

# Estimating Carbon Emissions from Less-than-Truckload (LTL) Shipments

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Submitted to the Engineering Systems Division in Partial Fulfillment of the  
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Master of Engineering in Logistics  
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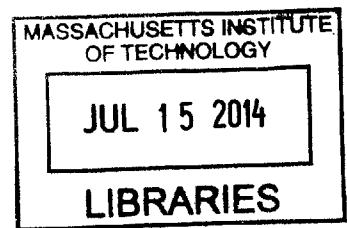
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## **ABSTRACT**

Less-than-truckload (LTL) is a \$32-billion sector of the trucking industry that focuses on moving smaller shipments, typically with weights between 100 and 10,000 pounds, that do not require a full trailer to be moved. Currently, there are no widely accepted methods to estimate carbon emissions from LTL shipments which take into account all the complexities of a typical LTL network. This thesis seeks to address this issue by suggesting a methodology that allows different parties to estimate the emissions of individual LTL shipments with minimal input information. Throughout this research, we worked with C. H. Robinson, a Third-Party Logistics Provider (3PL), and Estes Express Lines, a privately-owned freight transportation company, and analyzed more than 1.5 million shipments. We developed two calculation tools: a detailed model, specifically designed for and based on Estes Express' network and operations, and a lower-precision generic model, adapted from the detailed one so that it could be applied to carriers whose network characteristics are unknown. We also assessed current estimation methods and found that they tend to underestimate the emissions from LTL shipments primarily because (1) they rely on direct over-the-road distances as opposed to actual shipped distances, which must include the intermediate stops, and (2) they fail to factor in the pick-up and delivery (P&D) sections, focusing solely on line haul operations. Therefore, while existing initiatives such as the GHG Protocol and the EPA SmartWay program provide guidance on how to estimate carbon emissions from transportation in general, the LTL industry still needs a specific approach that takes into account all of its unique characteristics. This thesis provides a contribution in that direction by suggesting a methodology to better estimate the carbon emissions of individual LTL shipments.

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*- Mark Woolard*

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*- Guilherme Aguiar*

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## 1. INTRODUCTION

Trucking is the dominant mode of transportation for moving freight in the United States. In 2012, the trucking sector was responsible for roughly 84% of the revenue of commercial transportation, collecting more than \$650 billion in incomes, which represents 5% of the United States' Gross Domestic Product (USShip, 2013). Less-than-truckload (LTL) is a \$32-billion sector of the trucking industry that focuses on moving smaller shipments, typically with weights between 100 and 10,000 pounds, that do not require a full 48- or 53-foot trailer. LTL companies are characterized by serving multiple customers simultaneously with a single truck due to the need to consolidate shipments in order to build economical loads (Hejazi, 2009; Jindel, 2010).

The trucking industry also burns roughly 52 billion gallons of diesel fuel per year (USShip, 2013). A growing number of initiatives, such as the Greenhouse Gas Protocol (GHG Protocol) and the US Environmental Protection Agency's (EPA) SmartWay Program, have been concerned with the environmental impacts of the trucking industry, providing guidance for companies on how they may track and manage their carbon footprint. This topic has become increasingly important over the last few decades. On February 18, 2014, the President of the United States, Barack Obama, announced the development of new fuel standards for the country's fleet of heavy-duty trucks. The new rules are to be drafted by the EPA and the Transportation Department by March 2015 and seek to limit greenhouse gas pollution from trucks and require them to burn fuel more efficiently, improving overall gas mileage. This measure is part of Obama's administration target of reducing carbon pollution in the US by 17% from year 2005 levels by 2020 (Baker & Davenport, 2014).

While the GHG Protocol and the EPA SmartWay Program provide guidance for a variety of industries in terms of how to track their carbon emissions, some activities still lack an

approach that takes into account all of their intricacies. The less-than-truckload transportation industry is such a case; currently, there are no widely accepted methods to estimate carbon emissions from LTL shipments that take into account all the complexities of a typical LTL network. This thesis seeks to address this problem by suggesting a methodology that allows different parties to estimate the emissions of individual LTL shipments with minimal input information.

Throughout this research, we worked with C. H. Robinson, a Third-Party Logistics Provider (3PL) and a Fortune 500 company, and with Estes Express Lines, a privately-owned freight transportation company that operates primarily in the United States, Canada and Mexico. In order to achieve our goal of creating a methodology to estimate carbon emissions from individual LTL shipments, we developed two different, but related, calculation tools: a detailed model, specifically designed for and based on Estes Express' network and operations, and a lower-precision generic model, adapted from the detailed one so that it could be applied more generally to carriers whose network characteristics are unknown to the user of the tool.

In terms of structure, this thesis is organized as follows: Chapter 2 provides a review of the relevant literature on the topics of less-than-truckload transportation and emissions standards. Chapter 3 describes the data that was analyzed during this research and provides some initial insights. Chapter 4 focuses on the methodology of the research itself, presenting a detailed description of the development of our models for estimating carbon emissions from individual LTL shipments. Chapter 5 presents the results of the research and a discussion of the main findings. Emissions obtained from different methods of calculation, including the ones developed in this research, are presented and compared. This section also acknowledges some of

the limitations of the approach adopted in this thesis. Finally, Chapter 6 presents the conclusions of this research and suggests themes for future development.

## 1.1. Partner Companies

The partner companies for this thesis were C. H. Robinson, a Third-Party Logistics Provider (3PL), and Estes Express Lines, a privately-owned freight transportation company. These two companies provided the data that was the basis for this research.

### 1.1.1. C. H. Robinson

C. H. Robinson was founded in 1905 in Grand Forks, North Dakota. Currently headquartered in Eden Prairie, Minnesota, C.H. Robinson is a Fortune 500 company and one of the world's largest 3PLs, with \$12.8 billion in revenues in 2013. The company services more than 45,000 customers and provides access to more than 63,000 transportation providers worldwide (C. H. Robinson, 2013, 2014). Included in the \$12.8 billion are revenues from freight forwarding, intermodal solutions, and freight brokerage. In terms of freight brokerage, C. H. Robinson is the world's largest brokerage provider with \$1.3 billion in revenues in 2013. For comparison, the second largest brokerage company, Landstar System, amassed \$276 million in brokerage revenues in 2013 (Statista, 2014).

Data for this thesis was also provided by TMC, a division of C. H. Robinson. TMC provides transportation management system (TMS) solutions to its clients. It does not obtain revenue by handling freight, but instead by deploying technology, managing daily TMS operations and seeking continuous process improvement for its clients (TMC, 2014).

### 1.1.2. Estes Express Lines

Headquartered out of Richmond, Virginia, Estes Express Lines was founded in 1931 by W. W. Estes and is still owned by the Estes family. Robey W. Estes, Jr. has served as the President since 1990. The *Journal of Commerce* reports that in 2012 Estes Express Lines had \$1.7 billion in revenues, which ranks the company as the 7<sup>th</sup> largest LTL carrier and the largest privately-held LTL carrier in the US and Canada. Estes was one of the first trucking companies to join the EPA SmartWay program (Cassidy, 2013; Estes Express Lines, 2014).

Estes Express' network at the time of this research consists of more than 200 terminals in the United States, Canada, and Mexico. The company employs roughly 15,000 people, including almost 7,000 drivers. Estes' fleet comprises over 6,500 tractors and over 24,000 trailers in lengths from 28 to 57 feet. The vehicles were manufactured between 1992 and 2014, with an average age of eight years and a standard deviation of 4.5 years (Estes Express Lines, 2014).

## 1.2. Statement of Objectives

The main objective of this thesis is to develop a methodology for estimating carbon emissions from individual LTL shipments while considering the complexities of a typical LTL network. This general objective can be broken down into the following specific objectives:

1. Develop a detailed estimation method for the partner carrier's (Estes Express Lines) existing network;
2. Develop a lower-precision estimation method for the case when the carrier's network characteristics are unknown;
3. Identify the flaws of applying existing carbon emissions estimation methods to LTL shipments.

## **2. LITERATURE REVIEW**

There is a significant amount of literature regarding the procedures involved in measuring the greenhouse gas emissions from different types of organizations and industries. Different efforts and initiatives, such as the Greenhouse Gas Protocol (GHG Protocol), have focused on providing guidance to companies that wish to develop an inventory of their greenhouse gas emissions, achieving varying levels of success and industry acceptance. While there are standard procedures that apply to a variety of industries, some specific activities still lack an approach that takes into account all of their unique characteristics. The LTL transportation industry is such a case.

### **2.1. Less-than-Truckload (LTL) Transportation**

There are several ways to define LTL transportation, illustrating the varying scope and complexity of the term. As a basic definition, less-than-truckload shipping involves the pick-up, consolidation, line haul, and delivery operations of merchandise that are not large enough to justify a full truckload by themselves. LTL shipment weights may vary between 100 and 10,000 pounds, however, about 70% of all LTL freight are less than 1,000 pounds. The most common alternatives to LTL are full truckload (FTL), in which an entire truck is dedicated to moving a single shipment, and parcel service, which handles smaller packages, usually weighing up to 150 pounds (Hejazi, 2009; Jindel, 2010).

While full truckload and less-than-truckload are both trucking operations, they are significantly different in terms of complexity. According to Powell (1986), the main problem that LTL carriers face is “how to consolidate the freight over the network in such a way as to minimize total transportation and handling costs while satisfying level of service constraints in each market” (p. 246). Since each shipment is relatively small compared to a truck’s capacity, it

is economical to combine different shipments inside the same truck in order to achieve improved trucking capacity usage. Therefore, from an operational point of view, LTL has a high degree of complexity, since there are constant changes in shipping patterns and freight characteristics. Also, while in full truckload operations a truck is assigned to a single customer, in LTL the same truck is simultaneously serving several customers; on average, a single truck may carry 20 to 30 shipments with different origins and destinations (Hejazi, 2009, p. 4).

In typical LTL operations, freight is moved from many origins to many destinations using multiple connected moves or legs. The first and last sections involve moving shipments across short distances between their origin or destination points and end-of-line terminals. At the origin terminals, several shipments are aggregated before they are moved to the next terminal. This second terminal is often called a break-bulk terminal or a hub. There, freight is unloaded, sorted and reloaded from the previous truck to a new one. The new truck then moves the freight to the hub closest to its destination, where the shipment is again unloaded and moved to a truck that will transport it to an end-of-line terminal. Each hub is usually associated with several end-of-line terminals (“satellites”). From there, the shipment is moved across the final leg to its destination point (Hejazi, 2009; Kim, 1994).

Figure 1 below presents a conceptual model of a typical LTL complete movement. There may be some variations within a movement based on the structure of the network of a specific region or carrier, but the overall principle is still valid.

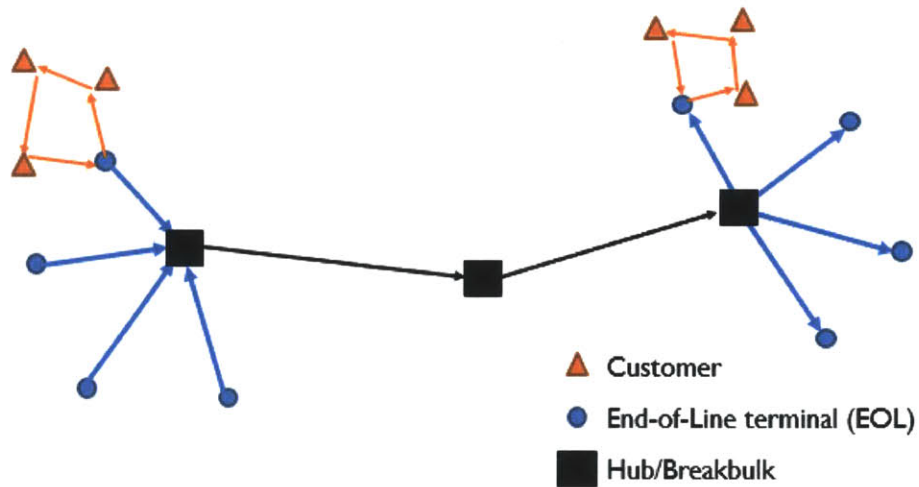


Figure 1 - Conceptual model of LTL operations showing the movement of goods between customers (Adapted from Klabjan, n.d.)

Another important aspect of LTL operations is the number of times freight is touched, that is, either loaded, cross-docked or unloaded onto different trucks. Accounting for the number of touches on freight is important, since this may be an indicator of how efficiently shipments move through the network. However, there is no specific research on how this may affect carbon emissions from LTL operations or how these dynamics can be taken into consideration for estimation efforts.

## 2.2. The Role of Third-Party Logistics Providers

Third-Party Logistics Providers (3PLs) are important players in the logistics industry. A recent study by Capgemini (2013) indicated that global revenues for the 3PL industry have grown from \$541 billion in 2010 to \$616 billion in 2011, a 13.7% increase. The study also included a survey of more than 2,300 industry executives showing that “far more shippers (65%) are increasing their use of 3PL services than returning to insourcing (22%) some 3PL services” (p. 4). We now



provide a brief explanation about these companies and how they relate to the process of estimating carbon emissions from LTL shipments.

According to the Council of Supply Chain Management Professionals' Glossary (Vitasek, 2013), a Third-Party Logistics Provider is a company that provides multiple logistics services to its customers, such as transportation, warehousing, cross-docking, inventory management, packaging and freight forwarding. These companies aim to facilitate the movement of freight across the supply chain. The term "3PL" was first used in the 1970s to identify intermodal marketing companies that acted as intermediaries in transportation contracts, accepting shipments from a shipper and tendering them to carriers.

According to Kim (2013, p. 10), some 3PLs are also referred to as non-asset-based carriers, since they provide transportation services without owning any fleet or directly employing any drivers. They often rely on a vast network of relationships with asset-based trucking firms and act as a broker between a shipper and a carrier.

Regarding emissions, Blanco and Craig (2009) comment that 3PL companies can play an important role in reducing the carbon output from transportation by matching a shipper's demand to a carrier's capacity in a way that minimizes empty miles and optimizes capacity utilization. However, quantifying this role can be difficult. Current estimation methods neglect the impact that a 3PL can have on total carbon emissions, and there are significant challenges in developing approaches that accurately account for the impact that shippers, carriers and 3PLs can have on reducing the carbon output of shipments.

In this thesis, we develop an approach that addresses the fact that 3PLs often have to work with limited data when trying to estimate carbon emissions from its partner LTL carriers. Our aim was to provide a tool that allows a 3PL to estimate carbon emissions from individual

LTL shipments with minimal information about a carrier's network. This estimation may then be used by the 3PL in the process of carrier selection or as an additional reporting item to its customers.

## 2.3. Carbon Emissions Standards

There are two common methods, currently accepted in a wide variety of industries, for estimating carbon emissions: the Greenhouse Gas Protocol Corporate Accounting and Reporting Standard, or simply GHG Protocol (WBCSD & WRI, 2004), and the US Environmental Protection Agency (EPA) SmartWay program (EPA, 2014). The GHG Protocol has a broad scope, while the SmartWay program focuses on the transportation industry, offering different tools for shippers, carriers and logistics companies.

### 2.3.1. Greenhouse Gas (GHG) Protocol

The Greenhouse Gas Protocol Initiative, developed by the World Business Council for Sustainable Development (WBCSD) and by the World Resources Institute (WRI), is a multi-stakeholder partnership that launched in 1998. The First Edition of the GHG Protocol Corporate Standard was released in September 2001. Since then, there have been many revisions and updates. The latest amendment at the time of this research was released in May 2013. The GHG Protocol is currently the most widely accepted tool when it comes to identifying, quantifying and managing greenhouse gas emissions. This protocol is written primarily from the perspective of an organization developing an inventory of emissions, but it can be applied to different types of businesses, such as government agencies and universities. Within the Initiative, the Corporate Accounting and Reporting Standard focuses on quantifying and reporting a company's

greenhouse gas emissions. For simplification purposes, we refer to it throughout this thesis simply as GHG Protocol (WBCSD & WRI, 2004).

Within the accounting standard, the GHG Protocol has defined three different scopes of emissions – Scope 1, Scope 2 and Scope 3 – in order to help determine direct and indirect emission sources, improve transparency, and avoid double counting of emissions by different companies. Scope 1 emissions are those considered direct GHG emissions, occurring from sources that are owned or controlled by the company. Scope 2 includes indirect GHG emissions from the generation of purchased electricity consumed by the company. Finally, Scope 3 is an optional category that may include all other GHG emissions that occur as a consequence of the activities of the company, but originating from sources not owned or controlled by the company itself (WBCSD & WRI, 2004).

Figure 2 further clarifies the definitions of scope within the GHG Protocol and provides some typical examples of sources of emissions for each scope.

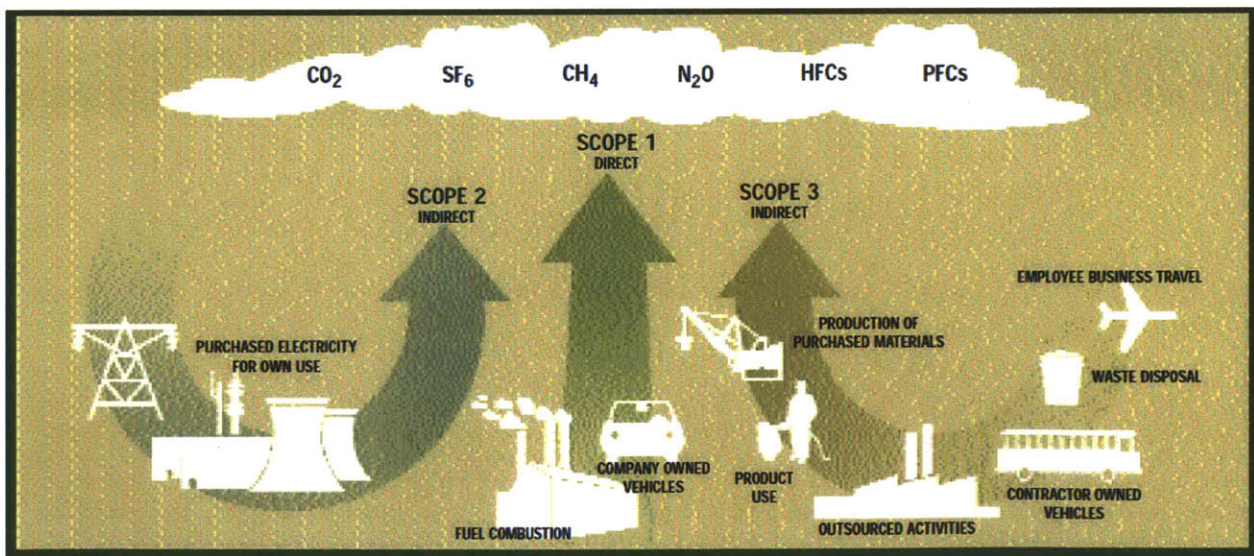


Figure 2 – GHG Protocol's definition of scope of emissions based on its source (WBCSD & WRI, 2004)

The GHG Protocol also offers guidance to different industries through its calculation tools, which can be applicable either to a specific sector or to multiple ones (cross-sector tools). Some examples of sector-specific tools are those dedicated to the iron and steel industry or to the cement industry. One of its cross-sector tools is the mobile combustion guide, which focuses on the transportation industry, and is especially relevant for this thesis (WBCSD & WRI, 2004, 2005).

The GHG Protocol Mobile Guide v1.3 (WBCSD & WRI, 2005) provides guidance on how to calculate direct and indirect CO<sub>2</sub> emissions from fuel combustion in mobile sources and presents emission factors for different modes of transportation (road, rail, water and air). The guide is intended to “facilitate corporate-level measurement and reporting of greenhouse gases emissions from transportation and other mobile sources” (p. 1); it is a cross-sectorial guideline that may be applied to different industries involving the combustion of fossil fuels in mobile sources. The latest version of the guide’s calculation spreadsheet at the time of this research was released in 2013.

