost components associated with the open DCs remain the same for both cases. Moving from $\bar{e} = 50$ to $\bar{e} = 55$, the unit-distance of diesel trucks has decreased, while that of electric trucks has increased (resulting in a decrease in DTR), leading to an overall reduction in transportation costs and consequently the total cost.

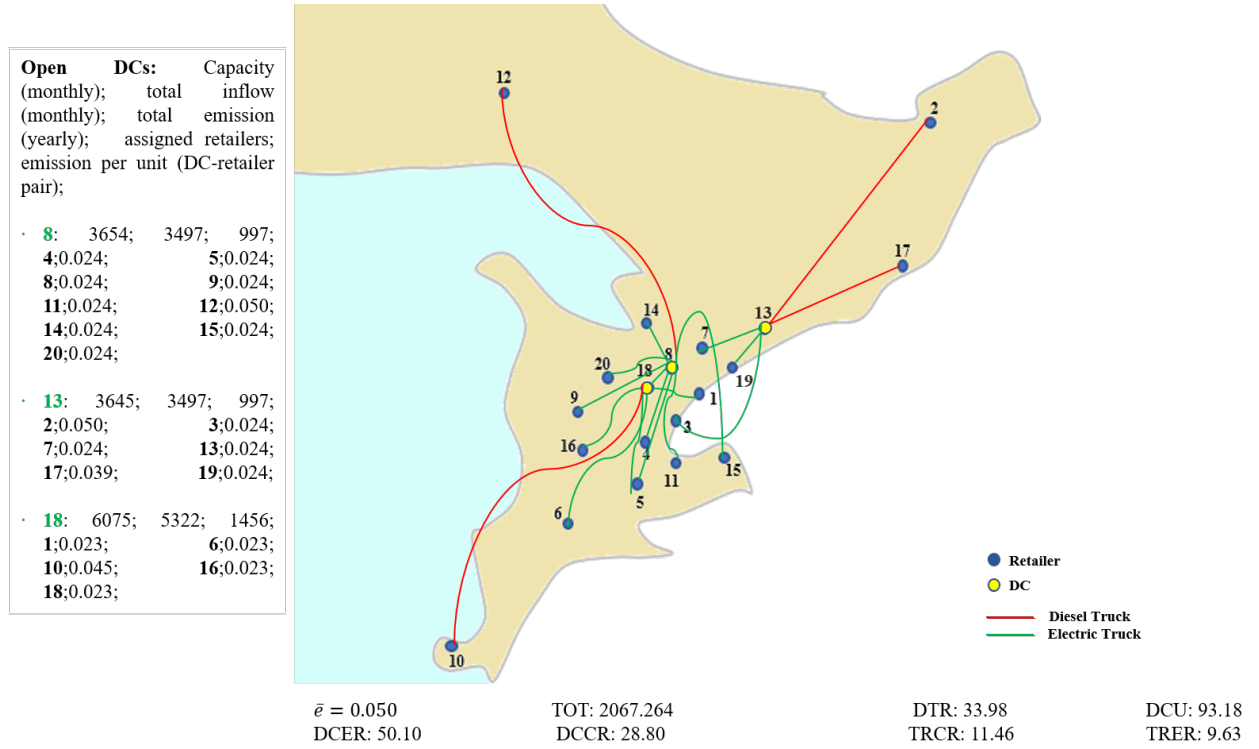


Figure 5.21: SCND: linear emission function; $\bar{e} = 0.050$; $R = 370$ km; electric trucks more cost efficient than diesel trucks

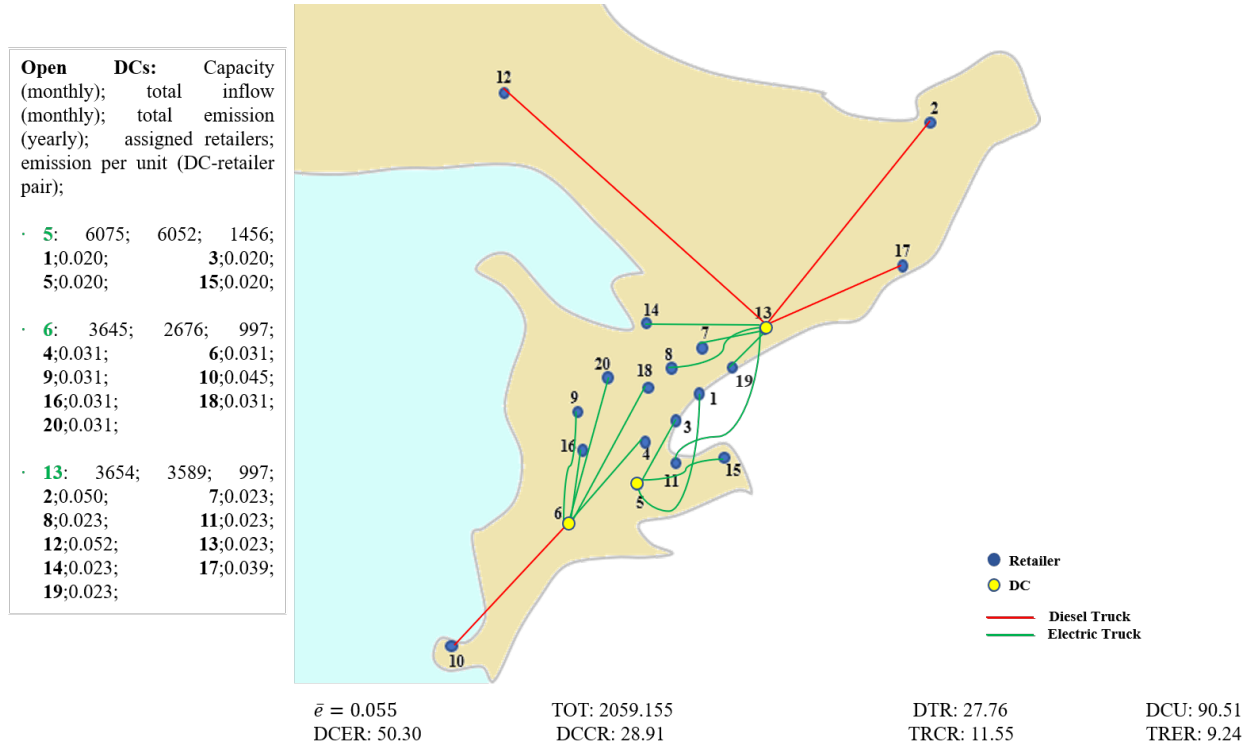


Figure 5.22: SCND: linear emission function; $\bar{e} = 0.055$; $R = 370$ km; electric trucks more cost efficient than diesel trucks

Table 5.7: Sensitivity analysis: linear emission function; $R = 370$ km; electric trucks more cost efficient than diesel trucks

Problem	Cost(%, %, %, %, thousands dollars)									Time (%, %, %, %, %, s)							
n, m, b	DCER	DCCR	TRCR	TRER	TOT	DCE	DCC	TRC	TRE	DTR	Iters.	HQ1	SP1	SP2	Hue	MP	tTOT
$\bar{e} = 0.050$																	
10,20,1	46.66	24.66	19.64	9.05	2366.42	3680.58	583.56	464.77	713.87	38.51	12	0.007	89.63	5.28	0.67	4.41	24.35
15,40,1	44.65	23.50	22.07	9.79	3886.26	5784.04	913.27	857.70	1268.21	27.82	10	0.000	99.39	0.26	0.04	0.31	497.31
20,100,1	45.13	22.75	22.26	9.86	8465.94	12735.60	1926.00	1884.52	2782.47	27.47	7	0.000	98.80	0.29	0.04	0.87	594.45
Min	44.65	22.75	19.64	9.05	2366.42	3680.58	583.56	464.77	713.87	27	7	0.000	89.63	0.26	0.04	0.31	24.35
Max	46.66	24.66	22.26	9.86	8465.94	12735.60	1926.00	1884.52	2782.47	39	12	0.007	99.39	5.28	0.67	4.41	594.45
Mean	45.48	23.64	21.32	9.57	4906.21	7400.07	1140.94	1068.99	1588.19	31.27	9.67	0.002	95.94	1.94	0.25	1.86	372.04
$\bar{e} = 0.055$																	
10,20,1	47.06	24.87	19.24	8.34	2346.12	3680.28	583.48	451.39	652.22	37.35	10	0.050	92.03	4.34	0.73	2.85	25.24
15,40,1	44.65	23.50	22.07	9.79	3886.26	5784.04	913.27	857.70	1268.21	27.82	10	0.000	98.90	0.46	0.07	0.57	410.45
20,100,1	45.13	22.75	22.26	9.86	8465.82	12735.41	1925.97	1884.49	2782.43	27.48	7	0.000	98.73	0.31	0.04	0.92	555.80
Min	44.65	22.75	19.24	8.34	2346.12	3680.28	583.48	451.39	652.22	27	7	0.000	92.03	0.31	0.04	0.57	25.24
Max	47.06	24.87	22.26	9.86	8465.82	12735.41	1925.97	1884.49	2782.43	37	10	0.050	98.90	4.34	0.73	2.85	555.80
Mean	45.61	23.71	21.19	9.33	4899.40	7399.91	1140.91	1064.53	1567.62	30.88	9	0.017	96.55	1.70	0.28	1.45	330.50
$\bar{e} = 0.070$																	
10,20,1	44.81	24.18	21.44	9.58	2234.49	3337.58	540.30	479.07	713.55	29.22	10	0.000	93.09	3.61	0.61	2.66	26.75
15,40,1	44.65	23.50	22.07	9.79	3886.26	5784.04	913.27	857.70	1268.21	27.82	10	0.000	99.17	0.32	0.06	0.45	456.38
20,100,1	45.13	22.75	22.26	9.86	8465.82	12735.41	1925.97	1884.49	2782.43	27.48	6	0.000	98.84	0.25	0.05	0.86	493.48
Min	44.65	22.75	21.44	9.58	2234.49	3337.58	540.30	479.07	713.55	27	6	0.000	93.09	0.25	0.05	0.45	26.75
Max	45.13	24.18	22.26	9.86	8465.82	12735.41	1925.97	1884.49	2782.43	10	0.000	99.17	3.61	0.61	2.66	493.48	
Mean	44.86	23.48	21.92	9.74	4862.19	7285.68	1126.51	1073.75	1588.06	28.17	8.67	0.000	97.03	1.39	0.24	1.32	325.54

