Old Lamps for New: Choosing Shipping Mode with a Carbon Emission Constraint

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Abstract

Decisions on the freight mode to use (and consequently, inventory) significantly impact the carbon footprint of the product. This paper explores the mode-choice problem when a voluntary carbon constraint is imposed. Slower transport modes like inland waterways and ocean freight are cheaper and likely have lower green house gas (GHG) emissions, but also necessitate higher inventories. On the other hand, faster modes like LTL-shipping are quick, warrant lower inventories but are expensive, and have higher GHG emission levels. Deciding on the appropriate mode to use is a tradeoff between the uncertainty of demand and lead time, the cost to transport, and GHG emission levels of transportation and warehousing. This paper presents a comprehensive inventory-transportation framework to explore these tradeoffs. Our model uses a stochastic demand and lead-time setting providing a realistic framework for deciding on mode choice.

Keywords: Freight mode choice, GHG emissions, inventory-transportation tradeoff

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1. Introduction

The fourth assessment of the Inter Governmental Panel on Climate change (IPCC) reports that[3]:

> "Warming of the climate system is unequivocal, as is now evident from observations of increases in global average air and ocean temperatures, widespread melting of snow and ice and rising global average sea level."

Since the 1750s, atmospheric concentrations of carbon dioxide have risen from about 280 to 379 parts per million (ppm) in 2005. This increase is largely the result of large-scale supply chains to sustain modern economies and lifestyles. Big contributors to greenhouse gases (GHG) emissions are energy use to run industrial processes, generate electricity, transport goods, and heat and cool residential and industrial structures. To mitigate the effects of global warming, the IPCC estimates that emissions to be reduced by 50% by 2050 and by 80% by 2080.

The premise of this paper is that by including GHG emission considerations into common decisions that supply chain managers frequently make, we can provide strategies and policies to reduce GHG emissions in the supply chain.

In this paper, we focus on the choice of the appropriate freight mode to use (like truck, rail, intermodal, etc.). The transportation sector is a significant contributor to GHG emissions. In the United States, for example, transportation accounts for 28% of all GHG emissions – and over half of

[3] see ipcc.ch

these emissions are from movement of freight[4]. Decisions on the appropriate freight mode to use (and implicitly the amount of inventory to hold) significantly impact the GHG emissions of a firm. In the United States, there are no "hard" constraints on GHG emissions from transportation or from warehousing. Firms that mitigate GHG emissions do so voluntarily. Current reasons for carriers and firms who hire them to mitigate GHG include satisfying stakeholder expectation of being "green"; reducing fuel usage and the associated cost; staying ahead of any potential climate change legislation; and mitigating risk (mainly the availability and price of fuel) in the supply chain.

The freight-choice problem – or the trade-off between inventory and transportation has a long history in the logistics and supply chain literature (see Baumal and Vinod, 1970; Tyworth, 1991 and the references within for a comprehensive review). The key idea is that while slower modes of transport necessitate higher cycle, safety, and in-transit cost, they are also cheaper to use. The conventional wisdom is that as freight volume gets higher, firms shift to slower and higher capacity modes. While research streams on sustainability has grown significantly in the last decade (see for example, Guide and Van Wassenhove 2006a & b; and Boone et. al. 2012), only recently have carbon constraints been part of generic-inventory logistics theoretic frameworks (Bonney and Jaber, 2011; Benjaffar et. al., 2013). The impact of GHG emissions have either been included as a cost (per unit of emission) or as a constraint on firm operations. Hua et. al. (2011) provide an inventory

[4]From http://www.epa.gov/climatechange/ghgemissions/sources/transportation.html, accessed September 15, 2014.

model, based on the EOQ model, to compute order quantity under carbon trading schemes. Hoen et. al. (2014) provide a freight-choice model in the context of an order-up-to policy that includes a carbon emission cost per unit as part of the cost function. They conclude that emission costs do not have a significant impact on mode choice. However, a cap on emissions may necessitate a significant increase in cost.

This paper adds to the growing research stream on carbon-mitigation by providing a model for freight-choice with voluntary carbon emission constraints. Our model is unique in multiple ways. First, it uses a continuous-review reorder-point stochastic inventory control context to compute the optimal lot size, reorder point, and mode choice for a given set of product and freight mode characteristics. Second, the model uses a comprehensive inventory-transportation cost framework, encompassing the cost of ordering; holding cycle, safety and in-transit inventory; and finally the cost of transportation. Third, we use emissions from transportation and warehousing as a voluntary constraint – these emission levels are motivated by well-established protocols such as the GHG protocol.

The paper is organized the following way. Section 2 introduces the notation and develops the cost model. In Section 3 are some observations on how the emission constraint impacts the mode-choice decision. Section 4 gives a numerical illustration which is based on our experience with a common carrier. In Section 5 we present our conclusions and directions for future research.