Since our goal was to develop a tool for estimating carbon emissions from LTL shipments, we were especially interested in the calculation procedures provided by these guidelines. Therefore, we will specifically present and explain them in section 2.4 of this thesis.

### 2.3.2. EPA SmartWay Program

The SmartWay Transport Partnership is a public-private initiative between the United States Environmental Protection Agency (EPA), trucking and logistics companies, rail carriers, and other stakeholders that seeks to improve fuel efficiency, reduce the environmental impacts of freight transportation and encourage overall supply chain sustainability. It was developed in

2003 by a multi-stakeholder group and launched in 2004. To date, more than 3,000 companies and associations are part of the program (EPA, 2014).

Participating companies use reporting tools that benchmark their performance against the industry and inform stakeholders about the company's operation figures. SmartWay partners demonstrate to customers and investors that they are keeping track of their emissions and working to improve overall efficiency and reduce their carbon footprint. Each of the tools provided is aimed at a different type of company, such as shippers, truck carriers, logistics companies, multimodal carriers and rail carriers. Along with the tools and worksheets, SmartWay also offers guides explaining the data entry and submission processes (EPA, 2014).

The Truck Carrier Partner 2.0.13 Tool (EPA, 2013) is aimed at trucking companies and provides basic information about the program, an overview of data collection requirements, and instructions for data entry into the worksheets. It is a detailed reporting tool that requires the company to keep track of operational and fleet data, such as:

- Total inventory of vehicles in fleet(s), sorted by vehicle class and engine model year, body type, and operational category for the reporting calendar year
- Total miles, revenue miles and empty miles
- Total diesel, biodiesel and/or other fuel use by class
- Reefer fuel use by class (if applicable)
- Average payload, average capacity volume, and percent capacity utilization by class
- Average idle hours per truck

Based on the data that is inserted by the company, the tool calculates the emissions footprint. The guide itself does not detail the calculation procedures, but rather focuses on enlightening companies on how to gather and insert data appropriately into the reporting tool.

## 2.4. Measuring Carbon Emissions from Transportation

The GHG Protocol Mobile Guide (WBCSD & WRI, 2005) is a comprehensive reference that presents the most widely applicable and accepted methods for calculating emissions from transportation. Therefore, we focused our analysis on the calculation procedures presented in this guide. The EPA also offers a more detailed approach, which is based on the GHG Protocol's guide, named "Climate Leaders Greenhouse Gas Inventory Protocol" (EPA, 2008), which we also examine. Both are similar in their content and approach and highly applicable to any company willing to better understand their carbon footprint.

The GHG Protocol Mobile Guide allows the calculation of both direct and indirect emissions. While direct emissions are those associated with owned or controlled sources, such as a company's fleet of vehicles, indirect emissions refer to all company-related activity, such as employee commuting and up- and downstream transportation emissions along the supply chain, as explained in section 2.3.1 of this thesis (WBCSD & WRI, 2005).

The guide also addresses the choice of greenhouse gases and mentions that only CO<sub>2</sub> emissions estimates are included in the tool, since N<sub>2</sub>O and CH<sub>4</sub> emissions are relatively small when compared to CO<sub>2</sub>. Additionally, CO<sub>2</sub> emissions are usually straightforward to estimate, since they depend primarily on the type and the quantity of fuel burned (WBCSD & WRI, 2005).

Additionally, according to the guide, there are two main ways to calculate carbon emissions from mobile sources: a fuel-based and a distance-based approach. Both are described

next. The guide mentions, that, if the data is available, the fuel based approach is generally preferred, since information on fuel is usually more reliable (WBCSD & WRI, 2005).

### 2.4.1. Fuel-based Approach

In this approach, CO<sub>2</sub> emissions are estimated by multiplying fuel consumption data by the emission factor of each fuel type. These factors are dependent on the fuel's heat content, the fraction of oxidized carbon and the carbon content coefficient. This approach may be used when vehicle activity and fuel economy data are available. The guide also presents standard emissions factors to be used if customizable ones are not available or cannot be calculated by the company, even though it is advisable that companies obtain their own numbers to account for differences in operation, location and other relevant factors.

The first step in the process is to gather fuel consumption data by fuel type. This data can be obtained from any fuel-related record that a company keeps, such as fuel receipts. Next, data on distance traveled by vehicle type and by fuel type must be collected and converted into fuel used, based on fuel economy or fuel efficiency factors. These are dependent on the type of vehicle that is being considered. This process can be represented by Equation 1 (WBCSD & WRI, 2005):

$$\text{Fuel Used} = \text{Distance} \times \text{Fuel Economy Factor} \quad (1)$$

Based on the fuel used, the next step is to calculate the CO<sub>2</sub> emissions by multiplying the amount of fuel by the fuel-specific emission factor. The guide mentions that there are different ways to perform this calculation, but recommends the approach that takes heating value into account, as presented in Equation 2 (WBCSD & WRI, 2005):

$$CO_2 \text{ Emissions} = \text{Fuel Used} \times \text{Heating Value} \times \text{Emission Factor} (2)$$

The Mobile Guide presents default values for emission factors for different types of fuel. For on-road diesel, which is usually applicable to freight transportation, the guide suggests a factor 10.15 kilograms of CO<sub>2</sub> per gallon of fuel burned for the US (WBCSD & WRI, 2005, 2012). The EPA Climate Leaders guidance suggests the same factor (EPA, 2008).

#### 2.4.2. Distance-based Approach

In this method, distance-based emission factors are used to obtain estimates of resulting emissions from the company's activity. While the fuel-based approach is preferred since fuel data tends to be more reliable, this method may be used when fuel data is not available to the company (WBCSD & WRI, 2005).

Similar to the fuel-based approach, the first step in the process is to gather data on distance traveled by vehicle and fuel type. The data may be either in direct distance (e.g., mile), freight distance (e.g., weight-mile) or passenger distance (e.g., passenger-mile), according to the type of the company's activity.

The next step is then to multiply the distance traveled by the appropriate distance-based emission factor considering the vehicle type and the activity. This may be represented by Equation 3 below (WBCSD & WRI, 2005):

$$CO_2 \text{ Emissions} = \text{Distance Traveled} \times \text{Emission Factor} \quad (3)$$

Equation 3 is presented above in its basic form, but it may also include additional coefficients that convert the units of the result. The mobile source guide also presents a series of



default values for distance-based emission factors for different types of vehicles and activity (WBCSD & WRI, 2005).

It is important to highlight that in Equation 3 above, the “distance traveled” variable takes into account the type of activity under analysis. For example, for freight transportation, which is the focus of this thesis, the “distance traveled” is expressed in weight-distance units (such as ton-mile), as opposed to pure distance (miles). For the freight transportation case, the GHG Protocol suggests an emission factor of 0.297 kilograms of CO<sub>2</sub> per short ton-mile (a short-ton is equal to 2,000 pounds), both for Light Goods Vehicles (LGVs) and Heavy Goods Vehicles (HGVs) (WBCSD & WRI, 2012).

## 2.5. Literature Review Summary

In general, LTL networks have a high degree of complexity, consisting of a variety of interconnected moves with intermediate stops and different levels of consolidation of freight. A single truck that operates in LTL is simultaneously serving several customers and moving shipments with different origins and destinations. Allocating emissions among these various loads is a challenging task, especially considering that sufficiently detailed data is not always available.

Currently, there are no widely accepted or established ways to estimate carbon emissions from LTL shipments. While initiatives such as the GHG Protocol and the EPA SmartWay Program are applied in a variety of industries and provide general guidance on the topic of emissions, they do not specifically address how to account for the complexities of a typical LTL network. These standards also focus on reporting emissions on a corporate level, without going down to individual shipments or specifying how total emissions can be allocated to single shipments. This thesis aimed at developing an emissions estimation methodology to the LTL

industry based on the guidelines provided by these initiatives, but in a way that allows shippers, carriers and 3PLs to estimate carbon emissions from single LTL shipments with minimal input information.

Additionally, as mentioned by McKinnon and Piecyk (2009), there is significant difficulty in “compiling an accurate and consistent set of emissions data for trucking. Emission estimates calculated in different ways and using different base data can yield widely varying aggregate measures and trends” (p. 1). The authors also highlight that there have been substantial revisions to official emissions estimates for road freight recently, which raises doubts about the credibility of the previous values.

Current research also fails to clarify how to treat the different levels of information available to shippers, carriers and 3PLs when estimating carbon emissions. A shipper may only know the origin, destination and basic characteristics of a piece of freight, such as weight, and not know what the actual network of the carrier is, but might still need or desire to estimate the carbon emissions from that shipment.

Finally, we highlight that the distance-based approach for freight transportation, described in section 2.4.2, was developed primarily for full truckload operations, which traditionally involve moving freight directly from origin to destination. Since this approach does not take into account the complexities involved in LTL operations, it is not an ideal method to estimate carbon emissions from LTL shipments.

### **3. DATA PROFILING**

In order to develop an estimation method for carbon emissions of individual LTL shipments, we analyzed data provided by the partner companies, C. H. Robinson and Estes Express Lines. Data provided by carrier Estes Express was used in the actual development of the calculation model, while data provided by C. H. Robinson's TMC division was used to test the results of our model and to compare the outputs of different estimation methods.

We analyzed information from more than three million individual shipments that were moved by Estes Express Lines between August and October of 2013. The data files were classified into two main categories: network and shipment. Network files contained information regarding the existing terminal infrastructure, service lanes and equipment usage (such as fuel consumption and miles driven). These files provided a snapshot of Estes Express' network and operations. Shipment files contained data on actual freight moved by Estes on three different four-week periods of time.

#### **3.1. Carrier Network Data**

Our estimation models were developed based on network and shipment data provided by Estes Express Lines relative to their operations over a period of three months in 2013. Before describing the procedures we followed to actually build our models, which will be presented in the Methodology section of this thesis, we provide general information about Estes' profile as a carrier, analyzing their terminal infrastructure, shipping lanes, and shipment weight distribution as a way to provide insight into the scope of their operations.

### 3.1.1. Terminal Infrastructure and Shipping Lanes

Estes Express Lines operates a network of more than 200 terminals across the United States, with 19 hubs. This number includes both terminals directly owned and operated by Estes as well as those owned by agents, but through which Estes also moves freight. Figure 3 below shows the distribution of the terminals across the US. Blue dots represent local terminals and orange dots represent hubs. It can be noticed that the network is well distributed across the entire country, with higher concentration of terminals on the East Coast. This gives Estes Express a national scope as opposed to a regional one, which is important for the purpose of this thesis of developing a model that may be applicable to other carriers as well.

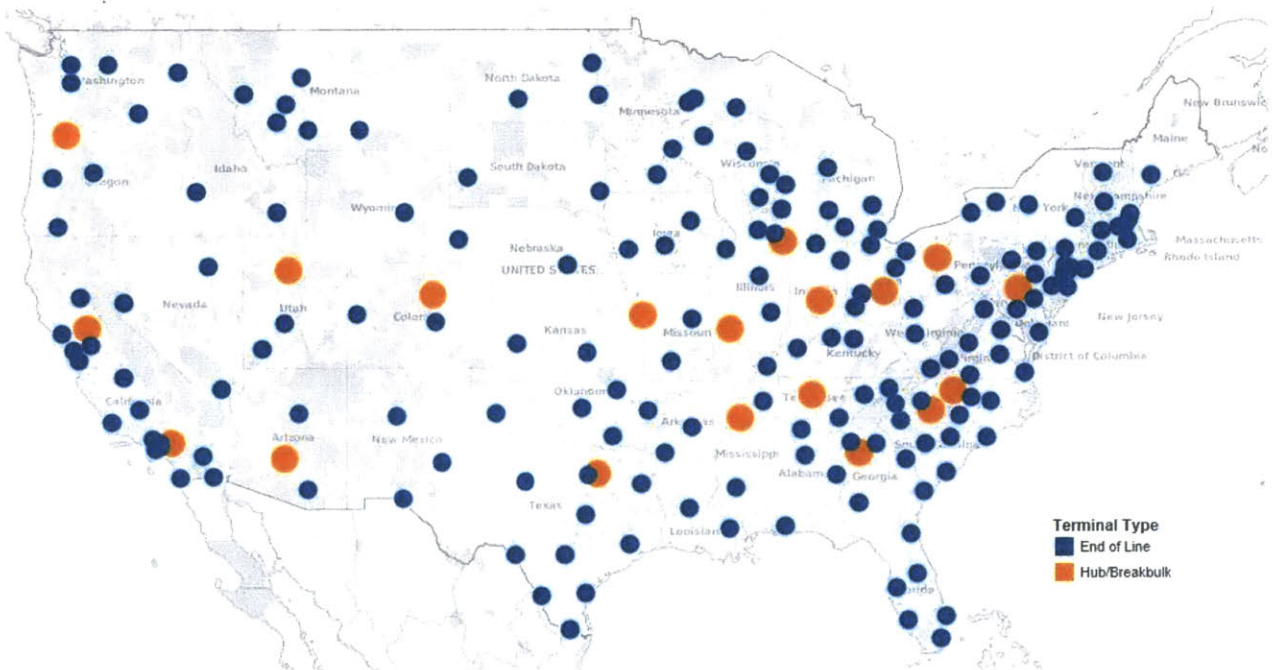


Figure 3 - Estes Express Lines' network of terminals

As explained in section 2.1 of the Literature Review of this thesis, as a shipment moves through the network, it goes through different terminals and different levels of consolidation. The number of terminals involved in a certain shipment's movement depends on the origin and

destination of that specific shipment and on the carrier's network. The path that a shipment goes through to get from its origin to its destination is often referred to as a "shipping lane."

Typically, in LTL networks, there are standard shipping lanes through which every shipment moving between a specified origin and destination pair goes through. However, due to the highly dynamic nature of LTL movements, shipping lanes may vary as additional terminals or stops are included and some terminals are removed from the standard shipping lane to accommodate customer needs or because of operational adjustments. Estes operates in the same way: there are standard shipping lanes to any origin and destination pair, but actual shipped distances and intermediate stops may vary based on immediate network conditions.

### 3.2. Carrier Shipment Data

To determine Estes Express' shipment weight profile, we initially worked with data relative to a single four-week period (period A). We then compared this four-week period to the two others (periods B and C) we had access to and observed if and how the shipment profile changed. This approach allowed us to identify the typical distribution of shipment weights that moved through Estes Express' network.

The total number of shipments that Estes moved in period A was 1.2 million. However, some of these shipments fell outside the scope of this thesis due to certain characteristics. The two main criteria we used to clean the shipment data before determining the weight profile were:

- Shipment weight: Since Estes Express also operates in the full truckload (FTL) market, we needed to distinguish FTL from LTL shipments. In order to do so, we only kept shipments with weights below 10,000 pounds, which is a traditional weight limit for LTL shipments, as indicated in section 2.1 of the Literature Review. We did

not eliminate shipments below 100 pounds since Estes does not specifically operate in the parcel industry; hence, any shipment below 100 pounds was included in the LTL business. We also eliminated from this analysis all shipments that had missing weight information.

- Shipment location: The data contained information about shipments that moved through Estes Express' terminals in Canada. Since we were interested only in understanding the behavior of the network in the United States, we eliminated shipments that involved one or more Canadian terminals. These shipments have a higher degree of complexity due to border crossing and clearance procedures, which fell outside the scope of this thesis.

After performing these cleaning procedures, we were left with roughly 758,000 shipments in the data relative to period A, or 68% of the original shipment file. This included only LTL shipments that moved entirely across the United States.

### 3.2.1. Weight Profile

Once we had the data ready for analysis, as described above, we created a histogram of weights in order to identify Estes' shipment profile. We divided the data into categories or "bins" with increments of 500 pounds for a total of 20 bins covering the entire weight interval up to 10,000 pounds. Table 1 and Figure 4 below present the results for this sample of 758,000 shipments. The relative frequency column on Table 1 indicates the percentage of shipments that fell within a certain weight interval.

Table 1 - Data for histogram of shipment weight (period A)

Bin	Bin Min	Bin Max	Bin Midpoint	Number of Shipments	Relative Frequency
Bin #1	0.00	500.00	250.00	429,290	56.6%
Bin #2	500.00	1000.00	750.00	136,325	18.0%
Bin #3	1000.00	1500.00	1250.00	59,411	7.8%
...	...	...	...	...	...
Bin #20	9500.00	10000.00	9750.00	1,278	0.2%

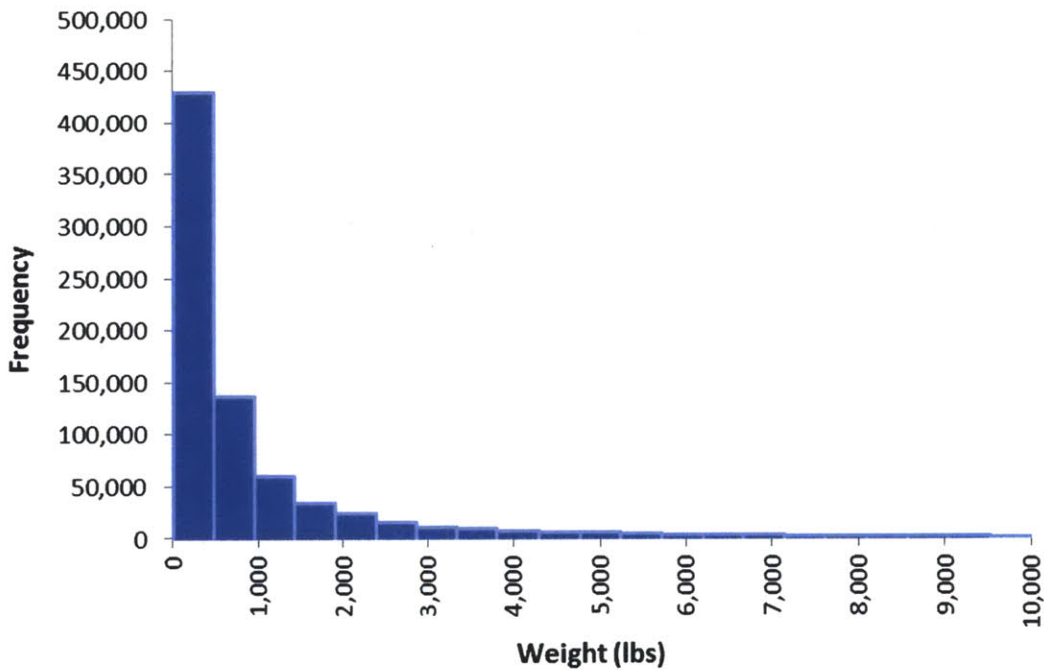


Figure 4 - Histogram of shipment weight in pounds (period A)

It is evident from the data that lighter shipments are significantly more frequent than heavier ones. For this sample, 74.6% of the 758,000 shipments displayed weights below 1,000 pounds, as can be seen from Table 1. This value is close to the 70% reference number presented in section 2.1 of the Literature Review as a typical value for LTL shipments.

Besides this sample, which refers to period A, we analyzed two other four-week periods of data (namely, periods B and C). The percentage of shipments below 1,000 pounds across all

three periods varied between 72% and 75%, with no significant changes in the overall profile between them, which shows that there is consistency in the pattern of shipments. The three periods of data we analyzed were consecutive, meaning that we did not capture seasonal changes in shipment profile over the year.

Additionally, using data provided by TMC, we were able to assess how Estes' weight profile compares to that of other carriers that C. H. Robinson partners with. The names of these carriers have been omitted to preserve their privacy.