5.3.2 Scenario 2: Diesel Trucks are more Cost-Efficient than Electric Trucks

In this section, we conduct on a similar analysis to the section, taking into account that diesel trucks are deemed to offer greater cost-effectiveness in transportation efficiency compared to electric trucks. The summary of our findings is presented in Table 5.8. The table clearly shows that the cost associated with emissions from open DCs stands out as the predominant component of the total cost. Depending on the values of $\bar{e}$ and the scale of the problem, the costs of opening DCs and transportation expenses emerge as the second most significant contributors to the total supply chain cost. The variations in DTR follow a pattern similar to that observed in the concave case, demonstrating a slightly more gradual increase in diesel truck usage as $\bar{e}$ rises. Further insights into the SCND when $\bar{e} = 0.050$ and $\bar{e} = 0.070$ are illustrated in Figures 5.23 and 5.24. Notably, the model exhibited no change in outputs when $\bar{e}$ was increased to 0.100 tonnes. As the figures illustrate, there is a subtle rise in DTR when $\bar{e} = 0.050$ compared to when $\bar{e} = 0.070$, coinciding with a slight decline in the reported values for DCU .

Scenario 2.1: The Range of Electric Trucks is Extended

In this section, we used a linear emission function for diesel trucks to replicate the experiments presented in sections 5.1.2 and 5.2.2. This resulted in the same figure as presented in Section 5.2.2.

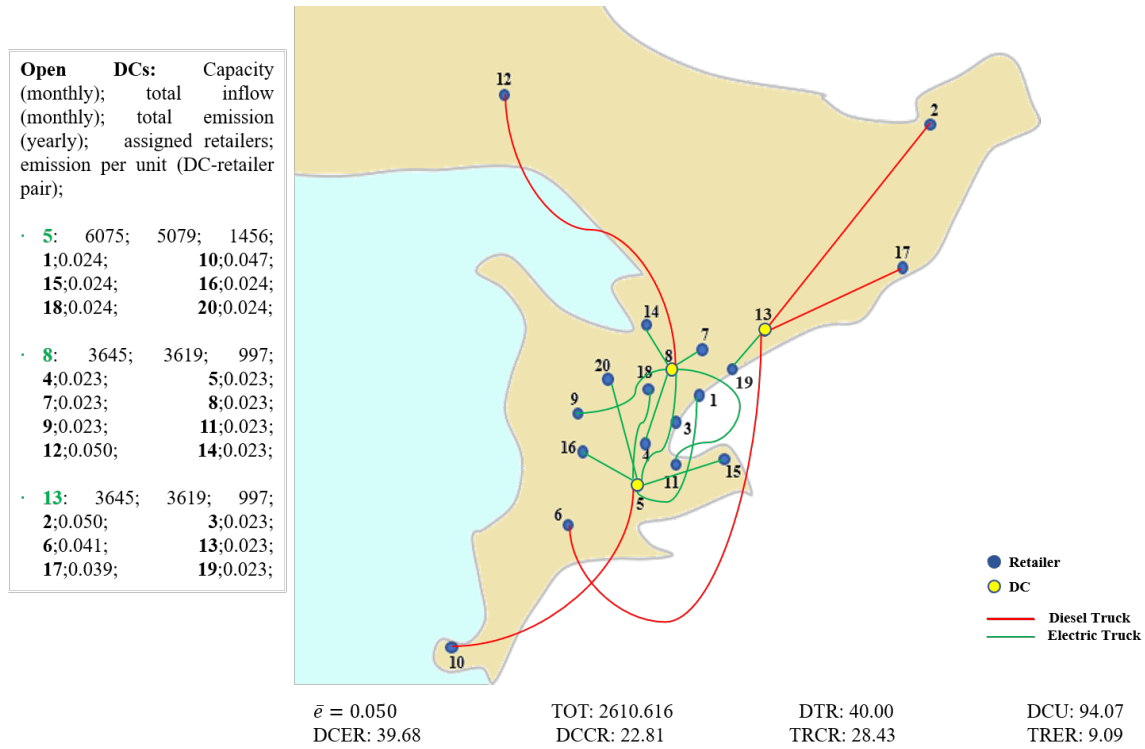


Figure 5.23: SCND: linear emission function; $\bar{e} = 0.050$; $R = 370$ km; diesel trucks more cost efficient than electric trucks

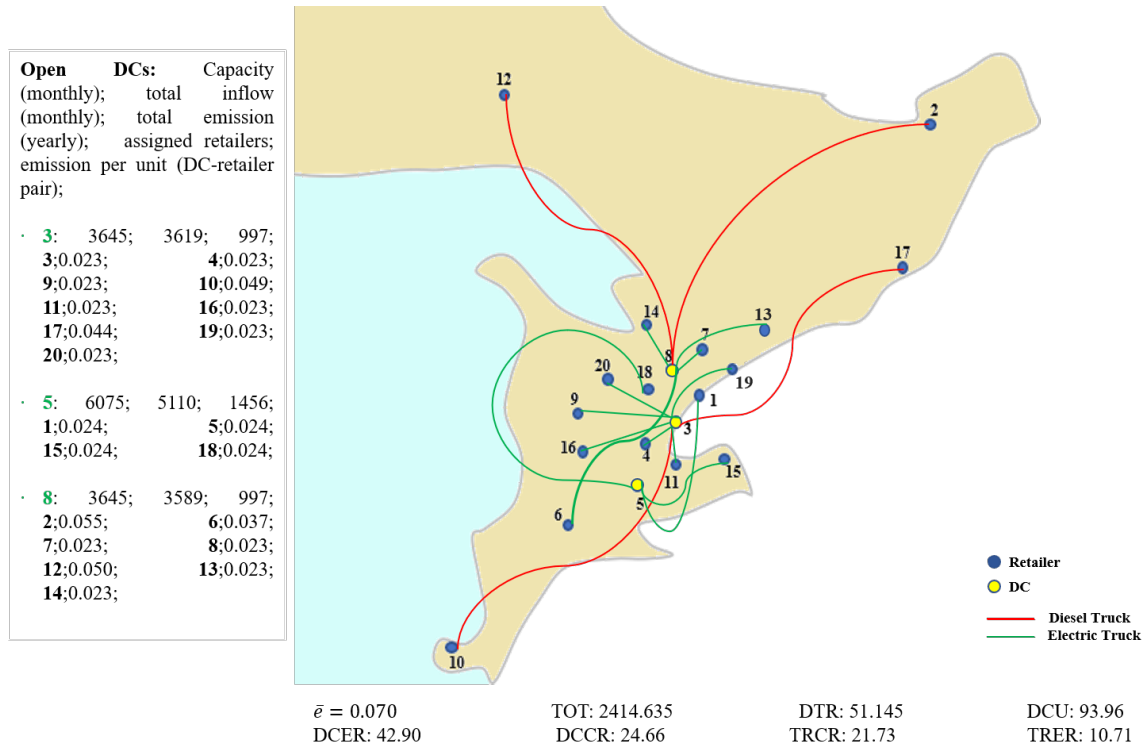


Figure 5.24: SCND: linear emission function; $\bar{e} = 0.070$; $R = 370$ km; diesel trucks more cost efficient than electric trucks

Table 5.8: Sensitivity analysis: linear emission function; $R = 370$ km; diesel trucks more cost efficient than electric trucks

Problem	Cost(%, %, %, %, thousands dollars)									Time (%, %, %, %, %, s)							
n, m, b	DCER	DCCR	TRCR	TRER	TOT	DCE	DCC	TRC	TRE	DTR	Iters.	HQ1	SP1	SP2	Hue	MP	tTOT
$\bar{e} = 0.05$																	
10,20,1	47.15	26.80	15.60	10.45	2355.98	3702.82	631.40	367.53	820.67	59.17	10	0.000	95.11	1.23	0.52	2.95	45
15,40,1	42.11	22.16	24.81	10.92	4240.77	5952.62	939.75	1052.13	1543.64	48.16	8	0.020	98.11	0.36	0.13	1.40	248.15
20,100,1	41.38	20.84	26.76	11.06	9242.66	12748.70	1926.17	2473.33	3407.46	46.53	8	0.000	98.79	0.25	0.04	0.92	413.19
Min	41.38	20.84	15.60	10.45	2355.98	3702.82	631.40	367.53	820.67	46.53	8	0.000	95.11	0.25	0.04	0.92	45.00
Max	47.15	26.80	26.76	11.06	9242.66	12748.70	1926.17	2473.33	3407.46	59.17	10	0.020	98.79	1.23	0.52	2.95	413.19
Mean	43.55	23.27	22.39	10.81	5279.80	7468.05	1165.78	1297.67	1923.92	51.29	8.67	0.007	97.34	0.61	0.23	1.76	235.45
$\bar{e} = 0.07$																	
10,20,1	45.89	24.76	17.45	11.91	2182.20	3338.03	540.31	380.79	866.33	59.65	11	0.001	94.81	1.44	0.52	3.23	47.15
15,40,1	46.73	26.22	15.58	11.47	4120.63	6418.56	1080.43	641.99	1575.45	61.58	6	0.002	97.20	0.51	0.19	2.09	115.98
20,100,1	41.38	20.84	26.76	11.06	9242.66	12748.70	1926.17	2473.33	3407.46	46.53	8	0.000	98.86	0.25	0.05	0.84	603.31
Min	41.38	20.84	15.58	11.06	2182.20	3338.03	540.31	380.79	866.33	46.53	6	0.000	94.81	0.25	0.05	0.84	47.15
Max	46.73	26.22	26.76	11.91	9242.66	12748.70	1926.17	2473.33	3407.46	61.58	11	0.002	98.86	1.44	0.52	3.23	603.31
Mean	44.67	23.94	19.93	11.48	5181.83	7501.77	1182.30	1165.37	1949.75	55.92	8.33	0.001	96.96	0.73	0.25	2.05	255.48
$\bar{e} = 0.100$																	
10,20,1	46.23	24.94	16.83	12.00	2166.02	3337.84	540.21	364.54	866.41	60.76	15	0.002	93.64	1.71	0.75	3.89	50.42
15,40,1	46.73	26.22	15.58	11.47	4120.63	6418.56	1080.43	641.99	1575.45	61.58	15	0.000	96.84	0.55	0.23	2.37	226.520
20,100,1	41.38	20.84	26.76	11.06	9242.66	12748.70	1926.17	2473.33	3407.46	46.53	8	0.000	98.85	0.25	0.04	0.86	640.98
Min	41.38	20.84	15.58	11.06	2166.02	3337.84	540.21	364.54	866.41	46.53	8	0.000	93.64	0.25	0.04	0.86	50.42
Max	46.73	26.22	26.76	12.00	9242.66	12748.70	1926.17	2473.33	3407.46	61.58	15	0.002	98.85	1.71	0.75	3.89	640.98
Mean	44.78	24.00	19.72	11.51	5176.43	7501.70	1182.27	1159.96	1949.77	56.29	12.67	0.001	96.44	0.84	0.34	2.37	305.97

Chapter 6

Conclusion

We considered a green supply chain network design problem where cost, as well as emissions from storage at the distribution centers and due to transportation, are accounted for. We proposed a nonlinear mixed-integer model where the location of distribution centers and transportation fleets, among diesel or electric trucks, is optimized. We additionally imposed a cap on carbon footprint as measured by per unit emissions. To solve the resulting model, we devised a Lagrangian relaxation to decompose the model by echelon to isolate the nonlinearity in one of the subproblems and presented a Lagrangian heuristic based on the solution of the other subproblem.

To validate the approach and derive insights from the proposed framework, we devised a realistic case study and carried out extensive testing. We analyzed the impact of different emission functions and varying levels of per unit emission limits on the selection of open DCs, the assignment of DCs to retailers, and the contribution of diesel and electric trucks to the distance-unit transported through the supply chain. Our numerical experiments revealed the following key insights. Firstly, considering the concave emission function,

when electric trucks are more cost-efficient, the use of diesel trucks slightly increases with the rise in the carbon footprint cap, although this trend is not universal, as the additional cost of more diesel trucks can outweigh the potential savings. However, when diesel trucks are cheaper, their usage can increase by about 30% as the emission restrictions loosen. In all scenarios with concave functions, the cost of emissions from opening DCs is the primary contributor to the total cost, while transportation fleet emissions contribute the least. Secondly, when a convex emission function is used, a different trend is observed in the DTR. Due to the convexity, the cost of transportation emissions often becomes the main contributor. The model does not necessarily favor diesel trucks over electric trucks as the carbon footprint cap increases, even when diesel trucks are more cost-efficient. As the coefficient of the convex function increases, the use of diesel trucks decreases. Third, when the range of electric trucks is extended, the model favors electric trucks for almost all trips when the emission function is convex. In contrast, with a concave function, an increase in diesel truck usage is observed as $\bar{e}$ increases. Finally, the trends observed with a linear emission function resemble those of the concave function in some scenarios, while in others, the behavior is similar to the convex case. These findings demonstrate the model's sensitivity to different emission functions and constraints, providing valuable insights into the optimal mix of transportation modes under various conditions. Extensions of the proposed framework could include exploring additional functions to model the payload-emission relationship for diesel trucks and considering supply chains with multiple plants and/or products.

Chapter 7

Extensions

The findings presented in this paper offer opportunities for further exploration. The following sections discuss one of how this research can be expanded.

7.1 Model-determined Truck Type Selection

In chapter 3, we introduced binary the parameters u'_{ij} and u'_j to differentiate between diesel and electric trucks for inter-echelon transportation. This approach mandates the use of electric trucks whenever their range is sufficient for the round trip between origin and destination. However, to grant the model greater autonomy in truck type selection, we can introduce binary variables u_{ij} and u_j . Consequently, $u_j, u_{ij} \in \{0, 1\} \quad \forall i, j, u_j \leq u'_j \quad \forall j$, and $u_j \leq u'_j \quad \forall i, j$ will be added to the constraints 3.1-3.6 and problem [P] is reformulated as follows:

$$\begin{aligned}
[\text{EP1}] : \min & \sum_{j=1}^n a_j z_j + \sum_{j=1}^n (u_j c_j^e + (1 - u_j) c_j^d) y_j + \\
& \sum_{i=1}^m \sum_{j=1}^n (u_{ij} t_{ij}^e + (1 - u_{ij}) t_{ij}^d) D_i x_{ij} + \\
& w \left(\sum_{j=1}^n g_j(v_j) z_j + \sum_{j=1}^n (u_j f_j^e(y_j) + (1 - u_j) f_j^d(y_j)) \right) + \\
& \sum_{i=1}^m \sum_{j=1}^n (u_{ij} f_{ij}^e(D_i x_{ij}) + (1 - u_{ij}) f_{ij}^d(D_i x_{ij})) \\
\text{s.t. } & \sum_{j=1}^n x_{ij} = 1 \quad \forall i \\
& y_j = \sum_{i=1}^m D_i x_{ij} \quad \forall j \\
& y_j \leq T v_j z_j \quad \forall j \\
& [\bar{e} - (u_j e_j^e + (1 - u_j) e_j^d) - (u_{ij} e_{ij}^e + (1 - u_{ij}) e_{ij}^d)] \sum_{l=1}^m D_l x_{lj} \geq \\
& g_j(v_j) z_j - M(1 - x_{ij}) \quad \forall i, j \\
& u_{jk} \leq u'_j \quad \forall j \\
& u_{ij} \leq u'_{ij} \quad \forall i, j \\
& y_j \geq 0 \quad \forall j \\
& u_j, u_{ij}, z_j, x_{ij} \in \{0, 1\} \quad \forall i, j, k
\end{aligned}$$

To linearize problem [EP1], we introduce variables y_j^e and y_j^d to indicate the number of units transported from the plant to DC j via electric and diesel trucks, respectively.