The sample data provided by TMC contained a total of 10,500 shipments moved by 96 different carriers between December of 2013 and March of 2014. However, we focused our analysis and comparisons on the carriers that moved most shipments in the sample data, plus Estes. The top eight carriers were responsible for roughly 80% of the total number of shipments in the sample. By adding the shipments assigned to Estes to our analysis set, we obtained a total number of 8,500 shipments for the group of nine carriers.

Figure 5, below, presents a Box-Whisker Plot comparing the shipment weights of these nine carriers. Estes is represented by the code EXLA. The codes for the other carriers have been altered to preserve their privacy.



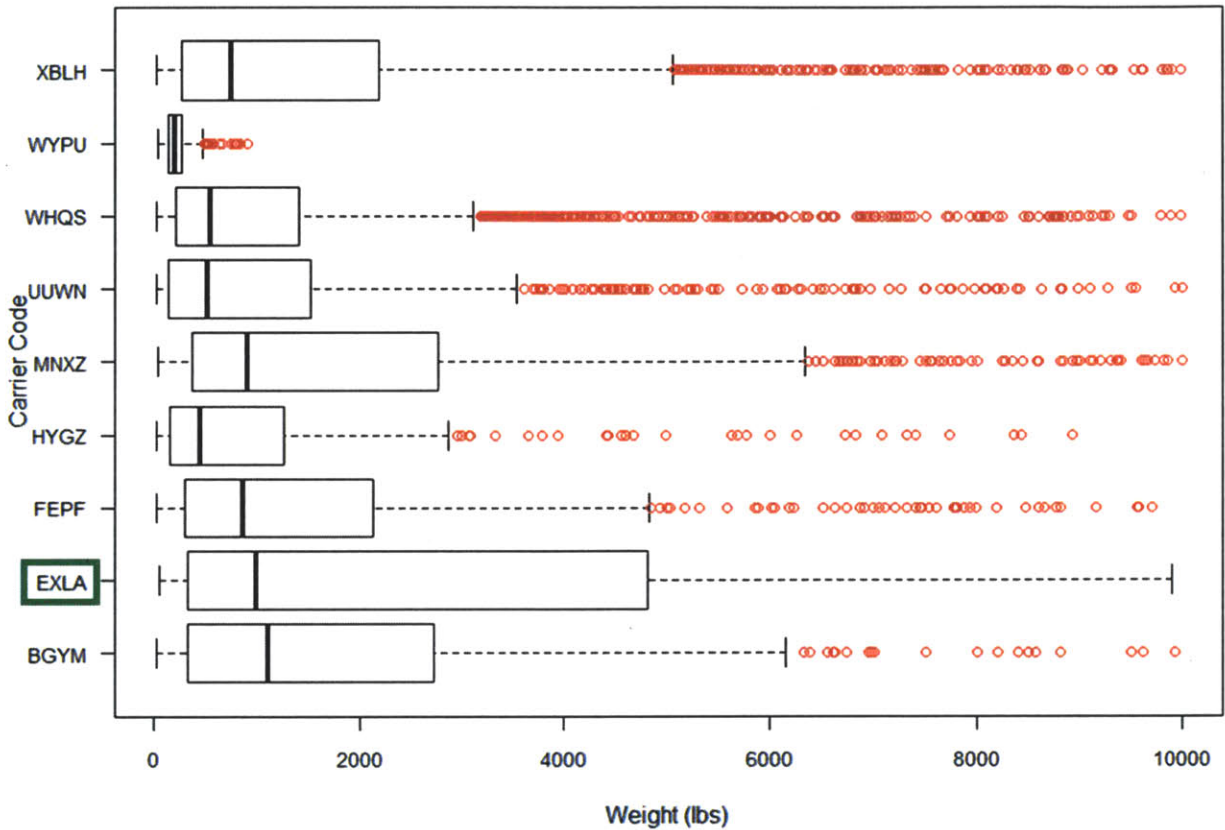


Figure 5 - Box-Whisker Plot comparison of shipment weight across different carriers

Figure 5 shows that Estes displayed the broadest weight profile of compared carriers for this sample of data, not focusing on any specific weight intervals. Carrier WYPU, for example, displayed a focus on moving lighter freight, at least on this sample of shipments. The fact that Estes has a wide weight distribution is important for the development of our model, since it means that Estes' operations capture the dynamics of different types of shipments.

## 4. METHODOLOGY

Our main goal in this research was to develop an approach to estimate the carbon emissions of individual LTL shipments based on minimal input information, and to assess the quality of the estimates using this approach. We focused on creating a detailed model that was representative of the network and operations of Estes Express Lines. However, we also developed a lower-precision generic model for the case when the carrier's network characteristics are unknown. The next sections describe all the procedures we followed in developing the detailed model. The low-precision model included the same parameters, but was modified to work with limited information about an LTL carrier's network and operations.

In order to develop our emissions estimation model, we worked with actual shipment data provided by the partner companies, C. H. Robinson and Estes Express Lines. We also assessed existing LTL estimation tools and searched for ways to improve them.

### 4.1. Model Overview

Our detailed model requires three basic inputs about a shipment: origin ZIP code, destination ZIP code and shipment weight in pounds. Based on the ZIP code information, the model determines which terminal serves that ZIP code, both on the origin side and on the destination side. It then calculates the line haul portion of the shipped distance between these two terminals, using one of two possible approaches. In the first approach, if actual shipment data for that lane (origin-destination terminal pair) is available and a minimum of five shipments in the database moved through it, the model sets the shipped distance equal to the average of the observed shipped distances – this includes all the intermediate terminals the freight moves through along the way. If, however, less than five shipments on that lane are available in the database, the model uses

the second approach, which relies on a regression model based on the great circle distance between the two terminals to estimate the shipped miles for the line haul portion. The model then adds a pre-determined percentage to the line haul distance to account for empty miles. This percentage is based on data provided by Estes.

Once the line haul distance is determined, the model calculates the total amount of fuel burned by dividing the line haul distance by the fuel economy factor (miles per gallon or MPG). The MPG is a parameter in the model based on mileage and fuel consumption data provided by Estes. Then, using an emissions factor provided by the EPA Climate Leaders guidance (2008), the model calculates the total amount of line haul emissions.

Next, the model allocates a portion of the total line haul emissions to the shipment based on the shipment weight inputted by the user and on a load factor. The load factor is a parameter determined by data provided by Estes.

Finally, the model adds emissions for the pick-up and delivery (P&D) sections of the shipment's movement. A number of P&D miles is assigned to the shipment based on the origin and destination terminals that move it. Then, using an MPG value for the P&D operations also based on data provided by Estes, the model computes the emissions. The final emissions number is the sum of the line haul emissions and the P&D emissions.

The low-precision model requires the same three basic inputs from the detailed one described above. However, it contains two main differences. First, since the carrier's network is unknown, it is not possible to determine the terminals that the shipment goes through. Therefore, the line haul distance is always determined by a regression model based on the great circle distance between origin and destination ZIP codes. Second, P&D miles cannot be determined for each specific terminal, but rather have possible pre-determined values that change based on the

origin and destination ZIP codes. All the other parameters (empty miles, MPG, emissions factors, and load factors) are equal to the detailed model ones. However, they can be adjusted by the user.

## 4.2. Main Challenges and Assumptions

While some of the challenges in developing our model were related to a lack of previous research in the field, most of them were related to data availability issues. The GHG Protocol, the EPA SmartWay and other sources provided guidance for an overall approach, but greater advancements were often limited by a lack of data to support them.

First, the shipment files provided by Estes Express Lines contained detailed information about every shipment that moved through the partner's company network. However, vehicle information was not included or associated with the shipment data in a consistent way. Because of this, it was not possible to match each shipment to a vehicle as it moved through the network or, in other words, to know which packages were inside of a specific trailer in every leg of the movement. As a result, we were not able to group shipments together in order to compute the total load or weight in a specific vehicle. In order to address this issue, we worked with overall load factors provided by Estes, valid for the entire network, as opposed to varying by lane.

Additionally, in this thesis, the emissions allocation process was based solely on weight rather than on class, volume or density. This was due to the fact that, according to the partner companies' industry experience, weight data is overall more accurate and reliable than class, volume or density information for individual shipments, since more checks are performed on weight than on these other variables.

Data for the pick-up and delivery operations (P&D) was also limited due to the highly dynamic nature of this section of an LTL movement. Therefore, we adopted a simplified

approach to account for P&D miles based on the aggregate number of miles driven and of shipments moved at each terminal.

Additionally, our model did not take into account emissions related to stationary fuel consumption at each terminal, such as those from local equipment operations.

We also did not make any distinctions in terms of vehicle type and assumed for simplicity that all vehicles were dry vans. We calculated the fuel economy factor (miles per gallon or MPG) for all the vehicles in Estes' LTL fleet regardless of vehicle type, as if they were all dry vans.

Finally, as described in the literature review, we focused only on carbon dioxide emissions ( $\text{CO}_2$ ), neglecting other types of gases such as  $\text{N}_2\text{O}$  or  $\text{CH}_4$ , since their concentrations are much smaller than that of carbon dioxide.

### 4.3. Calculating Distances

Determining the total shipped distance (both line haul and P&D sections) is one of the most important and challenging steps in estimating carbon emissions for LTL shipments. Since these shipments usually do not go directly from origin to destination, simple over-the-road miles between these two points are not a good estimate of the line haul distance; it is likely to be higher due to the intermediate stops and multiple levels of shipment consolidation. Additionally, pick-up and delivery miles are difficult to determine due to the dynamic nature of these operations coupled with data availability issues. We now describe the procedures we followed in order to calculate both line haul and P&D distances.

### 4.3.1. Line Haul Miles

Line haul miles refer to the distance between the first and the last terminal that a shipment goes through. Since Estes has more than 200 terminals in its network, there are multiple possible combinations of origin and destination terminals. Additionally, the intermediate stops may change even if the first and last terminals are the same for two different shipments. Our main goal for this step was to find a way to estimate the actual LTL shipped miles for any shipment based on some information easily obtained or inferred from the data inputted by the user of the calculation tool.

Our approach to estimating line haul miles was based on the distances between pairs of origin and destination terminals. Each possible combination of two terminals was considered an origin/destination pair (O/D pair). Estes Express provided a file containing the servicing area of each terminal, which allowed us to match any ZIP code in the US to one of their terminals, creating a consistent way of identifying the O/D pair of terminals for any two ZIP codes inputted by the user into our detailed model.

We then analyzed the shipment data provided by Estes and focused on the “shipped miles” metric. This number represented the actual shipped distance between the first and the last terminal for each shipment, including all intermediate stops. It was calculated by Estes through a combination of telemetry, odometer readings and software such as *PC Miler*. We focused our analysis on shipment data for one four-week period (period A), but tested the model against other periods of data that were available as well. We also only considered O/D pairs that contained information of at least five shipments in order to make the resulting shipped distances more consistent and eliminate excessive variability.

We compared the shipped miles to two different variables: direct over-the-road distances provided by Estes (i.e., how a full truckload shipment would be routed if no intermediate stops or consolidation were need), and great circle mileage between two terminals. It is important to note once again that this step includes only the line haul distance, excluding P&D operations for now.

After analyzing the data, we noticed that the direct over-the-road distance figures provided by Estes displayed consistency issues, either caused by infrastructure changes over time or by inaccuracy in the way they were first calculated. Therefore, they were not a good proxy for the actual shipped miles. We then elected to develop our distance estimation model based on the great circle miles between two terminals, calculated through the Haversine Formula, which is replicated in Equation 4 below (Craig, 2012, p. 165; Pearson, 2009).

$$D = r \times \left\{ 2 \arcsin \left( \sqrt{\sin^2 \left( \frac{\Delta\sigma}{2} \right) + \cos \phi_s \cos \phi_f \sin^2 \left( \frac{\Delta\lambda}{2} \right)} \right) \right\} \quad (4)$$

Where:

$r$  = Radius of the Earth

$\Delta\delta$  = Interior spherical angle between two points

$\Delta\sigma$  = Latitude of Point 1 – Latitude of Point 2

$\phi_s$  = Latitude P1

$\phi_f$  = Latitude P2

$\Delta\lambda$  = Longitude P1 – Longitude P2

Equation 4 above allows the great circle distance between any two points to be determined based on their latitude and longitude. Since our tool asks for ZIP codes as inputs,

they had to be converted to latitude and longitude before being inserted into the Haversine formula.

We then ran a series of regression models on the software package *R* using great circle miles as the independent variable and the actual shipped miles from the shipment data files as the dependent variable. Our goal was to predict shipped miles based on great circle distance between any two points for when historic shipment data is not available.

Since we wanted to check the validity of the model, our data was split into two groups: a modeling set and a validation set. The modeling set contained 90% of the data and the validation set contained the remaining 10%. Both were determined randomly. By doing this, we were able to perform different regression analyses on the modeling set and test them on the validation set in order to hedge against overfitting.

It was the team's initial expectation that the equations to predict shipped miles would change based on the original distance between origin and destination. By parsing the data into categories or "bins" of different sizes (such as 0 to 500 miles, 500 to 1000 miles, and so on), we obtained different regression coefficients for each individual bin. We also built a single regression model that included all of the data. We did not observe any significant advantage to working with various categories; the highest  $R^2$  value attained was .82 for the best particular bin, as compared to an  $R^2$  value of .96 for the regression model that included all of the data.

Ultimately, since Estes provided some information broken down into two major distance categories (short haul and long haul, which are described in detail in section 4.5 of this thesis), we decided to work with two separate regression models: one for distances of no more than 300 miles (short haul), and one for distances greater than 300 miles (long haul). It is important to note that we based the 300-mile threshold on great circle miles and not on shipped miles, since



the latter is what we were trying to predict, but the original separation of short and long haul by Estes was based on shipped miles. The inaccuracy that originated from doing this did not severely affect the model results. We also restricted the final models to have an intercept value of zero because of two main reasons. First, predicting the shipped miles with a single coefficient that multiplies the great circle distance makes the model more intuitive. Second, using an intercept different than zero penalized short distances too much; in some cases, the intercept by itself would be three times greater than the adjusted great circle distance. The equations and graphs for both models are presented below.

$$\text{Shipped Miles } (\leq 300) = 1.323 \times \text{Great Circle Miles} \quad (5)$$

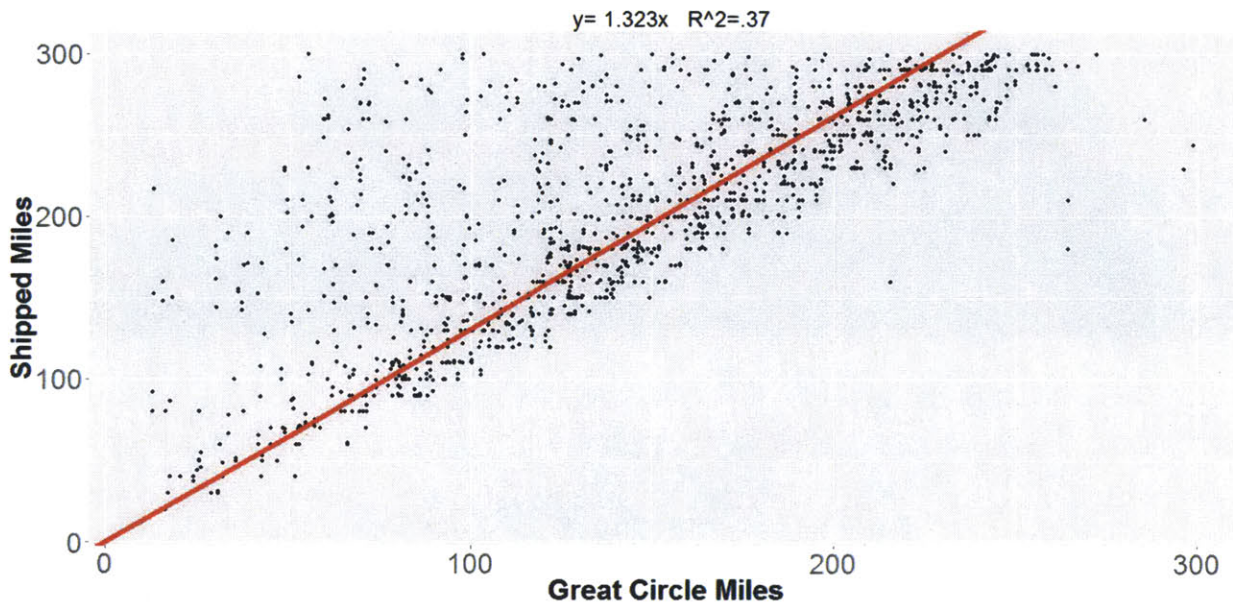


Figure 6 - Scatterplot and regression line for short haul (distance no greater than 300 miles)

$$\text{Shipped Miles } (> 300) = 1.26 \times \text{Great Circle Miles} \quad (6)$$

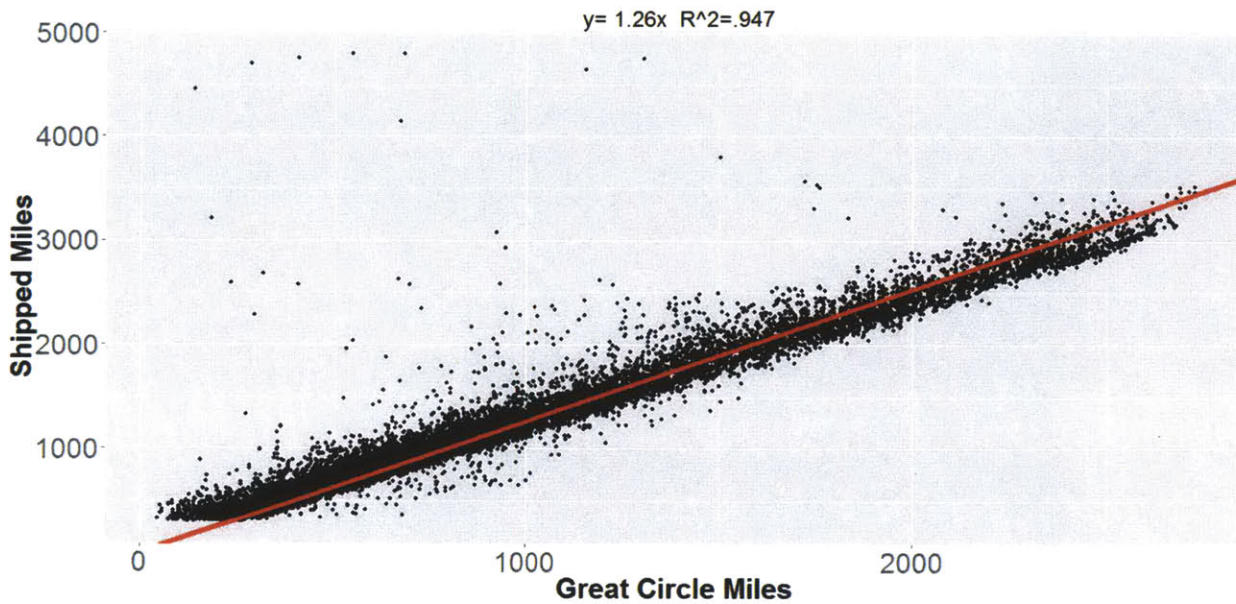


Figure 7 - Scatterplot and regression line for long haul (distance greater than 300 miles)

The  $R^2$  value obtained for the short haul model was 0.36, while the one for the long haul model was 0.947. While the short haul model presented a relatively low  $R^2$  value, we believe it is still a better predictor of the behavior of the network for short distances than a single model that included all the data. The scatterplot on Figure 6 above shows that data for short haul has more spread and is usually to the left of the regression line, which suggests that actual distances are larger than what the model predicts. By observing the coefficients on the two equations, we notice that the short haul model has a higher coefficient (1.323) than the long haul one (1.26), which shows that it captures some of this need to overestimate shipped miles for short distances.

Both models were then tested using the untouched validation data through the predict function in the *R* software package. The out-of-sample  $R^2$  were calculated to be .47 and .95 for the short haul and the long haul respectively, which attests to the predictive power of our models.

Again, predictions for short haul were expected to be less accurate due to their greater variability.

With regards to the low-precision model for the case when the carrier's network is unknown, the same two regression equations were used for short haul and long haul. The main difference was that, since the terminals are not known in this case, the origin and destination ZIP codes inputted by the user were the ones inserted into the regression equations; the step of matching a ZIP code to a terminal's servicing area was skipped. The resulting value for the regression equation was considered the line haul distance between the first and the last terminal.

#### 4.3.2. Pick-up and Delivery (P&D) Miles

Data for P&D operations was not as readily available or as accurate as from line haul. P&D is characterized by a highly dynamic nature, with frequent changes from day to day in routing, in the pattern of shipments that are moved and in the customers that are served.

Exact addresses for shipments that went through pick-up and delivery were not available from the data provided by Estes Express, neither the exact vehicles that moved each individual shipment on the P&D sections. However, the company did provide aggregate data on which vehicles were used for P&D at each terminal, not associated with any specific shipment. Estes was also able to provide aggregate data for total miles driven and total fuel consumption per period (each period represents four weeks) per vehicle.

In order to gain insight into the carbon footprint of P&D operations considering the limited data available, the approach we adopted was to examine the total number of shipments moved at each terminal for a certain period of time along with the total miles driven by the vehicles assigned to the terminals on that same period. Estes does both pick-up and delivery operations simultaneously in the same vehicle, so we considered shipments both originating and

ending at each specific terminal when determining the total number of shipments. Additionally, it is rare that either the pick-up or delivery vehicles reach their maximum capacity in either weight or volume. This information was then used to calculate a “P&D miles per shipment” figure for each terminal, as described in Equation 7 below (where  $i$  indicates the terminal number):

$$P\&D \text{ Miles per Shipment}_i = \frac{\sum \text{Miles Driven}_i}{\sum \text{Shipments}_i} \quad (7)$$

More than 1.5 million shipments were analyzed when determining the P&D miles per shipment values. This included shipments from two non-consecutive periods of shipment data (namely, periods A and C) in order to reduce the effects of any unusual number of shipments moved or miles driven at a single four-week period.

It is important to highlight that our approach to P&D disregarded the exact locations of origin and destination and the weight of individual shipments. Purely from an emissions perspective, it would be logical to take ZIP codes into account and compare distances from origin and destination to the first and last terminals, respectively. However, the nature of Estes Express’ business is that multiple customers and shipments are serviced simultaneously in a single P&D run; a truck rarely makes a trip solely for one shipment. Therefore, we opted for an approach that assigns a fixed number of P&D miles to shipments, regardless of their exact location or characteristics, by understanding that these shipments are part of a truck movement that involves other shipments as well.

Figure 8 below shows the histogram of the resulting P&D miles per shipment. Each value in the histogram corresponds to a terminal. Roughly 88% of the terminals in the analysis displayed a value of less than 10 P&D miles per shipment.

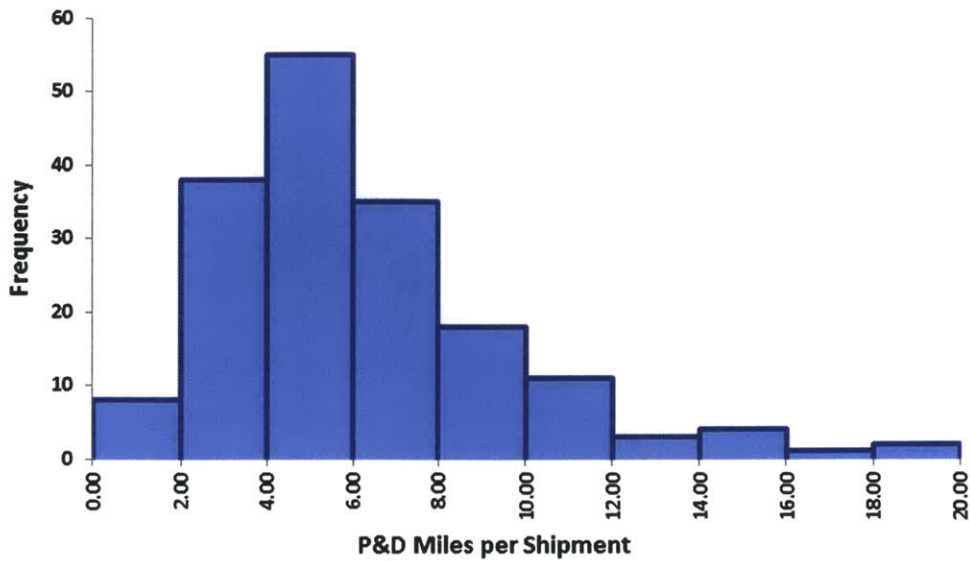


Figure 8 - Histogram of P&D miles per shipment per terminal

It is important to notice that this histogram contains data for 175 terminals, which is not equal to the total number of terminals that Estes operates in the US, described previously as more than 200. The difference in these numbers is explained by the fact that mileage data was not available for some terminals, primarily because they are owned by an agent or partner company and not directly by Estes, even though the latter does move freight through them.

Figure 9 below provides a heat map of P&D miles per shipment for the 175 terminals for which mileage data was available. Each dot represents a terminal and the color of the circle indicates the number of P&D miles: the closer to red, the higher the number of miles for that terminal.

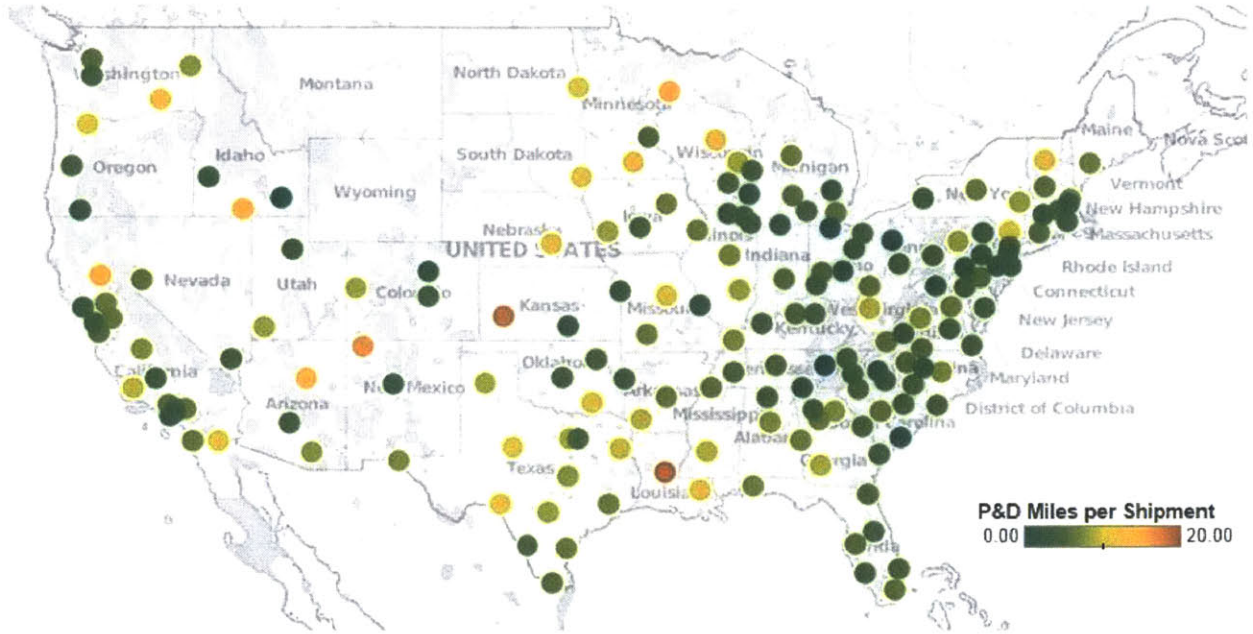


Figure 9 - Heat map of P&D miles per shipment per terminal

It is noticeable from Figure 9 above that there is a significant region in the northwestern part of the country (Montana, Wyoming, North Dakota and South Dakota) for which no data was available for this analysis. In order to account for this and because of the desire to also develop a low-precision generic model that was applicable to other carriers besides Estes, we grouped the 175 terminals for which data was available into six different regions and analyzed the P&D miles per shipment for each of those regions. The miles value for each region was the average of the values of the terminals that were part of that specific region. The six regions we created and the states that were included into each were (the remaining US states that are not listed below were not considered in this analysis):

- NE (North-East): CT, DC, DE, MA, MD, ME, NH, NJ, NY, PA, RI, VA, VT, WV
- NM (North-Mid): KY, OH, IN, MI, IA, IL, MN, SD, ND, MO, KS, NE, WI
- NW (North-West): ID, MT, OR, WA, WY

- SE (South-East): FL, GA, NC, SC
- SM (South-Mid): AL, AR, LA, MS, OK, TN, TX
- SW (South-West): AZ, CA, CO, NM, NV, UT

Considering this division, Figure 10 below shows how Estes' terminals classify into each region. This figure already includes the terminals which had missing data for the initial analysis; they were assigned to a region based on their location.

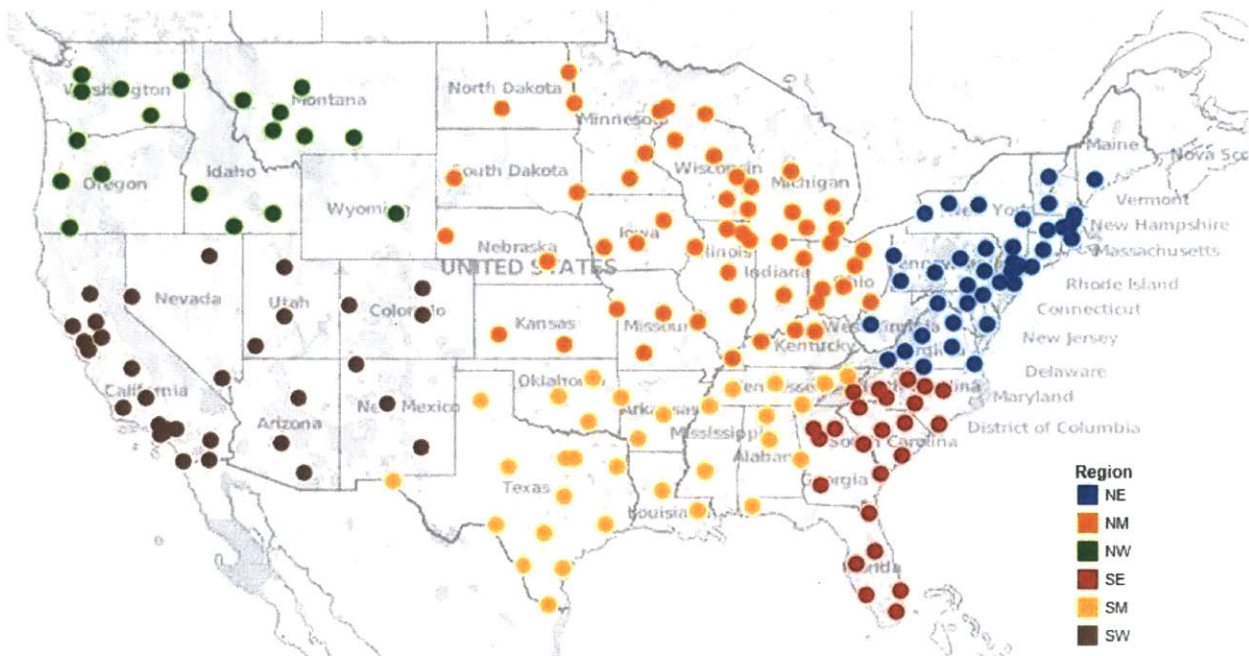


Figure 10 - Terminal classification by region

We then performed an ANOVA analysis comparing the mean value of P&D miles per shipment for each of the six regions described above. The 175 terminals were assigned to one of those regions based on their ZIP code, as shown in Figure 10 above. A summary of the results of the ANOVA test is presented in Table 2 below:

Table 2 - ANOVA results of P&D miles per shipment by region

Region	Sample Size (No. of Terminals)	Sample Mean (P&D Miles)	Sample Std Dev (P&D Miles)
NE	37	5.06	2.43
NM	44	6.33	3.68
NW	10	6.72	4.58
SE	24	4.83	1.84
SM	32	7.16	3.36
SW	28	6.57	3.74

The test yielded a p-Value of 0.03 and an F-Ratio of 2.4, indicating that the means of each region are likely to be statistically different. Based on these results, the terminals that had no mileage data were assigned a value of P&D miles per shipment based on their region according to the mean values of P&D miles per shipment shown on Table 2 above. This way, every terminal of Estes' network had a P&D miles value assigned to them, either calculated based on actual mileage and shipment data or determined based on the region in which it was located.

Table 2 also shows that there was high variability in the numbers for some regions, especially for NW. In spite of this issue, we used the sample mean as a reference value for P&D miles. Considering the data availability problem for P&D, this value is still a reasonable approximation. While there may be some variability, they correspond to short distances, so the final impact on emissions is not likely to be very dramatic.

With respect to the lower-precision model, Table 2 was also the reference for determining the P&D miles per shipment of the origin and destination terminals. Since this model is for the case when there is no information about the carrier's network, the origin and destination ZIP codes inputted by the user are considered the same ZIP codes of the first and last terminals.



These terminals were then matched to one of the six possible regions and assigned a P&D miles per shipment value as shown in Table 2.

#### 4.4. Estimating Total Emissions

Once the distances were determined, the next steps in calculating the total carbon emissions from the movement were related to fuel economy factors – traditionally expressed in miles per gallon (MPG) – and to emissions factors. MPG values allow the total amount of fuel burned in order to travel a certain distance in miles to be determined, while emissions factors convert the total amount of fuel burned into actual emissions.

##### 4.4.1. Fuel Economy Factors

Estes Express was able to provide data on total fuel usage as well as total miles driven per vehicle for multiple four-week periods in 2013. While shipment data was restricted to three periods, fuel and mileage data was much broader and extended beyond these three specific time windows.

Since line haul and P&D operations have significantly different characteristics and also considering that Estes utilized different vehicles for each, we did not expect fuel economy numbers to be equal across these two categories. Similarly, we expected the fuel economy of P&D and line-haul operations to vary from terminal to terminal based on their size, their region and other factors.

In order to account for some of these factors, we first segmented terminals by the amount of vehicles assigned to them as an indicator of their size. Terminals were classified into four categories (Category 1 being the least amount of trucks and Category 4 being the greatest),

separately for line haul and for P&D operations. The category breakdown for both line haul and P&D is shown by Tables 3 and 4 below, respectively.

The total number of terminals in both tables is less than 200 for the same reason described in section 4.3.2: data for some terminals was not available as they are not directly owned by Estes Express.

Table 3 - Terminal categorization by quantity of vehicles for line haul

Line Haul		
Category	No. of Vehicles	Qty. Of Terminals
1	no more than 7	50
2	7 to 14	61
3	14 to 21	24
4	more than 21	45

Table 4 - Terminal categorization by quantity of vehicles for P&D

P&D		
Category	No. of Vehicles	Qty. Of Terminals
1	no more than 7	62
2	7 to 14	63
3	14 to 21	32
4	more than 21	23

We performed ANOVA tests on the MPG of both operations and results showed no strong evidence of difference in the average MPG values across different terminal categories. Results for line haul were a p-Value of 0.24 and F-Ratio of 1.41, while results for P&D were a p-Value of 0.55 and F-Ratio of 0.71. The grand mean values of MPG were clustered around 5.9 for line haul operations and 6.3 for P&D.

We then performed an analysis of MPG based on terminals' regions, similar to what we conducted when looking at P&D mileage, to verify the variability of MPG based on geography. We utilized the same six regions from section 4.3.2: NW, NM, NE, SW, SM, and SE.

In order to better illustrate this, Figure 11 below shows a Box-Whisker Plot of the MPG of line haul operations for the terminals of these different regions.

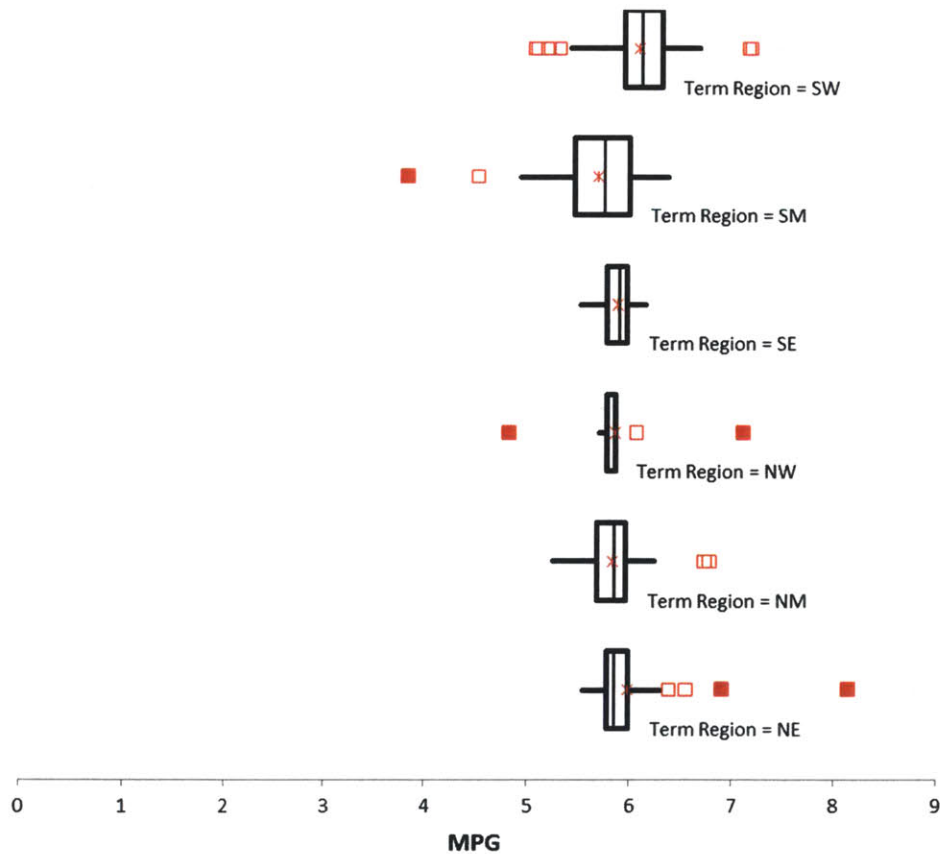


Figure 11 - Box-Whisker Plot of MPG per terminal by region for line haul

We performed an ANOVA test in order to check for differences in the mean value of each region. A summary of the results of the ANOVA test for line haul is shown in Table 5 below.

Table 5 - ANOVA results of MPG per terminal by region for line haul

Region	Sample Size (No. of Terminals)	Sample Mean (MPG)	Sample Std Dev (MPG)
NE	38	6.0	0.4
NM	45	5.8	0.3
NW	9	5.9	0.6
SE	24	5.9	0.2
SM	32	5.7	0.5
SW	28	6.1	0.5
<b>Totals</b>	<b>176</b>	<b>5.9</b>	-

The ANOVA test for line haul yielded a p-Value of 0.008 and an F-Ratio of 3.22. While these indicate that the means are statistically different, we decided to consider a single value for line haul MPG, equal to the grand mean of 5.9. This was due to two main reasons: the variations were not significantly large from region to region; and line haul operations usually involve terminals that span across different regions, which cases the numbers to average out and converge towards the grand mean of 5.9 MPG.