Additionally, binary variables x_{ij}^e are defined as 1 if retailer i is served by DC j using electric trucks, and 0 otherwise. Similar binary variables x_{ij}^d are introduced for diesel trucks. Thus, [EP1] can be reformulated as:

$$\begin{aligned}
\text{[LEP1]} : \min & \sum_{j=1}^n a_j z_j + \sum_{j=1}^n (c_j^e y_j^e + c_j^d y_j^d) + \sum_{i=1}^m \sum_{j=1}^n (t_{ij}^e D_i x_{ij}^e + t_{ij}^d D_i x_{ij}^d) + \\
& w \left(\sum_{j=1}^n g_j(v_j) z_j + \sum_{j=1}^n (f_j^e(y_j^e) + f_j^d(y_j^d)) + \right. \\
& \left. \sum_{i=1}^m \sum_{j=1}^n (f_{ij}^e(D_i x_{ij}^e) + f_{ij}^d(D_i x_{ij}^d)) \right) \\
\text{s.t.} & \sum_{j=1}^n x_{ij} = 1 \quad \forall i \\
& y_j = \sum_{i=1}^m D_i x_{ij} \quad \forall j \\
& y_j \leq T v_j z_j \quad \forall j \\
& [\bar{e} - (u_j e_j^e + (1 - u_j) e_j^d) - (u_{ij} e_{ij}^e + (1 - u_{ij}) e_{ij}^d)] \sum_{l=1}^m D_l x_{lj} \geq \\
& g_j(v_j) z_j - M(1 - x_{ij}) \quad \forall i, j \\
& y_j^e \leq M u_j \quad \forall j
\end{aligned}$$

$$\begin{aligned}
y_j^e &\leq y_j \quad \forall j \\
y_j^e &\geq y_j - M(1 - u_j) \quad \forall j \\
y_j^d &\leq M(1 - u_j) \quad \forall j \\
y_j^d &\leq y_j \quad \forall j \\
y_j^d &\geq y_j - Mu_j \quad \forall j \\
x_{ij}^e &\leq u_{ij} \quad \forall i, j \\
x_{ij}^e &\leq x_{ij} \quad \forall i, j \\
x_{ij}^e &\geq x_{ij} - (1 - u_{ij}) \quad \forall i, j \\
x_{ij}^d &\leq (1 - u_{ij}) \quad \forall i, j \\
x_{ij}^d &\leq x_{ij} \quad \forall i, j \\
x_{ij}^d &\geq x_{ij} - u_{ij} \quad \forall i, j \\
u_j &\leq u'_j \quad \forall j \\
u_{ij} &\leq u'_{ij} \quad \forall i, j \\
y_j^e, y_j^d, y_j &\geq 0 \quad \forall j \\
u_j, u_{ij}, z_j, x_{ij}^e, x_{ij}^d, x_{ij} &\in \{0, 1\} \quad \forall i, j
\end{aligned}$$

We solved [LEP1] in both convex and linear scenarios. Given the computational demands of larger-scale problems, we focused on small and medium-sized ones. Tables 7.1 and 7.2 present the outcomes for the convex scenario, while Tables 7.3 and 7.4 provide a summary for the linear case.

Considering the convex case, for both scenarios where either of the truck types is more cost efficient compared to the other one (Tables 7.1 and 7.2), for all scenarios, the same

DCs are open compared to the case where the selection of truck types was enforced in the model (Tables 5.6 and 5.5). Moreover, the assignment of retailers to open DCs is also unchanged. However, more diesel trucks are utilized for inter-echelon transportation. To be more detailed, when $b = 1.5$ or $b = 1.7$, whenever a retailer is assigned to a DC located in the same location, diesel trucks are chosen for transportation instead of electric trucks. Thus, compared to the scenario where only electric trucks could be utilized for these cases, removing the restriction on truck type selection now favors diesel trucks over electric trucks, resulting in larger DTR values. It is worth noting that since the distance is equal to zero in these cases, there is no additional cost incurred in the transportation cost/emission, and consequently, there's no increase in the overall cost of the supply chain. Due to the convex nature of the emission functions for diesel trucks, these are the only trips where diesel trucks are utilized instead of electric ones, in contrast to the scenario where electric trucks were mandatory for such trips. However, when $b = 1.2$ other trips that were previously completed by electric trucks are also handled by diesel trucks. This change explains why the objective function for these cases differs from the values presented in Table 5.6.

Figures 7.1 to 7.2 depict the SCND under different values of $\bar{e}$ for the case where electric trucks are cheaper than their diesel counterparts. It can be observed that all the details of the SCND are similar to those of Figures 5.12 to 5.14, except for the use of diesel trucks for connecting DC-retailer pairs of the same location, which are indicated in the former set of figures by highlighting the retailers' IDs in red. The same stands for Figures 7.4 to 7.6 compared to Figures 5.12 to 5.14 for the case where electric trucks are cheaper than their diesel counterparts.

The model shows different behavior under the linear emission function. While the costs associated with DCs remain the same, different DCs might be open comparing Tables 7.3

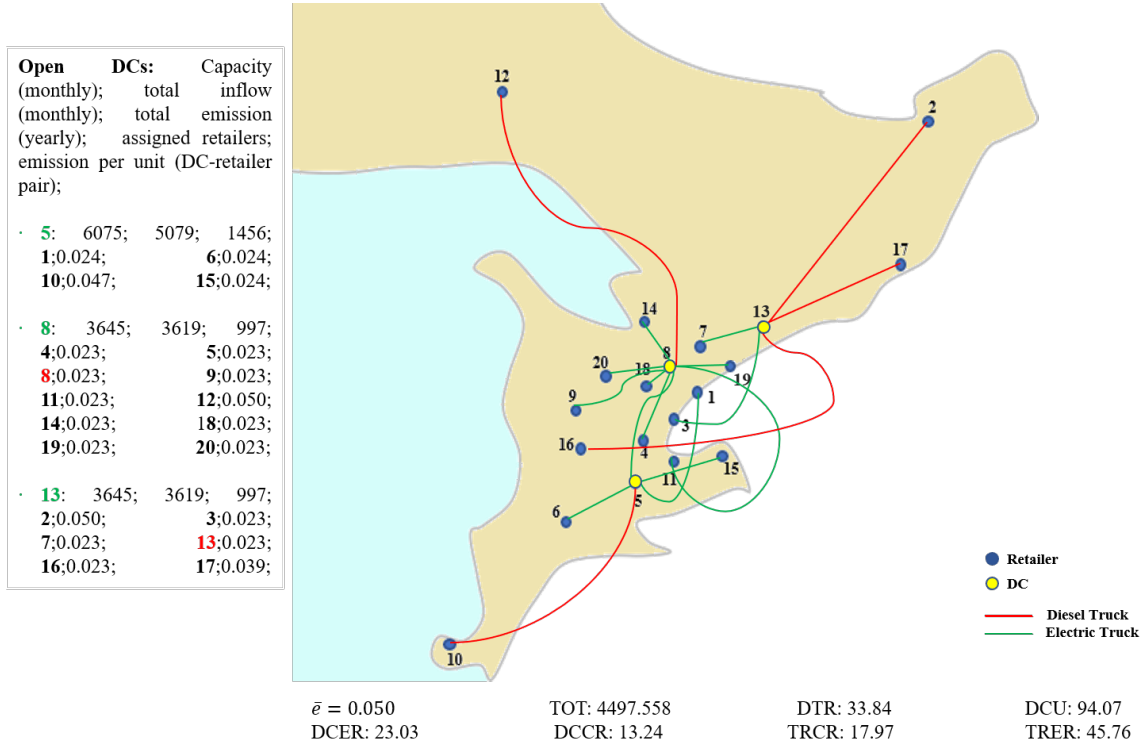


Figure 7.1: SCND: convex emission function; $\bar{e} = 0.050$; $R = 370$ km; model-determined truck type selection; diesel trucks more cost efficient than electric trucks

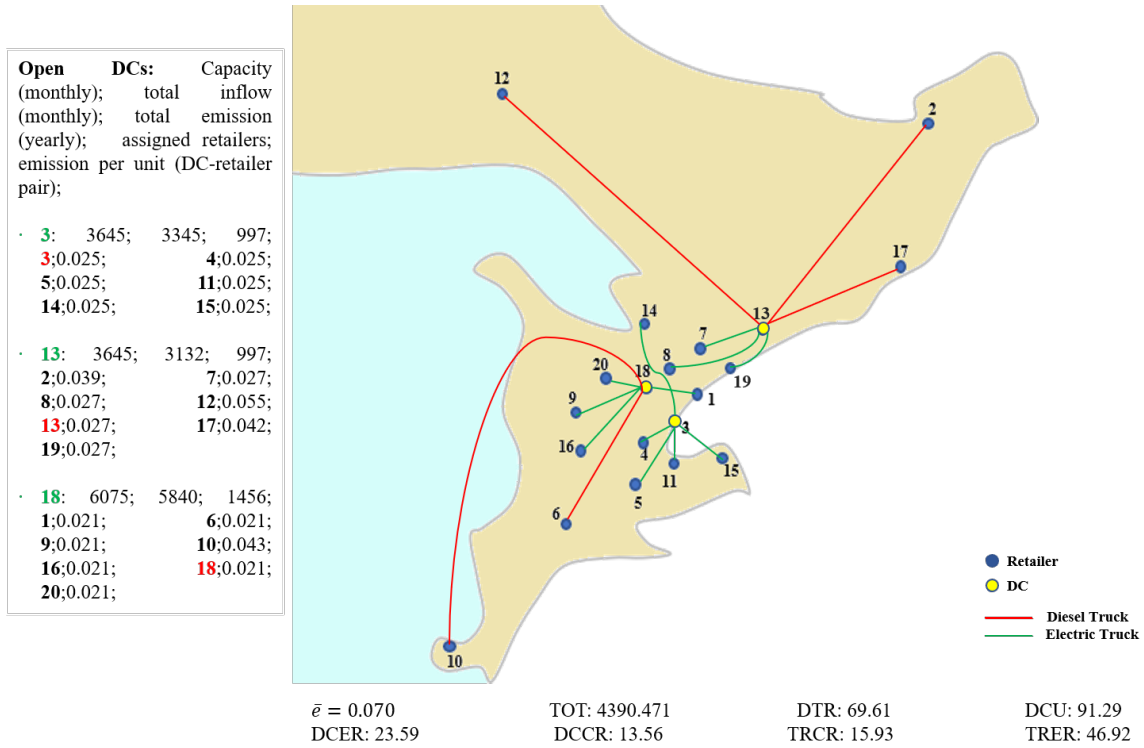


Figure 7.2: SCND: convex emission function; $\bar{e} = 0.070$; $R = 370$ km; model-determined truck type selection; diesel trucks more cost efficient than electric trucks

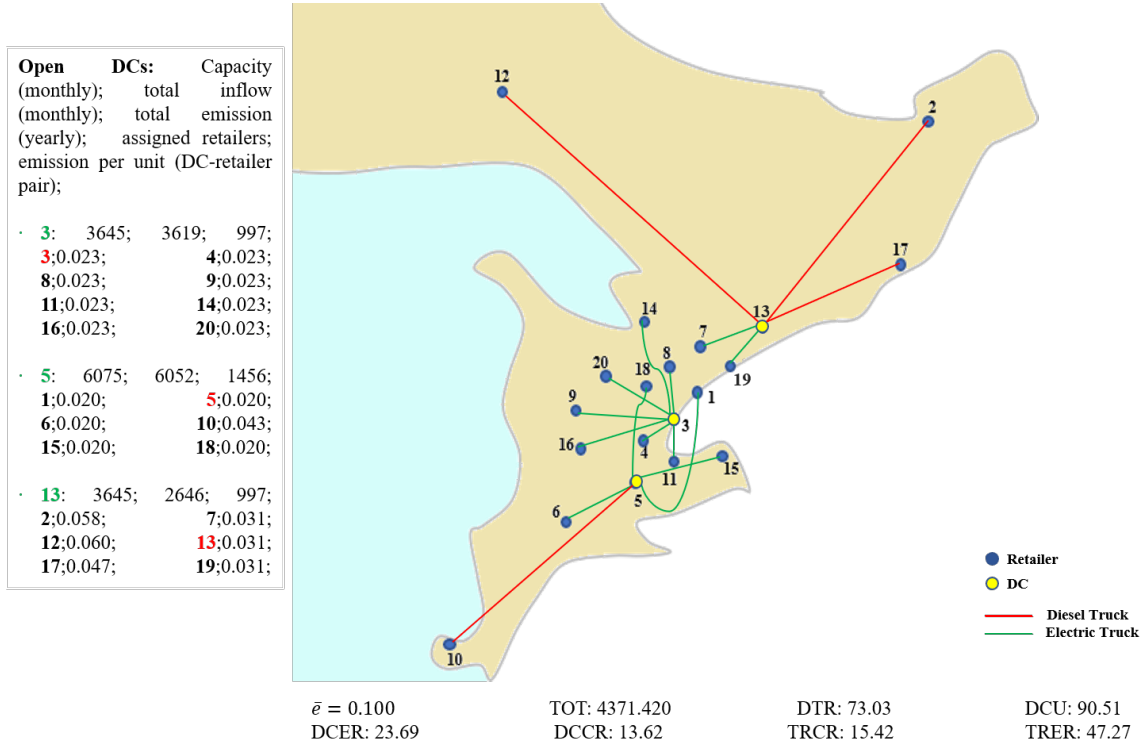


Figure 7.3: SCND: convex emission function; $\bar{e} = 0.100$; $R = 370$ km; model-determined truck type selection; diesel trucks more cost efficient than electric trucks

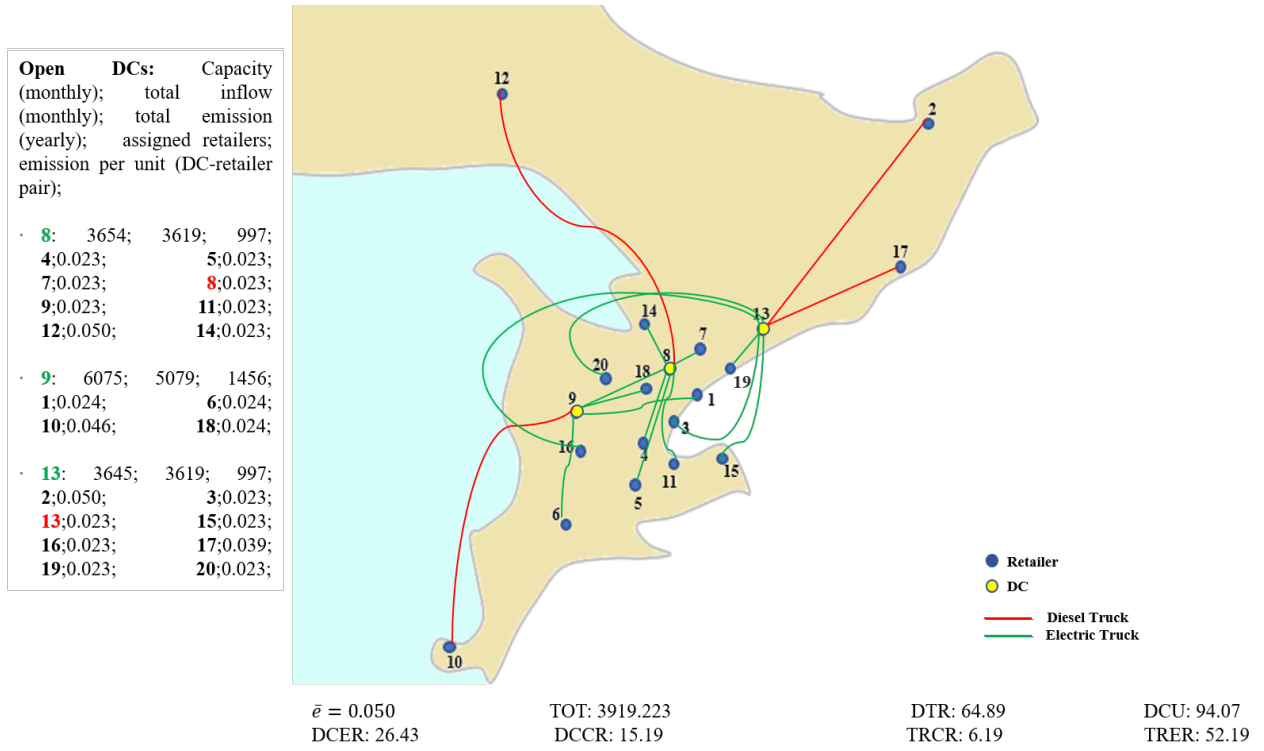


Figure 7.4: SCND: convex emission function; $\bar{e} = 0.050$; $R = 370$ km; model-determined truck type selection; electric trucks more cost efficient than diesel trucks