We then conducted the same analysis for the P&D operations. Figure 12 below shows the Box-Whisker Plot of MPG values for P&D and Table 6 shows the summarized results of the ANOVA test.

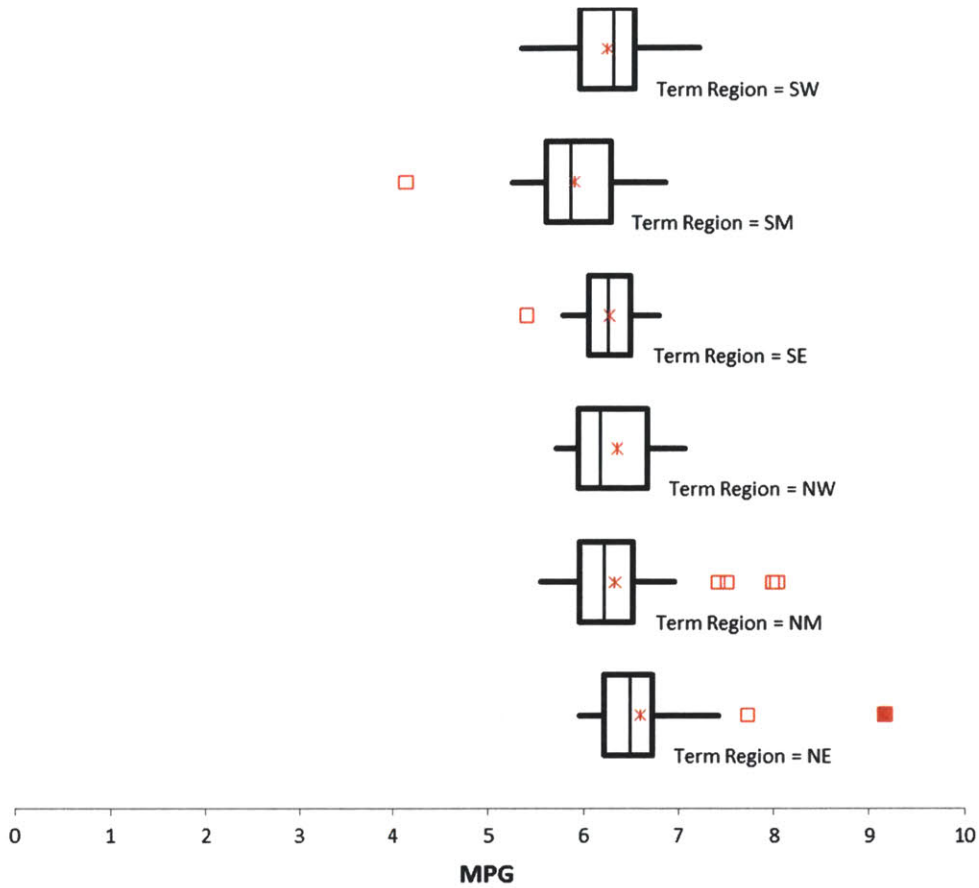


Figure 12 - Box-Whisker Plot of MPG per terminal by region for P&D

Table 6 - ANOVA results of MPG per terminal by region for P&D

Region	Sample Size (No. of Terminals)	Sample Mean (MPG)	Sample Std Dev (MPG)
NE	38	6.6	0.6
NM	45	6.3	0.6
NW	10	6.3	0.4
SE	24	6.3	0.3
SM	32	5.9	0.5
SW	28	6.2	0.5
<b>Totals</b>	<b>177</b>	<b>6.3</b>	-

The ANOVA test for P&D yielded a p-Value of less than 0.0001 and an F-Ratio of 6.47.

These results strongly indicate that the means of each group are statistically different. Since P&D

operations are concentrated around a terminal's servicing area, we decided to use different MPG values for terminals based on their region as shown in Table 6 above.

#### 4.4.2. Emissions Factors

Emissions factors allow a quantity of fuel burned to be converted into actual emissions, usually in units of weight, and is a function of the type of fuel that is being considered. We did not perform fuel analysis to calculate our own factors. Instead, we relied on guidance provided by the GHG Protocol and the EPA, as described in section 2.4.1 of the Literature Review. These guides suggest a factor of 10.15 kilograms of CO<sub>2</sub> per gallon of on-road diesel fuel burned (EPA, 2008; WBCSD & WRI, 2012). Our models allow this factor to be adjusted in case new research indicates that it needs to be updated.

#### 4.5. Allocating Emissions to Single Shipments

The previous sections described the steps we performed in order to calculate the total carbon emissions for an entire vehicle as it moved throughout the network. However, since the vehicles are utilized to move many shipments simultaneously and we were especially interested in calculating the emissions of a single shipment, we needed a method to allocate total carbon emissions to individual LTL shipments. This method relied primarily on load factors provided by Estes Express, as described next.

##### 4.5.1. Load Factors

Load factors have different meanings in different industries or businesses. For the purpose of this thesis and based on the way Estes Express operates, load factors represent the average total weight of freight that is loaded onto a truck. They may also be understood as vehicle utilization

rates and are indicators of how much of the vehicle’s capacity is actually being used. Load factor data from Estes was only available for line haul operations.

In order to allocate total emissions from a movement to a single shipment, the ideal approach would be to analyze how the shipments were grouped together inside each vehicle as they moved through the network and then compare the weights of those shipments and assign emissions accordingly (assuming weight is the allocation variable). However, based on the shipment data provided by Estes, it was not possible to determine how those shipments were grouped together as they were moved. In other words, it was not possible to link back the shipments to the specific vehicles that moved them.

Nonetheless, Estes was able to provide aggregate-level load factors or utilization rates for their line haul operations, representative of the network as a whole. Since every truck that leaves a terminal is weighed and documented, this is a widely tracked and very important metric for any LTL carrier. Table 7 below shows Estes’ load factors for the same three periods for which shipment data was provided, both in terms of weight and volume.

Table 7 - Estes Express Lines’ load factors

Period	Short Haul (<=300 miles)		Long Haul (>300 miles)	
	Volume (%)	Load Factor (lbs)	Volume (%)	Load Factor (lbs)
<b>8</b>	73.2%	22,534	82.0%	25,189
<b>9</b>	73.5%	22,597	81.9%	25,107
<b>10</b>	73.8%	22,838	81.9%	25,334
<b>Avg.</b>	<b>73.5%</b>	<b>22,656</b>	<b>81.9%</b>	<b>25,210</b>

Table 7 above shows that Estes breaks down the load factors by distance into two main categories: short haul and long haul. These are the same categories used in our regression

models, as explained in section 4.3.1. These categories refer to the distance between the first and the last terminals of the line haul operation. Short haul are movements in which this distance is no larger than 300 miles, while long haul encompasses everything that moves beyond 300 miles. This classification is somewhat typical for LTL carriers, although there may be variations in the number and size of categories across different companies.

Table 7 also shows that the load factors for Estes are relatively consistent for the three periods of shipment data that were analyzed. For the purpose of this thesis, we relied on the average of the three periods of data both for short haul and long haul. Therefore, short haul load factors were determined to be 22,656 pounds and long haul load factors were 25,210 pounds.

By using these load factors in conjunction with the shipment weight information inputted by the user, our model calculates the percentage of the total emissions that a specific shipment receives through a simple division of the shipment weight by the load factor (e.g., a 500-pound shipment with an overall load factor of 25,000 pounds would receive 2% of total emissions from a movement). As explained in section 4.2, volume, class or density data was not used in the allocation procedure since, according to Estes, they are significantly less reliable metrics than weight.

Since we assume that Estes' numbers are representative of a typical LTL carrier's network, we used the same average load factors shown in Table 7 in the low-precision model for an unknown carrier. However, this model allows the user to manually set the load factor to any number if more accurate information about the carrier is available or if there is reason to believe that Estes' numbers are not representative of a different carrier.



## 4.6. Adding Empty Miles

Besides the shipment data, Estes also provided information relative to the aggregate fleet mileage for different periods, including empty miles or deadhead. Empty miles refer to the distance traveled without actually moving shipments or generating direct revenue and are usually caused by the need to reposition vehicles after delivering a shipment and before picking up the next one. Table 8 shows Estes' total mileage numbers for the entire fleet for the same three periods that the shipment data was relative to.

Table 8 - Estes Express Lines' empty miles

<b>Period</b>	<b>Loaded Miles</b>	<b>Empty Miles</b>	<b>Total Miles</b>	<b>% of Empty Miles</b>
<b>A</b>	29,635,735	2,938,540	32,574,275	9.02%
<b>B</b>	28,508,934	2,937,536	31,446,470	9.34%
<b>C</b>	30,272,368	3,041,907	33,314,275	9.13%
<b>Avg.</b>	<b>29,472,346</b>	<b>2,972,661</b>	<b>32,445,007</b>	<b>9.16%</b>

It was not the focus of this thesis to address the issue of empty miles or how they should be allocated to different shipments. However, since we had access to this information, we adopted a simplified approach to this topic and included it in our emissions estimation model. Our approach was to add the average percentage of empty miles of these three periods (9.16%) to the total distance estimated by our models. This way, we added a number of miles to the shipped distance to account for the fact that the vehicles need to be repositioned after a shipment is completed and before a new one is collected.

We briefly analyze the issue of empty miles further in the discussion section of this thesis, addressing aspects such as how they were calculated and who should be held accountable for them. Regardless of who they get assigned to, we considered it important for our models to take them into account, even if through a simplified approach.

## **5. RESULTS AND DISCUSSION**

After developing our emissions estimation tools as described in the previous sections, we analyzed how the outputs of our models compared to those of other methods of estimating carbon emissions. We focused our analyses on the outputs of five different methods: TMC's current estimation formula, TMC's current formula with an adjusted load factor, GHG Protocol's short ton-mile approach for freight transportation, our detailed model for Estes' network, and our lower-precision generic model for an unknown carrier's network.

This comparison focused on testing these five different estimation methods on the set of roughly 8,500 shipments provided by TMC, mentioned in section 3.2.1 of this thesis. This sample of shipments already contained the results of TMC's current emissions estimation method, which allowed us to compute additional estimations based on different approaches and then compare the results.

However, in this sample data provided by TMC, only 75 shipments were moved by Estes Express Lines. In order to perform better comparisons and obtain more consistent results, we included additional shipments from the data provided directly by Estes into our analysis set, reaching a final quantity of roughly 2,700 shipments moved by the company for results comparison purposes. The shipment data that was used to build our models was not included in this set.

### **5.1. Compared Estimation Methods**

Table 9 below presents the five methods we analyzed and compared, as well as how we identify them throughout the next sections.

Table 9 - Compared estimation methods

Model	Description
A	Our detailed model for Estes Express
B	Our low-precision generic model
C	TMC's current formula
D	TMC's formula with adjusted load factor
E	GHG Protocol's short ton-mile approach

**A. Our detailed model for Estes Express Lines’ network**

This is the detailed model we developed for Estes Express’ network and operations. This method was used to estimate the emissions of the sample of 2,700 shipments that were moved by Estes in our analysis set.

**B. Our low-precision model for an unknown carrier’s network**

This is the lower-precision, generic model we developed for the case when the carrier’s network and operations are unknown. This method was applied to roughly 8,400 shipments in the data set provided by TMC that were not moved by Estes and for which we had no information in terms of the carrier’s terminal infrastructure or operations.

**C. TMC’s current formula for LTL carbon emission**

Equation 7 below represents how TMC calculated the emissions in the sample of 8,500 shipments we analyzed. We used the same formula to calculate emissions for the 2,700 shipments moved by Estes, including those that were not in the original sample provided by TMC but were added by us.

$$CO_2 \text{ Emissions} = \frac{\text{Miles} (x 1.1)}{5.8} \times 22.15 \times 0.99 \times \frac{\text{Weight}}{40,000} \quad (7)$$

The 0.99 multiplier refers to the fraction of fuel that is combusted. The “miles” variable is determined as the direct over-the-road distance between origin and destination ZIP codes, primarily using the software *PC Miler*. TMC also often includes a distance correction factor of 1.1 to account for extra mileage on LTL shipments, although this is not done on every case. For the comparisons in this thesis, we did not take this extra distance factor into account.

#### **D. TMC’s current formula with an adjusted load factor**

Equation 8 below is essentially the same as Equation 7, except for the fact that the load factor is adjusted to 25,000 pounds, which is more representative of typical LTL operations, as opposed to the original value of 40,000 pounds, which is often related to full truckload operations. This equation helped illustrate the impact that load factors have on estimating emissions from single shipments.

$$CO_2 \text{ Emissions} = \frac{\text{Miles}}{5.8} \times 22.15 \times 0.99 \times \frac{\text{Weight}}{25,000} \quad (8)$$

#### **E. GHG Protocol’s short ton-mile approach for freight transportation**

The approach in Equation 9 below is suggested by the GHG Protocol (WBCSD & WRI, 2012) for estimating emissions when fuel consumption data is not available for the carrier in question. Equation 3, presented in section 2.4.2 of the Literature Review, is the generic form of the distance-based calculation method. Equation 9 is an adaptation of the generic form to include the weight variable for freight transportation. The road emissions factor is 0.297 kg of CO<sub>2</sub> per

short ton-mile, as presented in section 2.4.2 of the Literature Review. We performed additional unit conversions in order to obtain results in terms of pounds of CO<sub>2</sub> to facilitate comparisons.

$$CO_2 = Road\ Distance \times Shipment\ Weight \times Road\ Emissions\ Factor \quad (9)$$

## 5.2. Analysis of Results

Since we developed two models (a detailed one and a low-precision generic one) and analyzed two separate sets of shipment data (shipments moved by Estes Express Lines and shipments moved by other carriers), we dedicate a specific section for the analysis of the results of each model. We also perform a comparison between the results of the two approaches for the same set of shipments.

To facilitate some of the comparisons, we normalized the emissions by distance and by weight, as shown by Equation 10 below:

$$Normalized\ CO_2 = \frac{Emissions}{Miles \times \frac{Weight}{2,000}} \quad (10)$$

The output of Equation 10 is in pounds of CO<sub>2</sub> *per short ton-mile*. This allowed us to perform additional comparisons beyond only analyzing total emissions, which make it difficult to assess how light and short-distance shipments compare to heavy and long-distance ones.

### 5.2.1. Detailed Model for Estes Express Lines

This analysis was focused on the set of 2,700 shipments that were moved by Estes Express Lines and compared the emissions of methods A, C, D and E from Table 9. Our low-precision model (method B) was not applied here since the carrier's network was known (Estes Express was the carrier).

Figure 13 below displays results in terms of total emissions for an initial comparison between the four methods. The distances on the horizontal axis are represented in direct miles. They were provided by TMC and calculated primarily through *PC Miler*. Methods C, D and E rely on direct miles for their emissions calculation, while the methods we developed calculated the shipped distance as part of the estimation procedures, as explained in section 4.3. The results were all plotted in terms of direct miles to facilitate the comparisons.

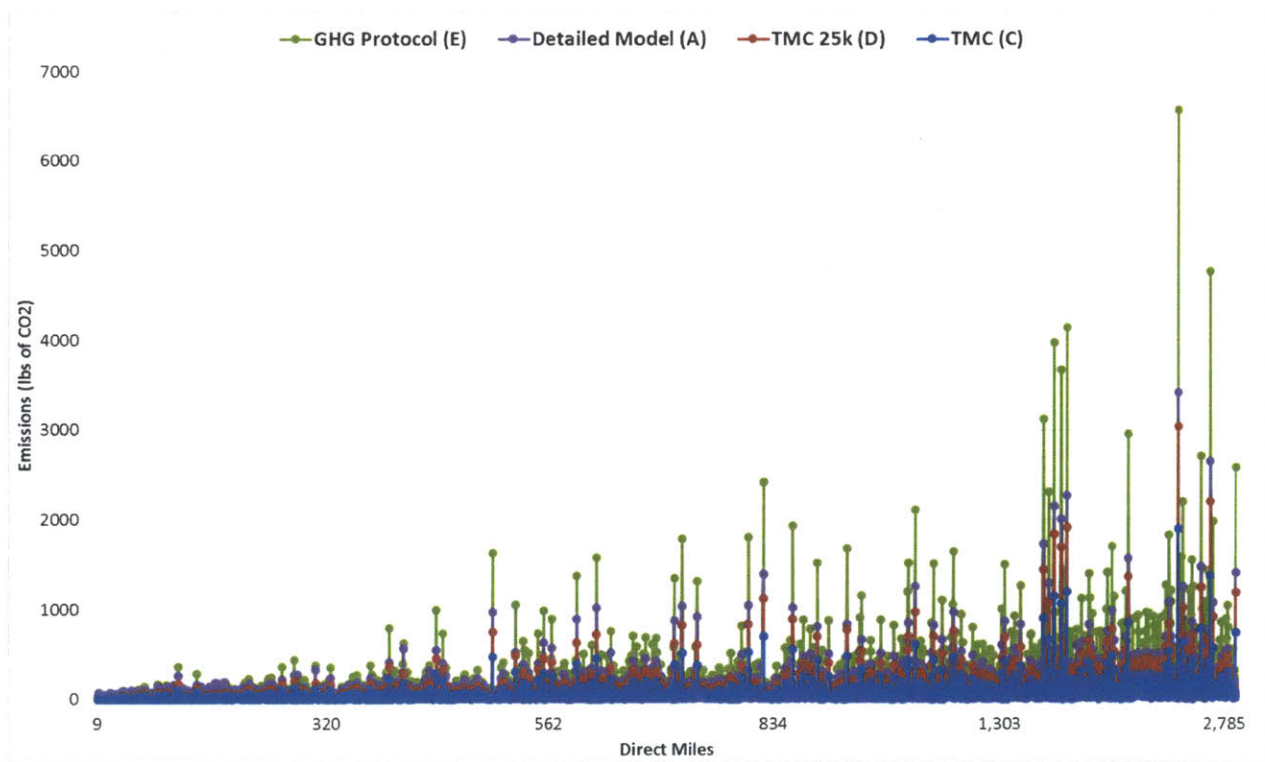


Figure 13 – Comparison of total emissions of methods A, C, D and E

Figure 13 reveals that the results of our detailed model tended to fall between those of TMC’s formula and the GHG Protocol, especially for long distances. In order to better visualize and understand the results for short distances, Figure 14 below presents the emissions only for short haul (distances no greater than 300 miles).