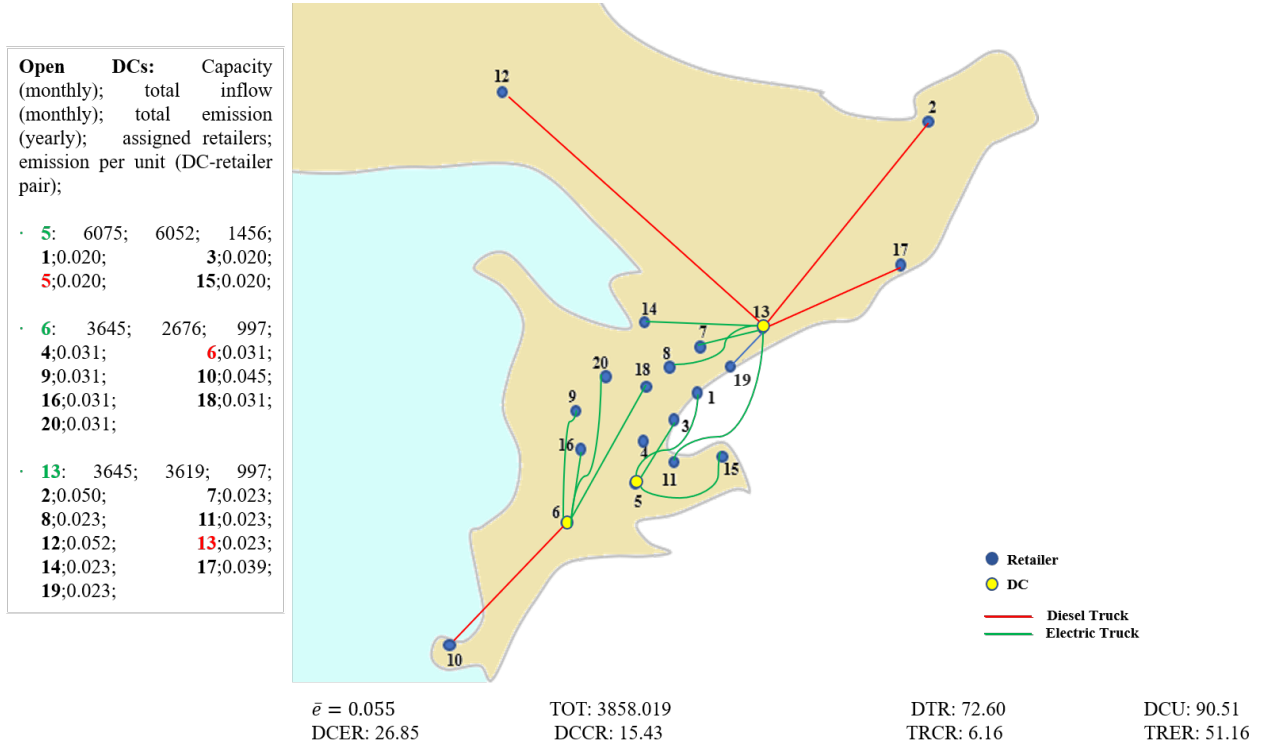


Figure 7.5: SCND: convex emission function; $\bar{e} = 0.055$; $R = 370$ km; model-determined truck type selection; electric trucks more cost efficient than diesel trucks

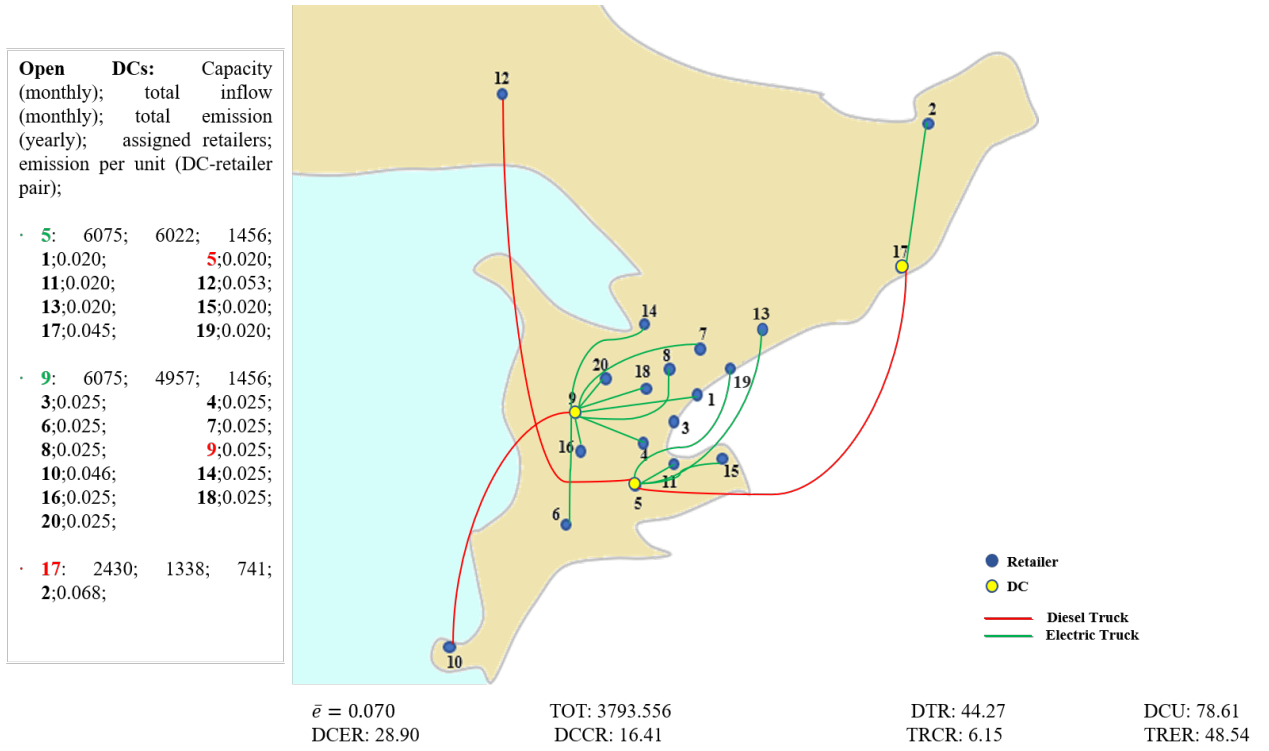


Figure 7.6: SCND: convex emission function; $\bar{e} = 0.070$; $R = 370$ km; model-determined truck type selection; electric trucks more cost efficient than diesel trucks

Table 7.1: Sensitivity analysis: convex emission function; $R = 370$ km; model-determined truck type selection; diesel trucks more cost efficient than electric trucks

Problem	Cost(%,%,% , %, thousands dollars)						Time(s)
n, m, b	DCER	DCCR	TRCR	TRER	TOT	DTR	tTOT
$\bar{e} = 0.050$							
10,20,1.2	52.27	29.71	7.57	10.46	2125.497	89.69	14.53
10,20,1.5	25.60	14.55	9.86	50.00	4339.862	77.53	16.00
10,20,1.7	6.79	3.86	2.76	86.59	16357.905	76.80	11.28
15,40,1.2	50.32	27.40	16.58	5.71	3666.102	76.67	1622.60
15,40,1.5	21.48	11.31	16.05	51.17	8077.011	75.83	4338.20
15,40,1.7	6.10	3.33	5.09	85.49	30682.403	75.75	4343.36
$\bar{e} = 0.070$							
10,20,1.2	53.08	28.64	2.17	16.12	1886.440	81.33	19.98
10,20,1.5	25.96	14.75	9.21	50.09	4280.067	77.31	9.54
10,20,1.7	6.87	3.90	2.30	86.93	16172.485	73.08	14.93
15,40,1.2	50.46	26.56	2.53	20.45	3438.864	81.88	838.43
15,40,1.5	23.29	12.70	12.33	51.68	8038.361	72.13	500.27
15,40,1.7	6.29	3.43	3.18	87.10	30632.147	74.46	174.20
$\bar{e} = 0.100$							
10,20,1.2	53.39	28.81	2.13	15.68	1875.558	81.26	11.65
10,20,1.5	26.09	14.83	8.74	50.35	4258.058	78.08	11.56
10,20,1.7	7.68	4.28	4.27	83.78	16159.622	73.33	10.87
15,40,1.2	50.46	26.56	2.53	20.45	3438.864	81.88	121.76
15,40,1.5	23.29	12.70	12.33	51.68	8038.361	72.13	128.20
15,40,1.7	6.29	3.43	3.18	87.10	30624.476	74.46	110.44

Table 7.2: Sensitivity analysis: convex emission function; $R = 370$ km; model-determined truck type selection; electric trucks more cost efficient than diesel trucks

Problem	Cost(%,%,% , %, thousands dollars)						Time(s)
n, m, b	DCER	DCCR	TRCR	TRER	TOT	DTR	tTOT
$\bar{e} = 0.050$							
10,20,1.2	53.43	28.24	12.02	6.31	2066.312	67.19	6.36
10,20,1.5	27.27	14.41	6.14	52.18	4048.145	67.19	10.02
10,20,1.7	6.98	3.69	1.57	87.76	15821.368	67.19	12.34
15,40,1.2	51.54	27.13	14.10	7.23	3366.242	72.96	62.36
15,40,1.5	24.43	12.86	6.68	56.02	7101.005	72.96	55.16
15,40,1.7	6.40	3.49	1.55	88.57	29277.891	71.46	68.04
$\bar{e} = 0.055$							
10,20,1.2	51.68	27.88	12.95	7.49	1937.552	71.83	11.44
10,20,1.5	27.28	14.41	6.13	52.18	4047.998	67.47	11.02
10,20,1.7	7.90	4.40	1.49	86.21	15703.764	60.25	12.75
15,40,1.2	51.54	27.13	14.10	7.23	3366.242	72.96	80.16
15,40,1.5	24.43	12.86	6.68	56.02	7101.005	72.96	71.00
15,40,1.7	6.40	3.49	1.55	88.57	29277.891	71.46	76.36
$\bar{e} = 0.070$							
10,20,1.2	51.70	27.90	12.92	7.49	1936.675	72.01	13.70
10,20,1.5	27.28	14.41	6.13	52.18	4047.998	67.47	12.26
10,20,1.7	7.91	4.40	1.46	86.23	15699.856	63.32	8.68
15,40,1.2	51.54	27.13	14.10	7.23	3366.242	72.96	61.21
15,40,1.5	24.43	12.86	6.68	56.02	7101.005	72.96	74.04
15,40,1.7	6.40	3.49	1.55	88.57	29277.891	71.46	62.30

Table 7.3: Sensitivity analysis: linear emission function; $R = 370$ km; mode-determined truck type selection; diesel trucks more cost efficient than electric trucks

Problem	Cost(%,%,% , %, thousands dollars)						Time(s)
n, m, b	DCER	DCCR	TRCR	TRER	TOT	DTR	tTOT
$\bar{e} = 0.050$							
10,20,1	57.68	30.48	9.24	2.60	1914.185	78.19	12.16
15,40,1	55.63	29.28	12.22	2.86	3118.777	78.53	41.76
$\bar{e} = 0.070$							
10,20,1	61.65	33.27	2.46	2.62	1624.094	81.26	27.42
15,40,1	61.34	32.29	3.08	3.29	2828.511	71.88	97.25
$\bar{e} = 0.100$							
10,20,1	61.65	33.27	2.46	2.62	1624.094	81.26	28.84
15,40,1	61.34	32.29	3.08	3.29	2828.511	71.88	67.54

Table 7.4: Sensitivity analysis: linear emission function; $R = 370$ km; mode-determined truck type selection; electric trucks more cost efficient than diesel trucks

Problem	Cost(%,%,% , %, thousands dollars)						Time(s)
n, m, b	DCER	DCCR	TRCR	TRER	TOT	DTR	tTOT
$\bar{e} = 0.050$							
10,20,1	56.39	29.80	12.68	1.13	1958.009	67.19	12.50
15,40,1	54.98	28.94	14.73	1.34	3155.681	75.83	54.96
$\bar{e} = 0.055$							
15,40,1	55.13	29.75	13.82	1.30	1816.170	71.83	16.62
15,40,1	54.99	28.94	14.72	1.34	3155.311	75.16	84.31
$\bar{e} = 0.070$							
10,20,1	55.16	29.76	13.78	1.30	1815.294	72.01	17.73
15,40,1	54.99	28.94	14.72	1.34	3155.311	75.16	35.47

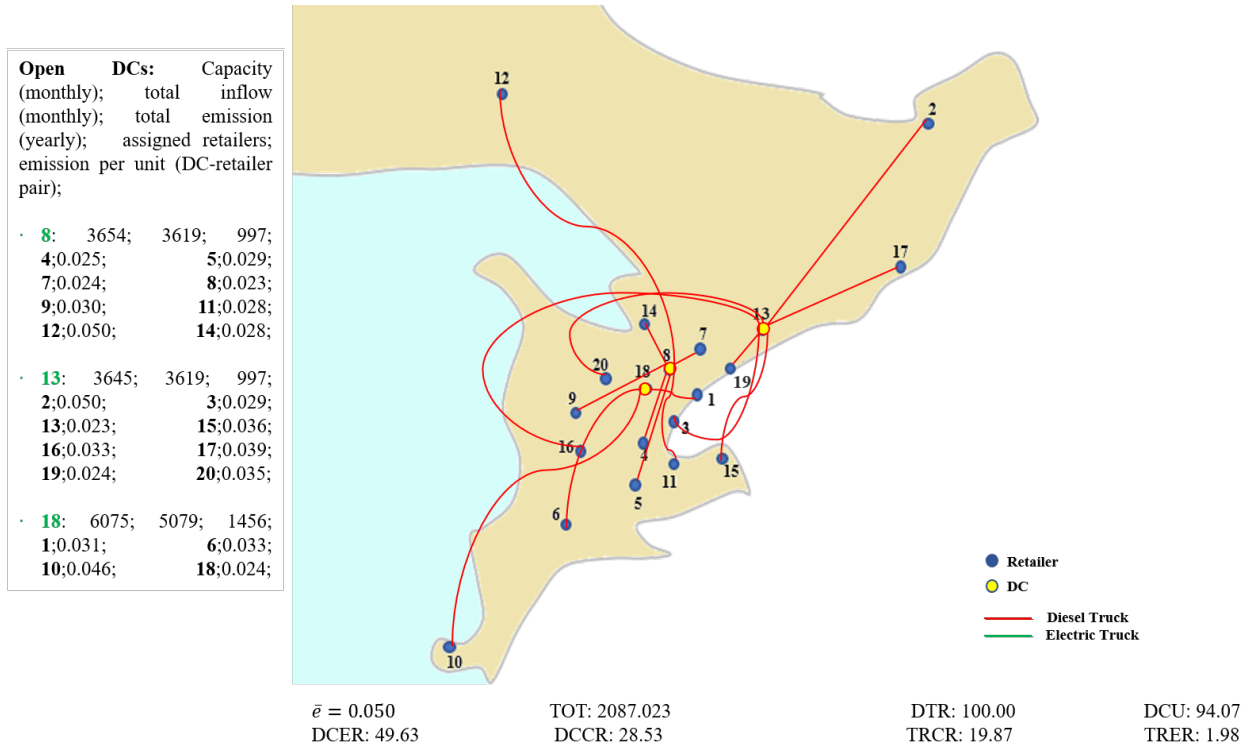


Figure 7.7: SCND: linear emission function; $\bar{e} = 0.050$; $R = 370$ km; model-determined truck type selection; diesel trucks more cost efficient than electric trucks