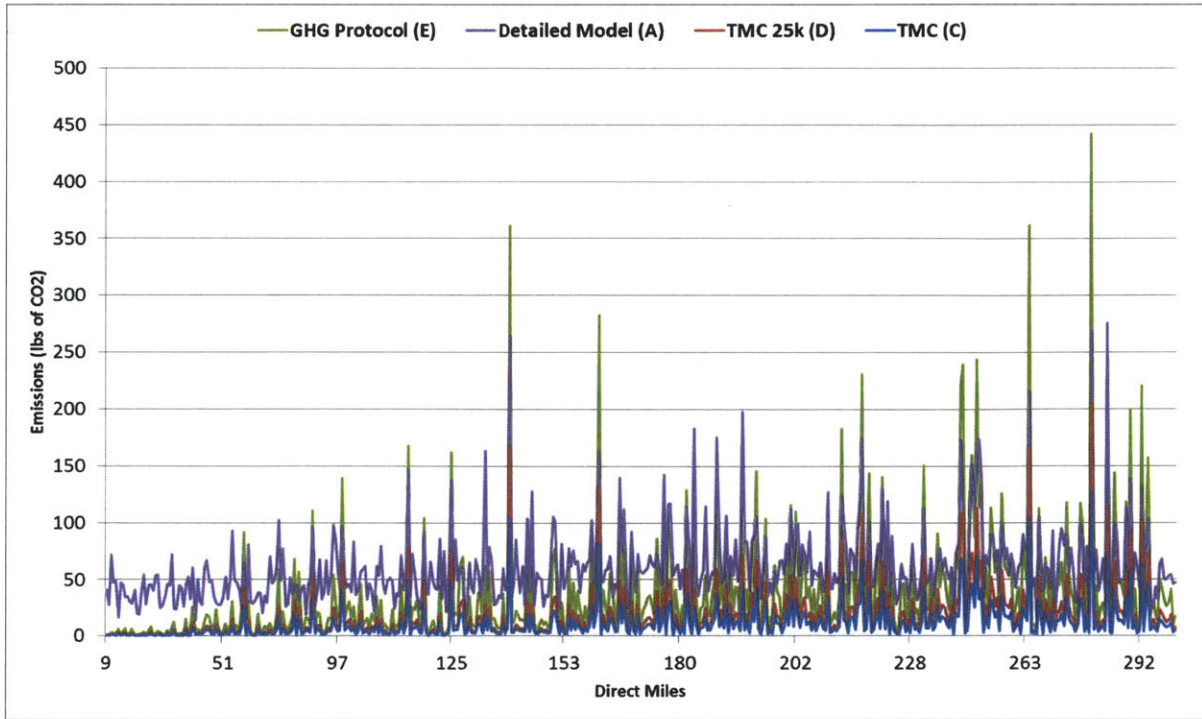


Figure 14 - Comparison of total emissions of methods A, C, D and E for short haul

Figure 14 reveals that, for short distances (especially below 100 miles), our detailed model produced the highest emission results. This was primarily caused by emissions from P&D operations, which are not factored in the comparison methods C, D, and E. However, as the distance shipped increased, P&D emissions became less relevant and the results of our model started to fall in between TMC’s formulas’ and GHG Protocol’s results.

For additional comparisons, Figure 15 below shows the results of these four methods in terms of normalized CO<sub>2</sub> emissions (pounds per short ton-mile, as explained by Equation 10 above) as the distance traveled by the shipment increased. The results for our detailed model are represented by the dots, while the results for the comparison methods are represented by lines.

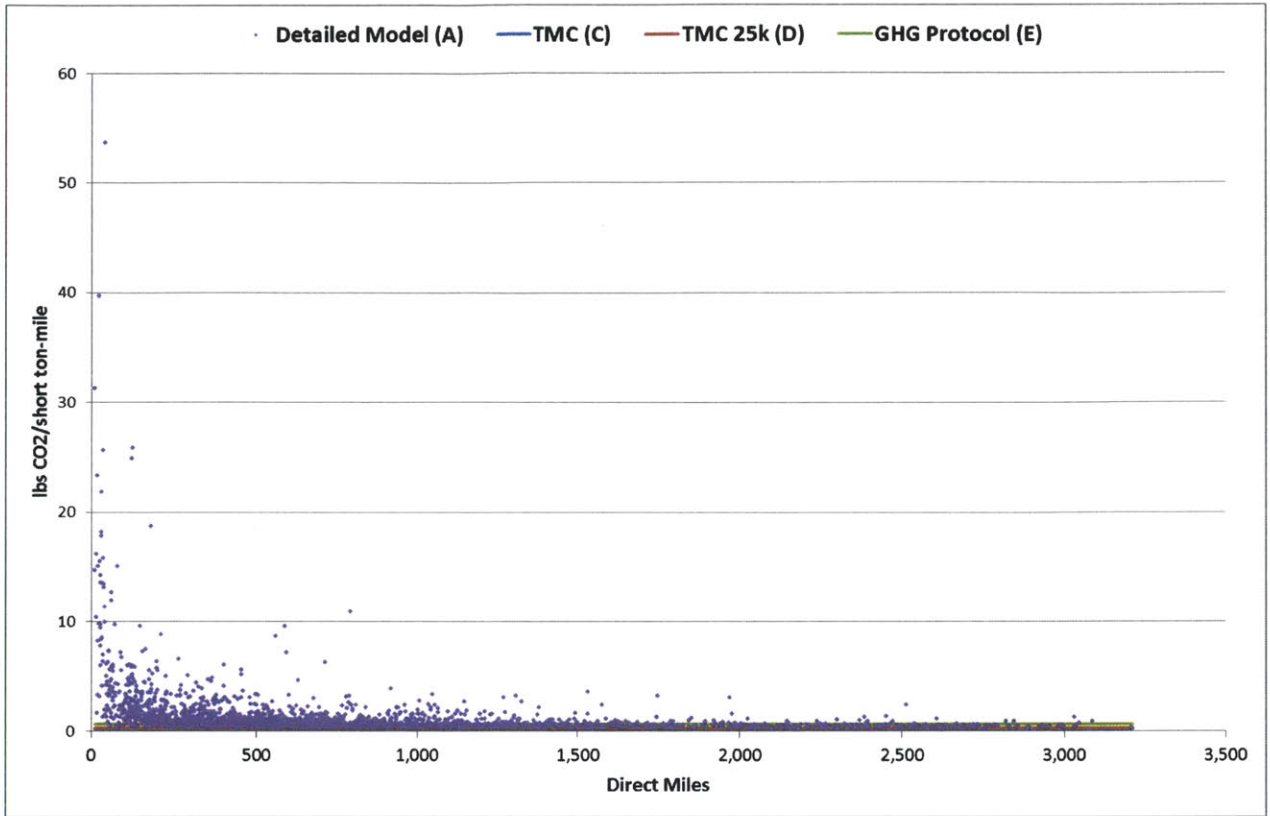


Figure 15 - Comparison of normalized emissions of methods A, C, D and E

In order to better visualize the results for specific distance intervals, Figures 16 and 17 below present the same results from Figure 15, but split into short haul (no more than 300 miles traveled) and long haul (more than 300 miles), respectively. We highlight the difference in the *scale of the vertical axis* of both graphs.



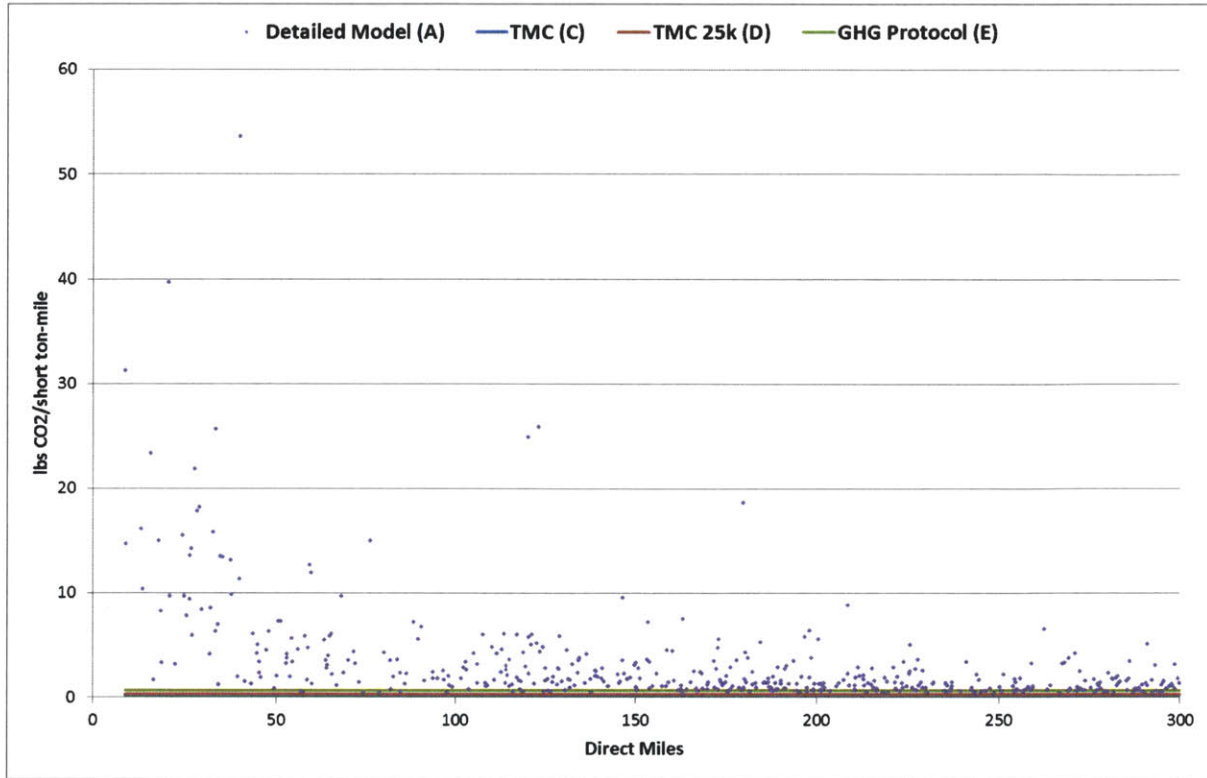


Figure 16 - Comparison of normalized emissions of methods A, C, D and E for short haul

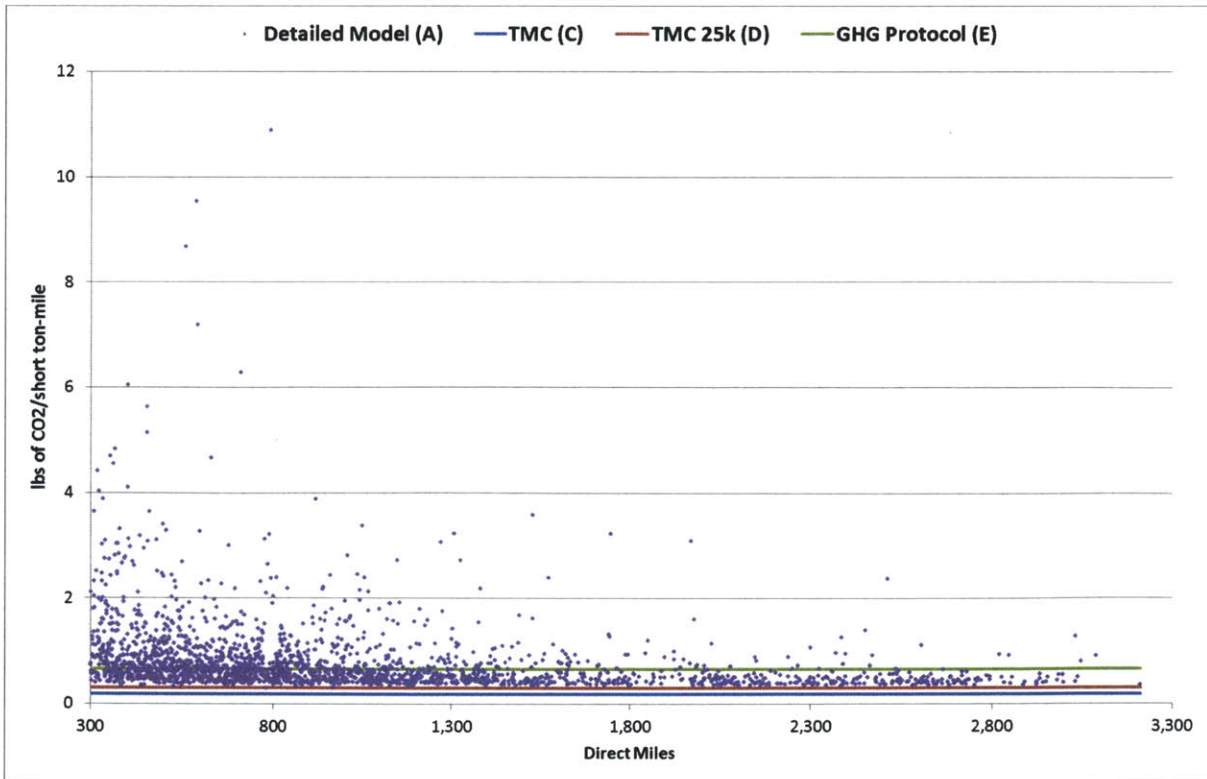


Figure 17 - Comparison of normalized emissions of methods A, C, D and E for long haul

Figures 15, 16 and 17 above provide insights into the behavior of these calculation methods. First, TMC's current formula (method C) presented the lowest results: 0.19 pounds of CO<sub>2</sub>/short ton-mile (without the 1.1 distance correction factor that is sometimes included). Adjusting the load factor from 40,000 pounds to 25,000 pounds (method D) resulted in a 60% increase of the resulting emissions, from 0.19 to 0.30. If other variables remain unaltered, the ratio of the increase in emissions is equal to the ratio of decrease in load factors, which illustrates the impact of this parameter. GHG Protocol's approach (E) yielded 0.65 pounds of CO<sub>2</sub> per short ton-mile, which is almost 3.5 times higher than TMC's initial formula. This approach (E) produced higher results in order to hedge against the fact that data on fuel was not collected.

Second, TMC's formulas (C and D) and GHG Protocol's approach (E) have a *fixed* coefficient of pounds of CO<sub>2</sub> per short ton-mile, regardless of the characteristics of the shipment (they were normalized both by distance and weight, as explained by Equation 10). Our detailed model (A), however, presented much more sensitivity and responsiveness to specific shipment characteristics and demonstrated that, in general, shorter shipments are much *less* efficient than longer ones in terms of emissions per short ton-mile.

One of the main reasons for this behavior was the fact that P&D emissions are taken into account in our method, but not in the comparison ones. Since some of our parameters, such as P&D miles and MPG, changed based on shipment characteristics as explained in sections 4.3.2 and 4.4.1, our detailed model exhibited higher oscillations. This oscillation was especially observed in short distances. The results of our model converged towards the comparison methods for longer distances, when P&D started to have less impact on total emissions, as can be seen by Figures 16 and 17.

Figures 16 and 17 also show that, while the pounds of CO<sub>2</sub> per short ton-mile for short haul were as high as 54, for long haul, they did not go beyond 11. This reinforces the observation that shipments that traveled shorter distances tended to be *less* efficient per short ton-mile than those that traveled longer distances, primarily due to the prevalence of P&D in their total emissions.

We also observed how P&D emissions related to shipment weight. Figure 18 below presents a scatterplot of shipment weights versus the percentage of their total emissions that was represented by P&D operations. These results were all obtained from our detailed model (method A), since the other comparison methods (C, D and E) do not take P&D emissions into account.

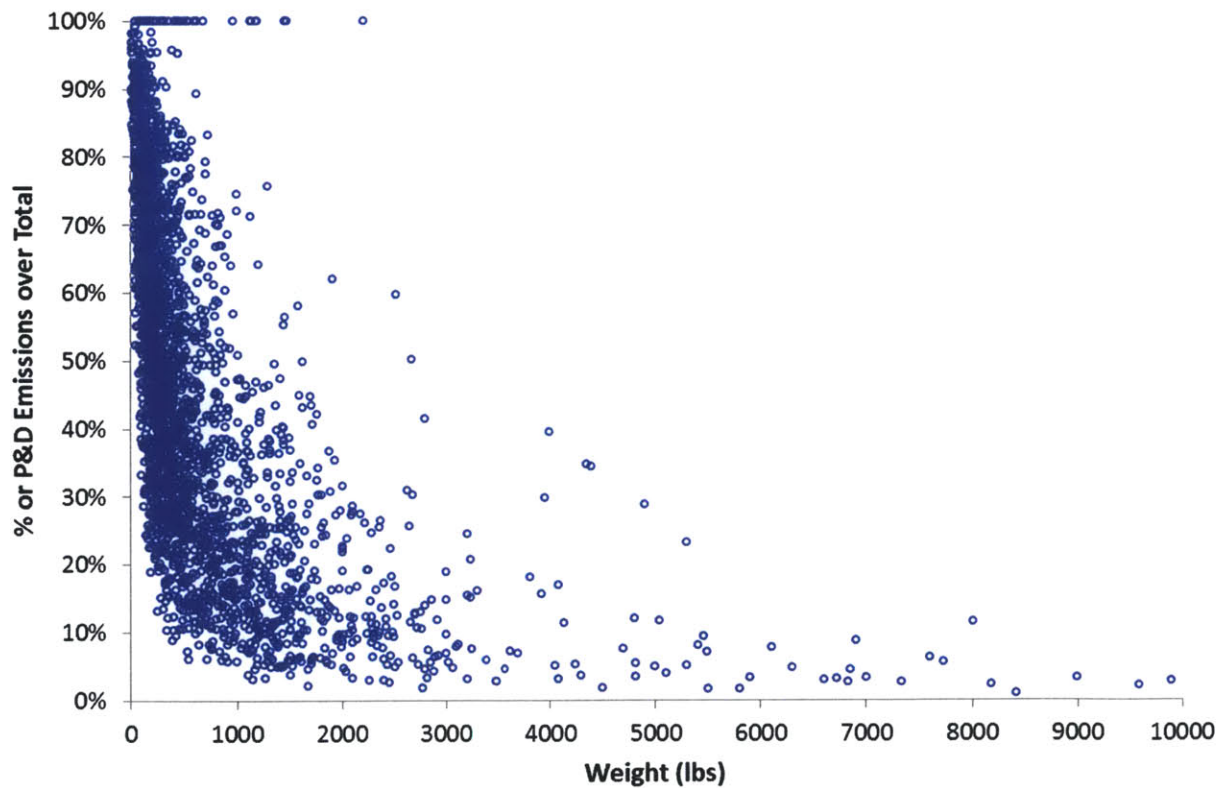


Figure 18 - Percentage of P&D emissions by shipment weight (detailed model)

Figure 18 shows that P&D operations had a high impact on emissions of lighter shipments, but their influence decreased exponentially as shipment weight increased. The main

reason for this was that, as the weights increased, our model allocated more emissions of the line haul section to that shipment, and the P&D emissions became smaller in comparison.

In order to provide better insight into this behavior, Table 10 below presents an example of two fictitious shipments, both being moved from Charlotte, NC (ZIP code 28206) to Nashville, TN (ZIP code 37213), but one with weight of 100 pounds and the other with weight of 3,000 pounds. The resulting emissions were obtained from our detailed model.

Table 10 - Comparison of P&D percentage for different shipment weights

Shipment 1		Shipment 2	
Origin ZIP	28206	Origin ZIP	28206
Destination ZIP	37213	Destination ZIP	37213
<b>Weight (lbs)</b>	<b>100</b>	<b>Weight (lbs)</b>	<b>3,000</b>
Line Haul emissions (lbs CO <sub>2</sub> )	7.3	Line Haul emissions (lbs CO <sub>2</sub> )	219
P&D emissions (lbs CO <sub>2</sub> )	32.2	P&D emissions (lbs CO <sub>2</sub> )	32.2
Total emissions (lbs CO <sub>2</sub> )	39.5	Total emissions (lbs CO <sub>2</sub> )	251.2
<b>% P&amp;D</b>	<b>82%</b>	<b>% P&amp;D</b>	<b>13%</b>

Table 10 above shows that the absolute value of the P&D emissions of both shipments was the same (32.2 pounds of CO<sub>2</sub>), since they had the same origin and destination and were handled by the same terminals. However, the percentage of P&D emissions was much higher for the light shipment (82% of total emissions) than for the heavy shipment (13% of total emissions) because the latter has much higher line haul emissions than the former, which reduces the relative impact of P&D emissions.

The few shipments on the top-left corner of Figure 18 that displayed 100% of emissions being originated from P&D were those that moved between two ZIP codes that were in the servicing area of the same terminal. In this case, since there was only one terminal involved,

there were no line haul emissions at all; all resulting emissions were those generated from P&D operations.

As an additional analysis, Table 11 below shows how far shipments of different weights would have to travel in order to have the P&D emissions equal the line haul emissions. It should be noted that shipment 1 used the load factor for long haul operations while shipments 2 and 3 used the load factor for short haul operations. The number of P&D miles was determined as an average across a single four-week period of shipment data solely for comparison purposes.