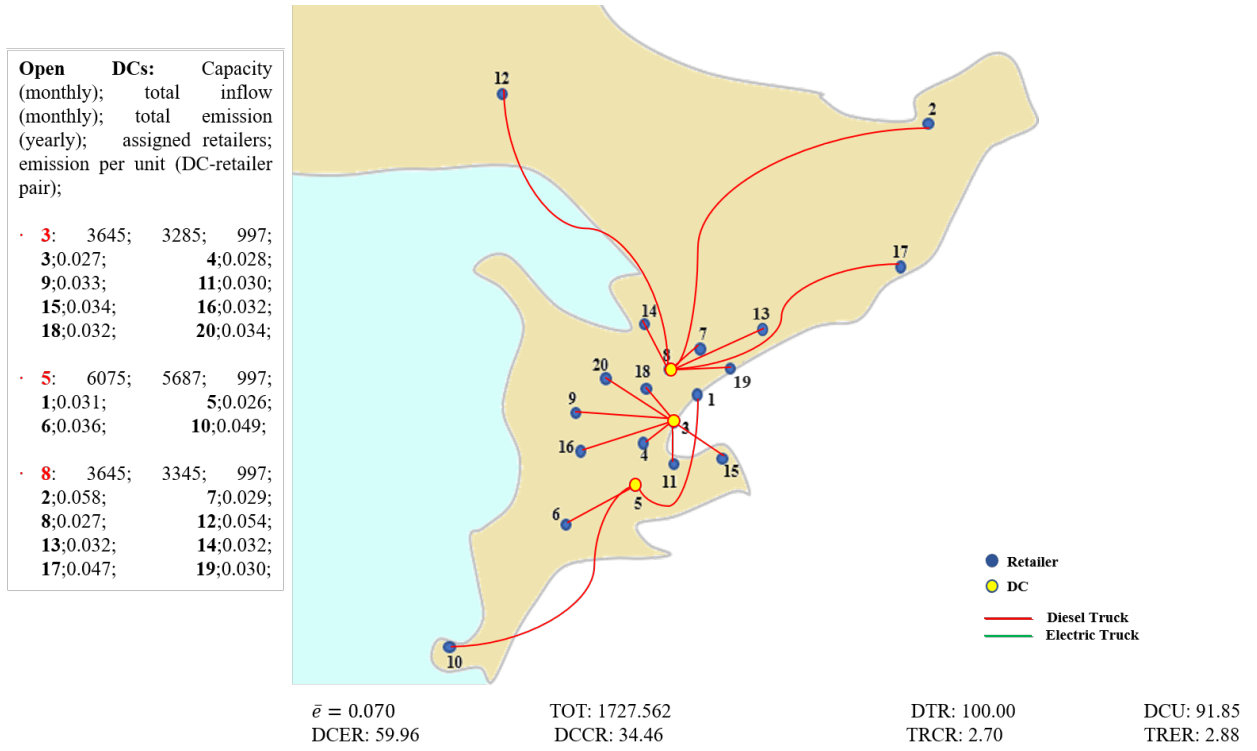


Figure 7.8: SCND: linear emission function; $\bar{e} = 0.070$; $R = 370$ km; model-determined truck type selection; diesel trucks more cost efficient than electric trucks

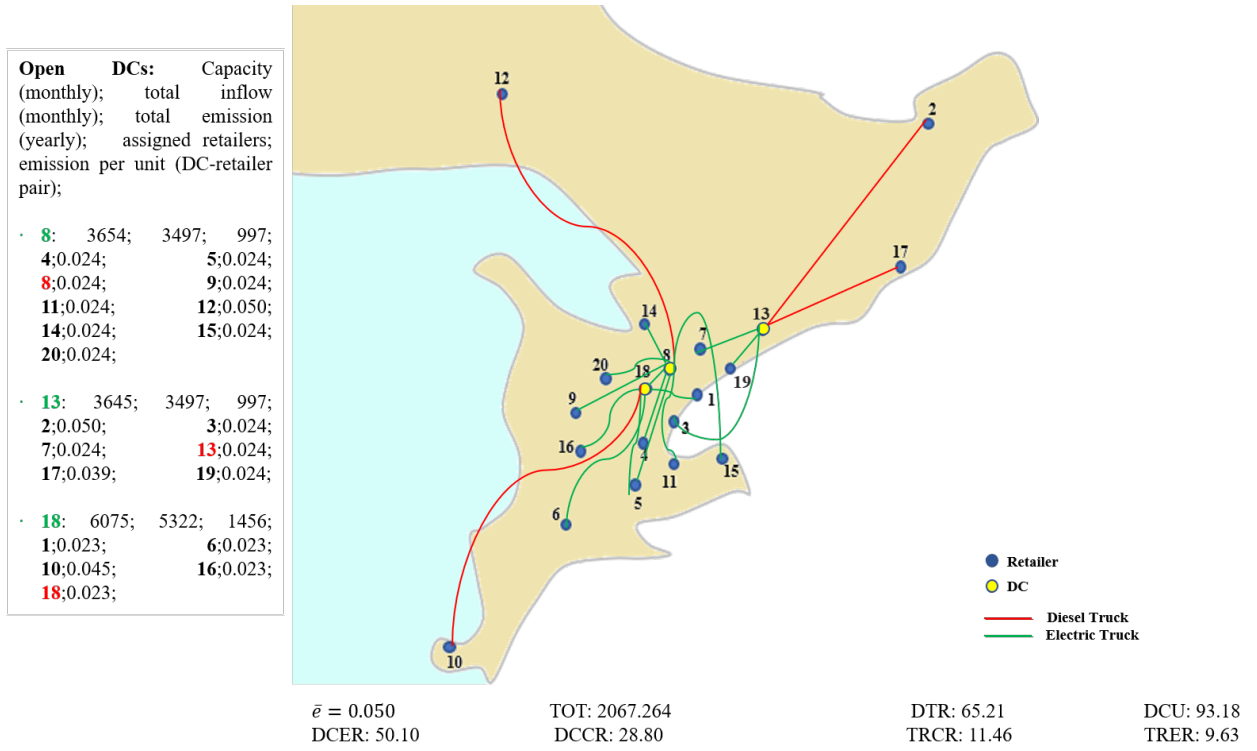


Figure 7.9: SCND: linear emission function; $\bar{e} = 0.050$; $R = 370$ km; model-determined truck type selection; electric trucks more cost efficient than diesel trucks

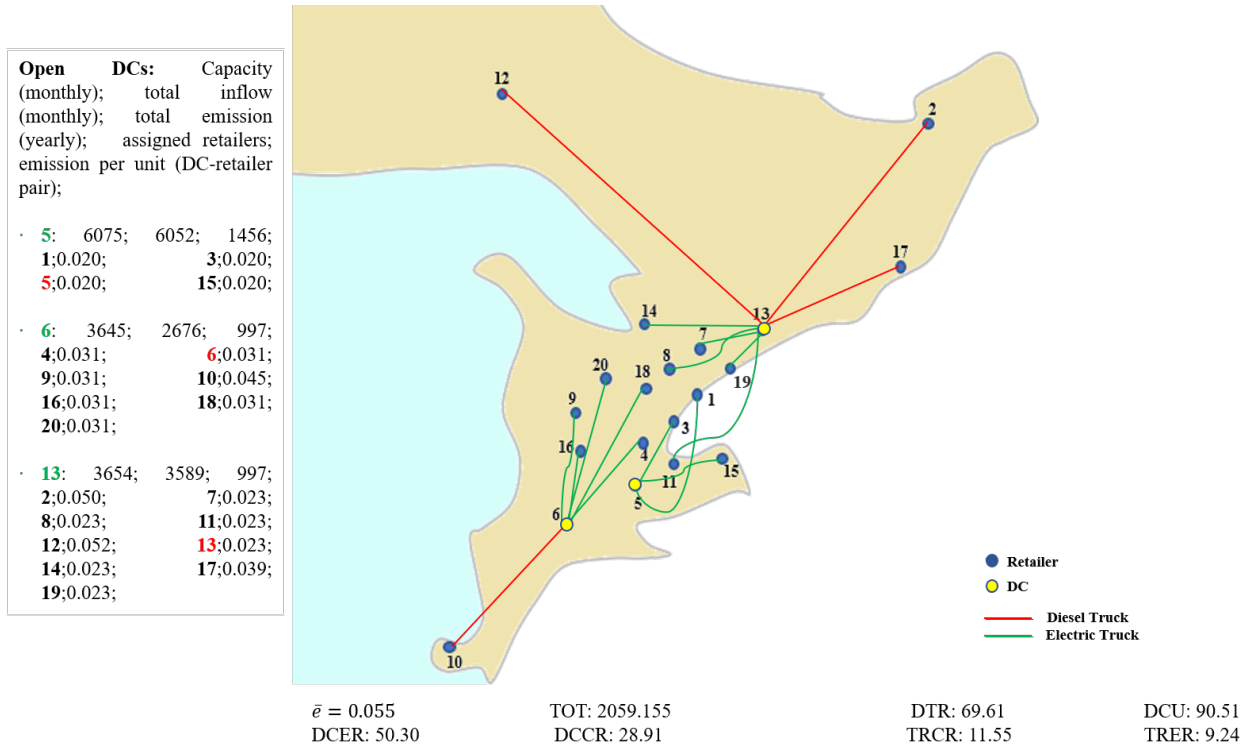


Figure 7.10: SCND: linear emission function; $\bar{e} = 0.055$; $R = 370$ km; model-determined truck type selection; electric trucks more cost efficient than diesel trucks

and 7.4 with Tables 5.8 and 5.7. One thing that can be seen in both cases, diesel trucks being cheaper or electric trucks being cheaper, is an increase in the use of diesel trucks in trips that used to be done by electric trucks. As depicted in Figures 7.9 and 7.10, since electric trucks are cheaper, the only trips for which diesel trucks are used, except for the ones that cannot be covered by electric trucks, are the DC-retailer trips of the same location. However, considering the case in which diesel trucks are more cost-efficient, almost all trips are covered by diesel trucks (Figures 7.7 and 7.8).

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