Table 11 - Comparison of mileage for shipments of different weights but same emissions

<b>Item</b>	<b>Shipment 1</b>	<b>Shipment 2</b>	<b>Shipment 3</b>
Weight	<b>100</b>	<b>1,000</b>	<b>10,000</b>
Line haul miles	<b>2,235</b>	<b>201</b>	<b>20</b>
P&D miles	5.2	5.2	5.2
Line haul emissions	36.7	36.7	36.7
P&D emissions	36.7	36.7	36.7
Total Emissions (Lbs CO2)	<b>73.4</b>	<b>73.4</b>	<b>73.4</b>
% of Emissions LH	<b>50%</b>	<b>50%</b>	<b>50%</b>
% of Emissions P&D	<b>50%</b>	<b>50%</b>	<b>50%</b>

Table 11 reveals that a shipment with weight of 100 pounds could travel 2,235 miles of line haul and it would have the same emissions as a shipment of 10,000 pounds traveling only 20 miles of line haul. This illustrates the impact that shipment weight had on resulting emissions from line haul, which in turn affected the relative importance of P&D emissions.

Finally, Table 12 below presents a summary of the results of the four methods (A, C, D, and E) for the sample of 2,700 shipments moved by Estes Express. Values are in pounds of CO<sub>2</sub>.

Table 12 - Summary of results of methods A, C, D and E for sample of shipments

Item	A - Detailed Model	C - TMC's current formula	D - TMC's adjusted formula	E - GHG Protocol
Total Emissions	370,285	140,435	224,697	486,425
Total Line Haul Emissions	268,359	140,435	224,697	486,425
Total P&D Emissions	101,925	0	0	0
P&D Percentage	28%	0%	0%	0%
<b>% Difference of Total</b>	<b>BASE</b>	<b>-62%</b>	<b>-39%</b>	<b>31%</b>

Table 12 reveals that P&D emissions accounted for 28% of the total emissions according to our detailed model. The comparison methods do not account for any P&D emissions. Also, TMC's current formula yielded total emissions 62% lower than our detailed model, while TMC's adjusted formula yielded results 39% lower than ours. The difference between these two was solely caused by the change in the load factor from 40,000 pounds to 25,000 pounds, which represents its importance. GHG Protocol's freight transportation approach yielded total emissions 31% higher than the ones obtained from our detailed model. These results reinforce the pattern observed in Figure 13 that our emissions tended to be between those of TMC's current formula and GHG Protocol's freight transportation approach, except for short distances.

### 5.2.2. Low-precision Generic Model

This analysis was focused on roughly 8,400 shipments of the set provided by TMC that were moved by other carriers besides Estes. The methods compared were B, C, D and E, as described in Table 9. Our detailed model for Estes (method A) was not applied here since Estes did not move any of these shipments.

The analysis for the low-precision model was conducted in the same way as for the detailed model, presented in the previous section. Figure 19 below shows the total emissions for methods B, C, D, and E. We also present the total emissions for short haul on Figure 20 below.

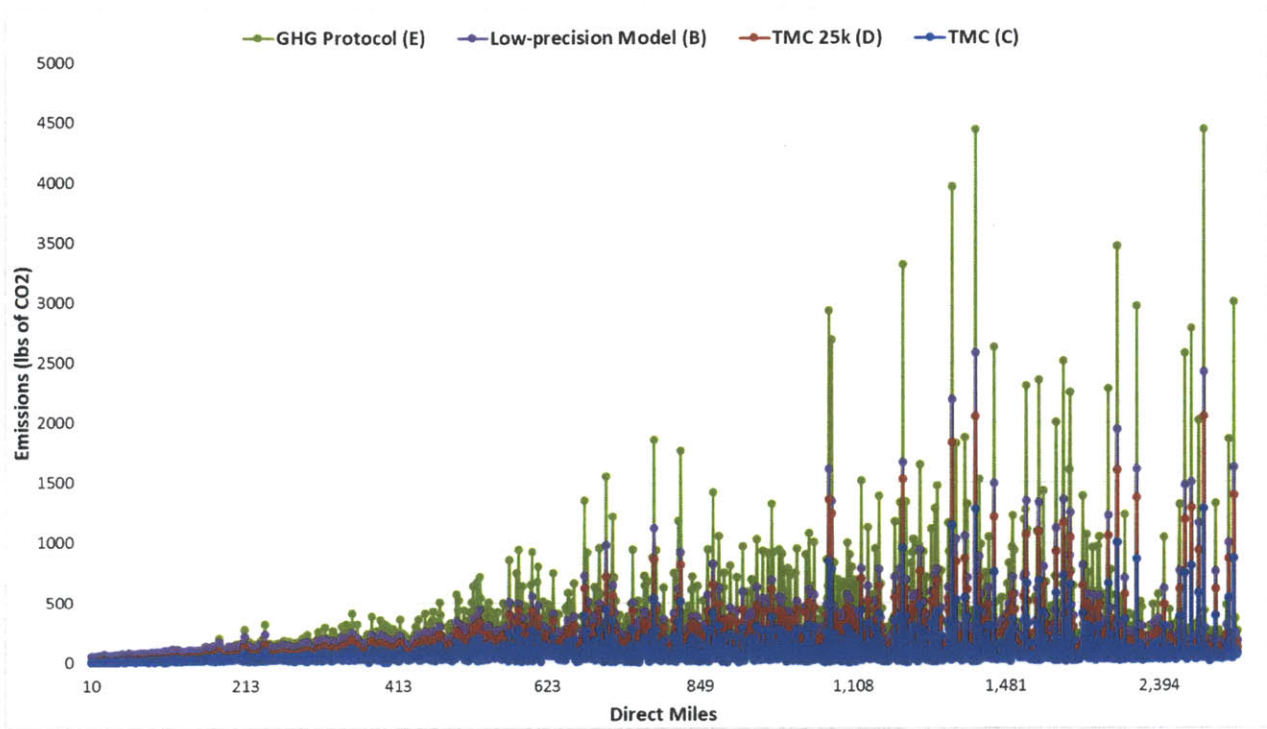


Figure 19 – Comparison of total emissions of methods B, C, D and E

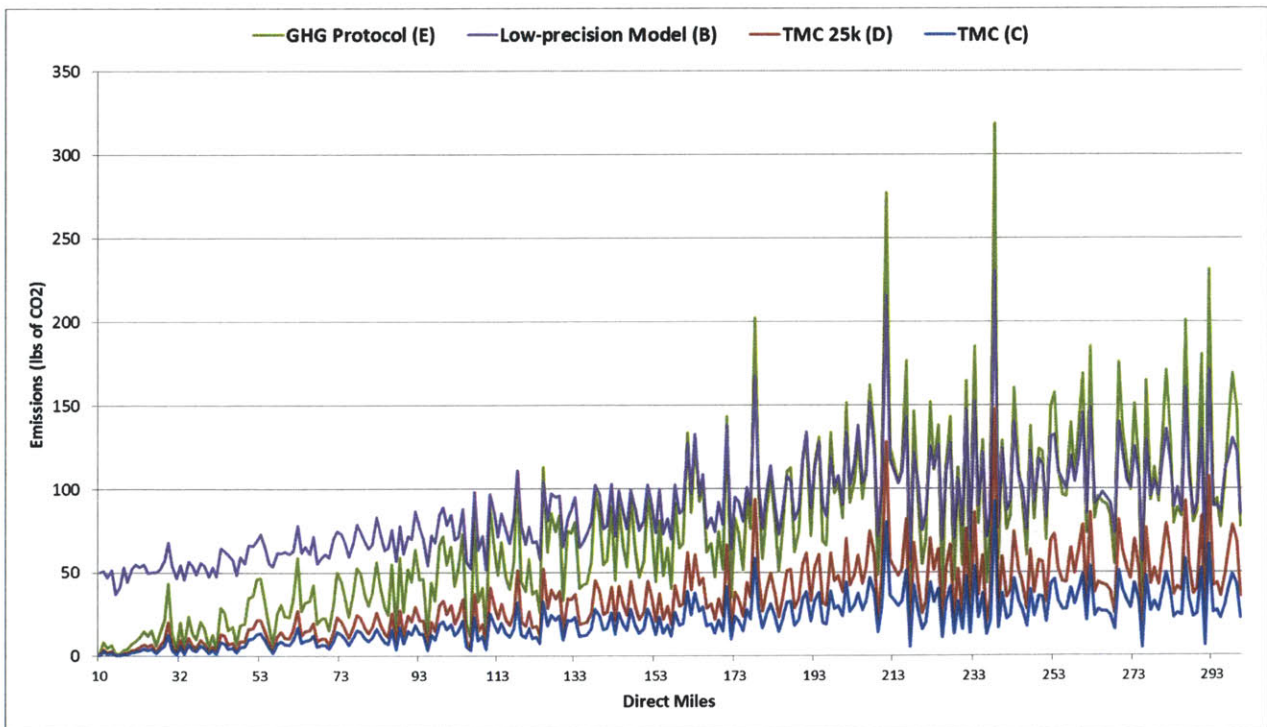


Figure 20 – Comparison of total emissions of methods B, C, D and E for short haul

Figure 19 shows that the results of our low-precision model tended to fall between those of TMC's adjusted formula and the GHG Protocol's freight transportation approach, except for short distances. This behavior is similar to the one of the detailed model, shown in Figure 13.

For short distances, Figure 20 reveals that the resulting emissions from our low-precision model were higher even than those from the GHG Protocol's approach. This, again, was primarily caused by the emissions from P&D operations, as the comparison methods do not take them into account at all. As the distance increased, however, the emissions from P&D became less relevant, and the results from our model fell in between those of TMC's formula and GHG Protocol's approach. These findings were also analogous to the ones from the detailed model, shown in Figure 14.

For further comparisons, Figure 21 below presents the results of methods B, C, D and E in terms of normalized CO<sub>2</sub> emissions by distance traveled. The distances on the horizontal axis are represented in direct miles to facilitate the comparisons.



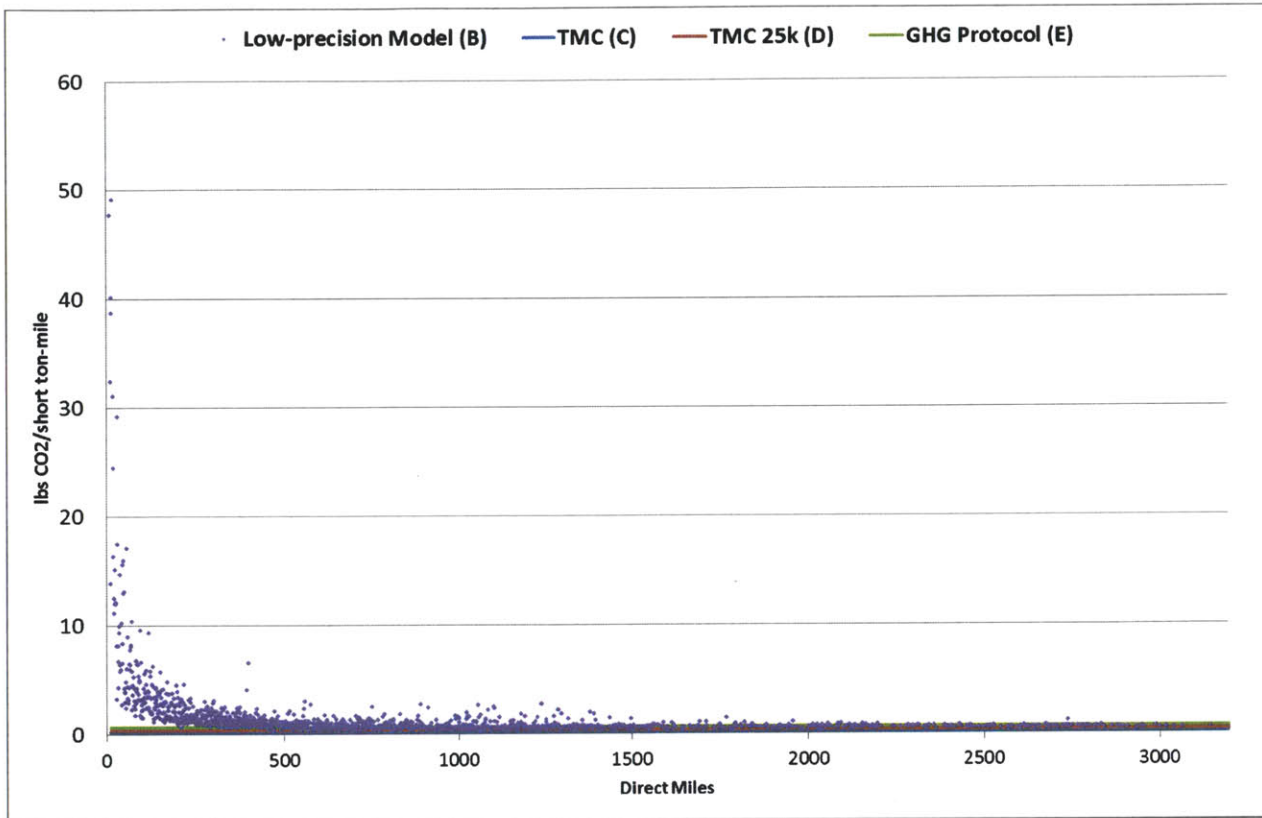


Figure 21 - Comparison of normalized emissions of methods B, C, D and E

The overall behavior displayed in Figure 21 is the same as the one shown in Figure 15 for the detailed model. Methods C, D and E did not present any changes, since they do not take the carrier’s network into account in any way; the only changing parameters are the shipment’s weight and distance traveled. Our low-precision model also displayed high oscillations in the normalized emissions for short distances, which were highly influenced by P&D operations, but as the distance increased, the magnitude of the oscillations was reduced and the results of our model converged towards those of the comparison methods.

However, the low-precision model displayed lower oscillations than the detailed model for short haul distances. This was due to the fact that, since in the low-precision model the carrier’s network was unknown, the number of P&D miles was determined by region, not by terminal. Since there were only six regions (as explained in section 4.3.2), there were only six

possible values for P&D miles. The detailed model, on the other hand, assigned a number of P&D miles for *each terminal* based on data provided by Estes, which added to the accuracy, but also to the variability of the results.

Figures 22 and 23 below present the same results from Figure 21 for our low-precision model, but split into short haul (no more than 300 miles traveled) and long haul (distances greater than 300 miles), respectively. Once again, we highlight the difference in the *scale of the vertical axis* of both graphs.

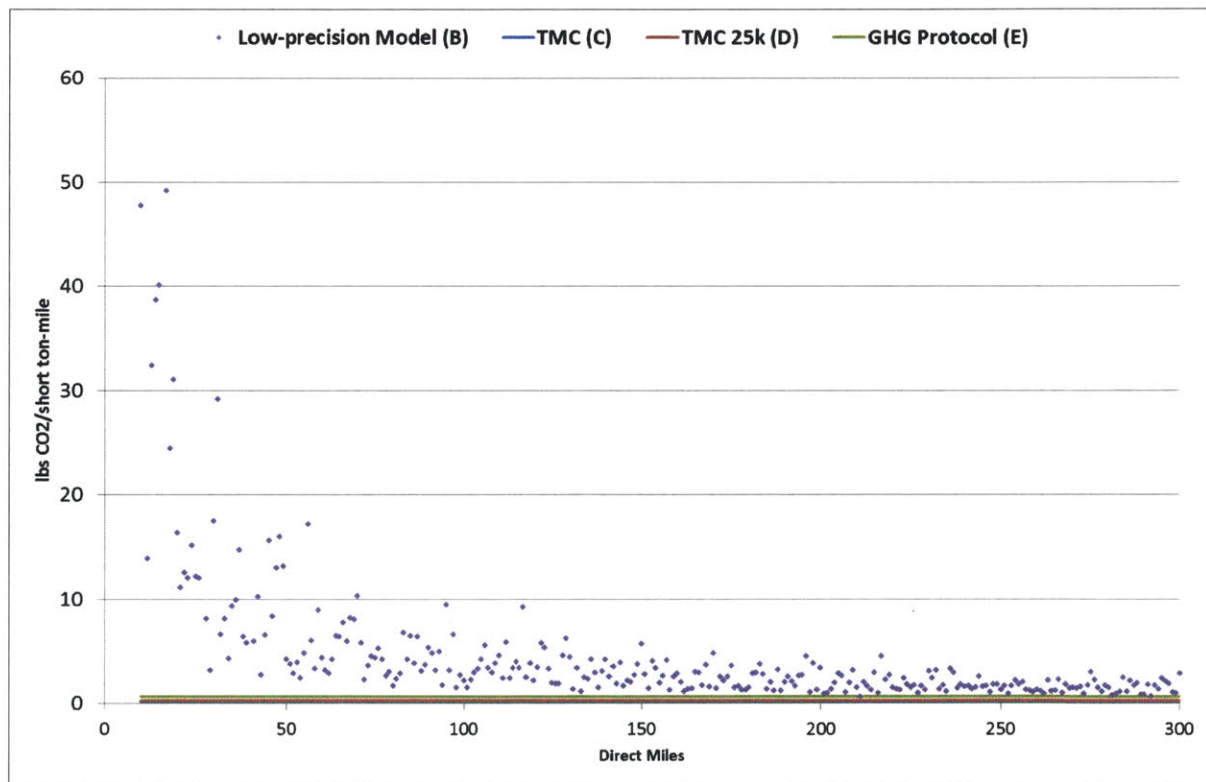


Figure 22 - Comparison of normalized emissions of methods B, C, D and E for short haul

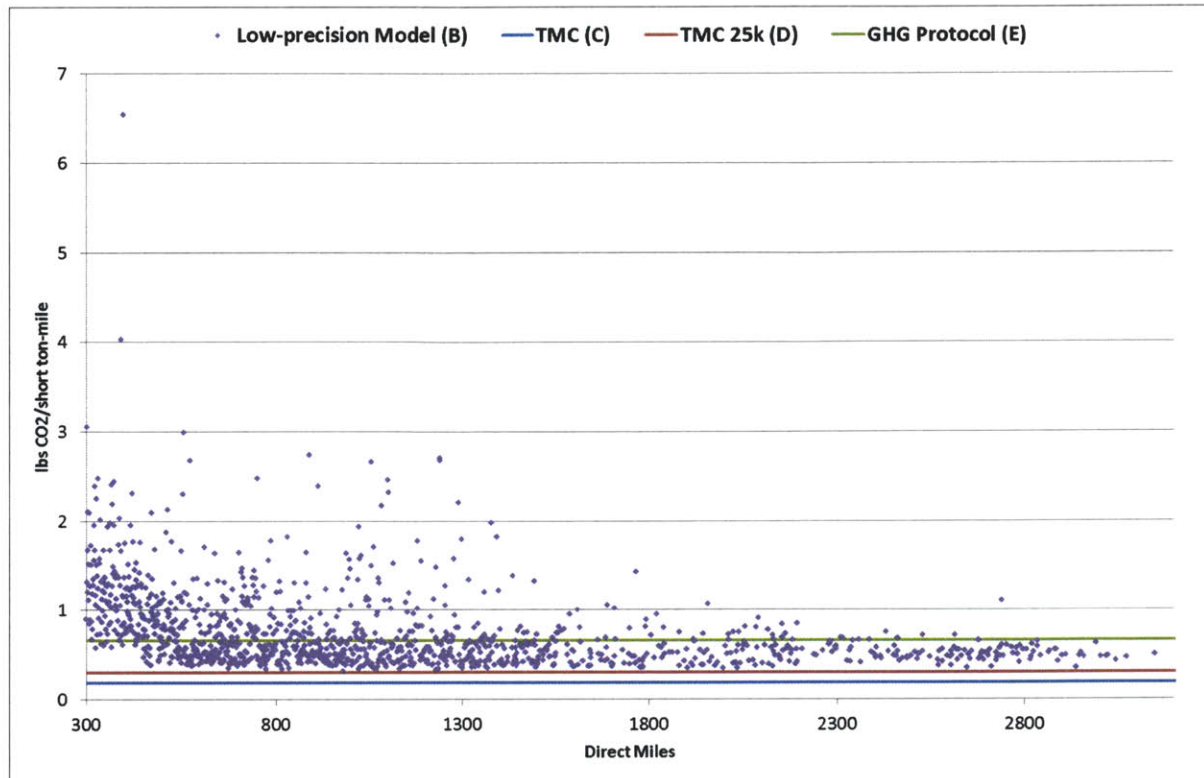


Figure 23 - Comparison of normalized emissions of methods B, C, D and E for long haul

The maximum resulting normalized emissions for the short haul were around 50 pounds of CO<sub>2</sub> per short ton-mile, while they did not go beyond seven for the long haul. Once again, the convergence towards the comparison methods was observed for longer distances.

We also performed the same analysis as for the detailed model in terms of how P&D emissions related to shipment weight. Figure 24 below presents the percentage of total emissions represented by P&D based on shipment weight. These results were obtained from our low-precision model (method B), since the other comparison methods (C, D and E) do not take P&D operations into account.

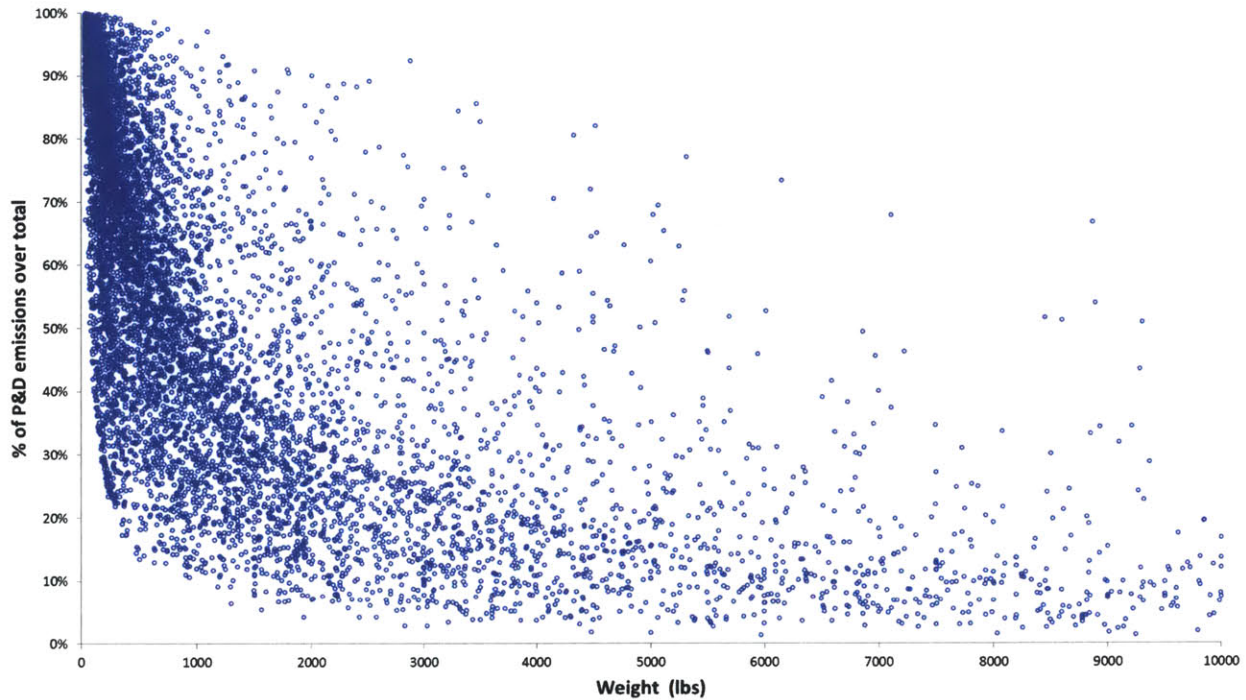


Figure 24 - Percentage of P&D emissions by shipment weight (low-precision model)

The pattern observed in Figure 24 is the same as from the detailed model: the relevance of P&D on total emissions decreased exponentially as the shipment weights increased (Table 10 provided an example of this behavior). It is worth highlighting that the low-precision model did not present as many shipments with 100% of P&D emissions as the detailed one did (Figure 18). Since the carrier's network was unknown, shipments did not get assigned to any terminals, as there was no information about servicing areas. Because of this, even if origin and destination ZIP codes were close to each other, the low-precision model still calculated a small amount of line haul distance between them.

Finally, Table 13 below presents a summary of the results of methods B, C, D and E for the sample of roughly 8,400 shipments. Emissions are in pounds of CO<sub>2</sub>.

Table 13 - Summary of results of methods B, C, D and E for sample of shipments

Item	B - Low-precision Model	C - TMC's current formula	D - TMC's adjusted formula	E - GHG Protocol
Total Emissions	1,180,457	439,598	703,357	1,522,636
Total Line Haul Emissions	811,865	439,598	703,357	1,522,636
Total P&D Emissions	368,592	0	0	0
P&D Percentage	31%	0%	0%	0%
<b>Comparison of Total Emissions</b>	<b>BASE</b>	<b>-63%</b>	<b>-40%</b>	<b>29%</b>

Table 13 reveals that P&D accounted for 31% of the total emissions according to our low-precision model (as opposed to 28% for the detailed model). Again, it is worth highlighting that the comparison methods do not account for any P&D emissions. Also, TMC's current formula yielded total emissions 63% lower than our low-precision model, while TMC's adjusted formula yielded results 40% lower than ours. The GHG Protocol's freight transportation approach resulted in total emissions 29% higher than the ones obtained from our low-precision model. These numbers are very similar to the ones obtained from the detailed model (Table 10) and reinforce the pattern observed in Figure 19 that our emissions tended to be between those of TMC's formulas and GHG Protocol's freight transportation approach.

### 5.2.3. Comparison between Detailed and Low-precision Models

As an additional assessment of our approaches, we compared the results from our detailed and low-precision models when applied to the *same* set of shipments. The set on which we conducted this analysis was the one with 2,700 shipments that were moved by Estes, used in section 5.2.1. We inserted these same shipments into the low-precision model in order to assess the differences in the results if we assume we don't have information about the carrier's network, as opposed to knowing that they were moved by Estes Express.

A summary of the total emissions from both our detailed and low-precision models is presented in Table 14 below. The total emissions for both models are also presented in Figure 25.

Table 14 - Comparison of results from detailed and low-precision models for same set of shipments

Item	A - Detailed Model	B - Low-precision Model
Total Emissions	370,285	382,692
Total Line Haul Emissions	268,359	266,355
Total P&D Emissions	101,925	116,338
P&D Percentage	28%	30%
<b>Comparison of Total Emissions</b>	<b>BASE</b>	<b>3.4%</b>

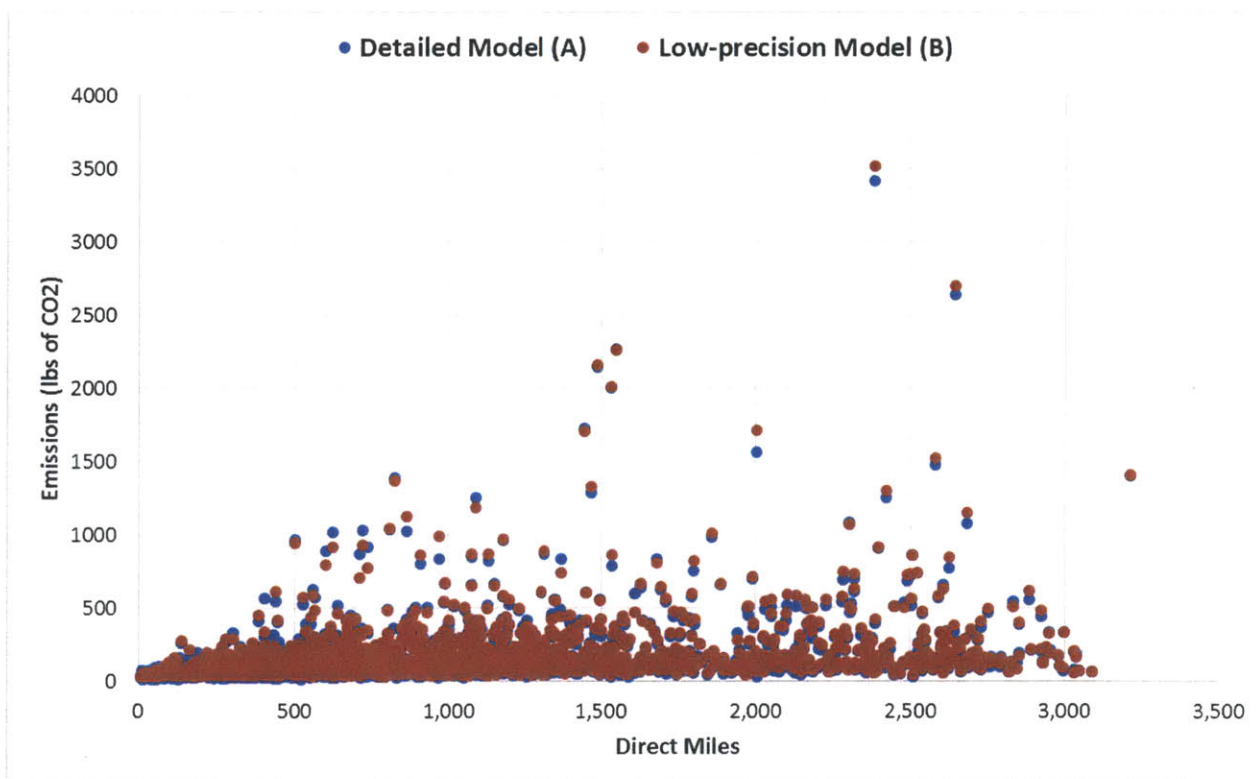


Figure 25 - Total emissions from detailed and low-precision models for same set of shipments

Table 14 shows that the results obtained from our two models were very similar *on aggregate*: the low-precision model resulted in total emissions only 3.4% higher than the

detailed model. It is worth highlighting that line haul emissions were actually *lower* for the low-precision model, but P&D emissions were 14% higher and offset the lower emissions from line haul.

The differences in results can be explained by the fact that (1) our low-precision model always calculated distances using our regression models (described in section 4.3.1) instead of using historic shipped distance data when it was available; (2) line haul distances were calculated between the origin and destination ZIP codes instead of the actual terminals servicing those ZIP codes; and (3) P&D mileage was aggregated by region instead of being determined for each specific terminal.

However, while the aggregate results from both our models were very similar, we looked at how estimates for individual shipments differed between the two and the variations were much more significant. Figure 26 below presents a histogram of the differences in terms of percentage.

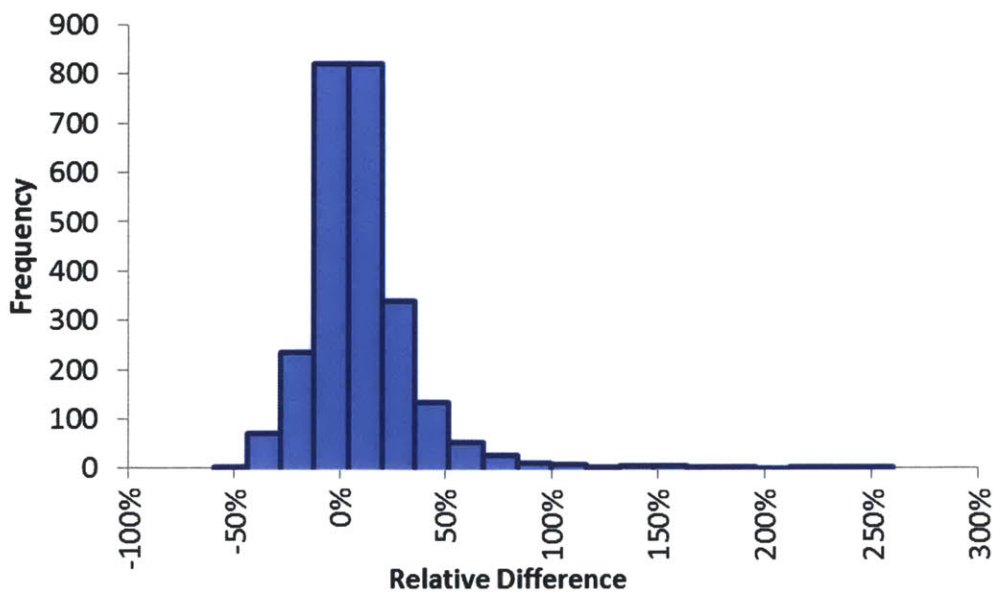


Figure 26 - Histogram of differences between low-precision and detailed model results

Figure 26 reveals that, while the aggregate results were very similar, individual estimates could be different by as much as 250% on some very specific cases. Still, about 85% of the shipments displayed differences between -30% and 30%.

Therefore, we observed that our low-precision model provided very good approximations of total emissions when compared to the detailed one, especially on aggregate level. However, for estimations of individual shipments, differences could be more noticeable and the detailed model should overall be preferred whenever information is available.

### 5.3. Limitations of Our Approach

While we believe the methodology we developed in this thesis is successful in providing a way to better estimate carbon emissions from individual LTL shipments, we also acknowledge that there are limitations to the approach we adopted.

First, our method relies on using only weight for the allocation of emissions from line haul without taking class, volume or density information into account. This approach potentially penalized dense shipments more than what would be ideal. As an example, in some specific lanes with high concentration of low density shipments, volume may be a much better proxy for emissions allocation than weight. The main challenge in addressing this issue was related to the accessibility and reliability of information regarding shipment volume and density, since weight is usually a much better tracked variable by carriers.

We also relied on overall network load factors for our emissions allocation, as opposed to lane-specific load factors. A lane-specific approach would provide insights into how different lanes and regions of the network focus on diverse types of freight and display different efficiency figures. Since we were not able to link individual shipments to specific trucks in order to understand how these shipments were grouped together inside a trailer, we relied on network-



wide load factors. While they are a good representation of a carrier's overall operations, some specific lanes may have a different profile, which would impact the resulting emissions.

Additionally, our approach to P&D was also limited by data availability and reliability issues. A better approach to the P&D portion of the movement may only be possible once more detailed information about these operations is collected and made available by carriers.

Finally, our approach to empty miles was simplified. It was not the focus of this thesis to specifically address this issue and study how this extra distance should be allocated to single shipments. There is a high degree of complexity in the dynamic of empty miles in a carrier's network, as the numbers often change across regions and seasons according to shifts in the supply and demand of different types of freight and local characteristics such as population and road density. While we did not focus on addressing this topic, we did account for empty miles through a simplified approach, since they are one possible indicator of a carrier's overall network efficiency. Therefore, we considered empty miles as a "penalty" to a shipment's distance and emissions, which in turn incentivizes carriers to work on ways of reducing them.

## 6. CONCLUSION

The purpose of this thesis was to develop a methodology to estimate carbon emissions from individual LTL shipments while considering the complexities of a typical LTL network. In order to achieve this goal, we developed two models: a detailed one, based on Estes Express Lines' network and operations, and a low-precision one, for the case when the carrier's network characteristics are unknown. These models provide a contribution in terms of better estimating carbon emissions from individual LTL shipments with minimal inputs.

While initiatives such as the GHG Protocol, through its Mobile Source Guidance, and the EPA, through its SmartWay program, provide guidance on how to estimate carbon emissions from transportation activities in general, they do not specifically address how the complexities of an LTL network can be taken into account when estimating the emissions from LTL shipments.

These initiatives also focus on corporate-level accounting, as opposed to shipment-level calculations. Because of this, there is an important consideration to be made in terms of how 3PLs can impact the resulting emissions of movement by better matching loads to more efficient carriers. Relying solely on corporate-level reports to compare different carriers may not be the ideal approach, even though it is a good starting point, because some carriers may be more carbon-efficient overall as a corporation, but less efficient than some of their competitors on specific regions and lanes or to move certain types of shipments. This differentiation is only possible if the emissions of each shipment are compared at the individual level, as opposed to comparing the emissions of carriers as a whole.

We also found from our research that the existing estimation tools we analyzed tended to underestimate the carbon emissions from LTL shipments, especially for short distances and light freight. Even the GHG Protocol's freight transportation approach, which yielded overall

emissions 30% higher than our models, underestimated the emissions from short-distance and light shipments. We believe this happened primarily for two reasons: (1) these methods rely on direct over-the-road distances as opposed to actual LTL shipped distances, which must include all the intermediate stops; and (2) they fail to factor in the pick-up and delivery (P&D) sections, focusing solely on line haul operations between the first and the last terminals. We found that P&D operations were responsible for 28% to 31% of total emissions on our models.

Additionally, we observed that load factors are a very important parameter when estimating carbon emissions from LTL shipments. It is essential to acknowledge that load factors from LTL operations are usually significantly lower than those of full truckload, and this has a substantial impact on the resulting emissions. Also, while an overall load factor for a carrier's entire network is a good starting point, analyzing factors by specific lanes or regions can add accuracy to the estimates.

We were also able to assess the power of detailed information. By developing two separate models, a detailed one and a low-precision one, we were able to compare the results of the two approaches and understand their differences. We observed that the aggregate results from both approaches were very similar: the low-precision model yielded total emissions only 3.4% higher than the detailed one, as shown in section 5.2.3. However, estimates for individual shipments displayed much more variability, with the low-precision model yielding results 250% higher than the detailed one in very specific cases. Still, about 85% of all shipments displayed differences between -30% and 30% the estimates of the two models.

Therefore, we believe both our approaches captured more of the dynamics of LTL shipments than other current methods, providing more representative estimates of emissions. The low-precision model provided a good approximation for when detailed information about a

carrier's network is not available, especially for aggregate emissions of multiple shipments, but the detailed model should be preferred particularly for estimates of individual shipments.

Finally, we noticed from our research that, when developing a methodology to estimate carbon emissions from LTL shipments, it is important to consider the depth of the proposed solution, the consistency of the numbers obtained and, perhaps most importantly, how comparable the numbers are across different companies, regions or industries. This is only possible through extensive data analysis that allows the different dynamics of a certain activity to be captured. We observed that data availability is often a limiting factor in the development of more sophisticated solutions.

### 6.1. Suggestions for Future Research

While we believe our research provides an improved methodology for better estimating carbon emissions from LTL shipments, we acknowledge that there are many opportunities for further research and development.

One important topic that deserves further analysis is how to account for shipment class, volume and density information in the process of allocating total emissions to individual shipments. These characteristics of a shipment may provide more realistic results than allocating emissions based purely on weight in some cases, especially for low-density shipments.

Also related to shipment characteristics, analyzing load factors by region or by lane, as opposed to using an overall value for the entire carrier network, can provide valuable insights into how the emissions may vary across different regions. For example, in lanes that focus on moving lighter shipments, a lower load factor would result in higher emissions for individual shipments. Using an overall load factor for the whole network can mask some of the less efficient lanes while penalizing the most efficient ones.

P&D operations demonstrated to have a significant impact on emissions and also deserve further analysis. One of the main challenges to further assessing the impact of P&D operations is related to data issues, since detailed information is often unavailable or unreliable. However, we expect to see improvements in the visibility of P&D operations as communication technologies improve and become more widely used, which will progressively allow carriers to better track their own operations.

Finally, a more advanced analysis would consider how LTL carriers may operate in order to minimize their resulting emissions. This analysis, however, requires that LTL emissions be measured in a consistent and comparable way so that they may be used as the basis for adjustments in a carrier's operations. We believe this thesis may provide the starting point for moving in this direction.

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