2. Model Development

Notation

Decision Variables:

- Q = Order size from supplier. This will also determine the freight mode that is used.
- r = Reorder quantity.
- m = Choice of freight mode.

Variables and constants:

- λ = Yearly demand
- u = Daily demand, a random variable with mean μ_d and standard deviation σ_d
- m = index representing mode. Typical mode choices include Less-than-Truckload (LTL), Truckload (TL), Intramodal (TOFC/COFC), Railcar, and Air freight
- L_m = Lead time for mode m, a random variable with mean μ_m and standard deviation σ_m
- D_{ltd} = Lead time demand a random variable with mean μ_{ltd} and standard deviation σ_{ltd}
- w = Weight of the product
- S = Ordering cost

- h = Inventory cost per unit of inventory per year
- ρ = Desired service level
- $\eta(r)$ = Backorders per replenishment cycle
- π = cost of backordering one unit
- D = Distance the freight is moved
- $TC_m(Q, D)$ = Transportation cost for a given mode m moving a lot size Q a distance D.
- M = Freight movement expressed in weight-distance. If Q units are moved a distance D, then $M = QwD$
- $f_{m,T}$ = Efficiency of freight mode m expressed in weight-distance per unit of fuel.
- e_T = Emission factor of an unit of fuel
- e_I = Emission factor per unit of product held in inventory.
- C_B = The carbon emission budget for the year

Model Context

The context of our model is a firm that faces an annual demand λ. The daily demand u is a random variable. The firm continuously monitors the inventory levels at the warehouse and based on a chosen service level ρ, places an order for Q units from the supplier when the inventory level falls below a critical level r. The firm is also deciding on the choice of freight mode, i.e., how the lot-size will be shipped. The freight mode m has an uncertain lead-time L_m, assumed to be a random variable. The firm also tracks its emissions related to freight and warehousing operations. The firm has voluntarily imposed a constraint on emissions of GHG to a level C_B. The overall objective is to find the optimal levels of Q, r, and m that minimizes the total cost of ordering, holding inventory, and transportation cost. The solution must satisfy service and emission constraints, in addition to restrictions on mode capacity.

Slower transport modes like inland waterways and ocean freight are cheaper and likely have a lower transport-related GHG emissions, but also necessitate higher cycle, safety, and in-transit stocks, making inventory costs (and the corresponding carbon emissions from inventory) higher. On the other hand, faster modes like LTL-shipping are quick, warrant lower stock (and lower warehouse-related emissions) but are expensive, and on average, have higher GHG emission levels during transport. Deciding on the appropriate mode to use is a tradeoff between the uncertainty of demand and lead time, the cost to transport, and GHG emission levels of transportation and warehousing.

Model

The key objective of the model is to find Q, R, and m to minimize the expected total annual cost, $ETAC$:

$$\begin{aligned} ETAC(Q, r, m) &= \lambda/Q * S + [Q/2 + (r - \mu_{ltd}) + \lambda * \mu_m/d]h \\ &+ \eta(r) * \lambda/Q * \pi \end{aligned}$$

$$+ \quad TC_m(Q, D)\lambda/Q \tag{1}$$

subject to:

$$\eta(r) \leq Q(1-\rho) \tag{2}$$

$$M/f_{m,T}e_T * \lambda/Q + [Q/2 + (r - \mu_{ltd})]e_I \leq C_B \tag{3}$$

$$Q \leq Q_m \tag{4}$$

$$Q, r \geq 0 \tag{5}$$

The first term in equation(1) is the ordering cost. If Q units are ordered, there are λ/Q replenishment cycles in a year, so the total cost is $\lambda/Q * S$. The second term of the cost function is the inventory holding costs. It is made of three components. The first is the cycle inventory and is denoted by $Q/2$. The second component is the safety stock – the stock held in excess of the mean lead-time demand μ_{ltd} to meet a given service level ρ. The third component is the n-transit inventory – the average stock in transit over the course of the year. Since the total demand is λ, and μ_m/d is the average lead-time in years, the in transit inventory is simply $\lambda * \mu_m/d$. The three components are multiplied by h, the cost of holding an unit for a year. The third term in the cost function is the total backorder cost. $\eta(r)$ is the total number of backorders per replenishment cycle, with each unit backordered costing π. The fourth term is the cost of transportation cost for a given distance and lot size.

The Constraints

Equation (2) is the service level constraint. If ρ is the level of service that is desired, then the planned shortage per replenishment cycle is $Q(1-\rho)$. For a given r, the expected shortage is $\eta(r)$. Equation (3) is the constraint on the total carbon emissions per year. As the ensuing section will show, the total emissions is the sum of the emissions from transportation, given a type of fuel added to the emissions incurred when the product is held in inventory. C_B is the planned or budgeted level of emissions. Equation (4) is the constraint on freight mode capacity, and Equation (5) are the non-negativity constraints on Q and r.

2.1. Computing $\eta(r)$

For a given reorder point r, a freight mode m, and lead-time demand D_{ltd},

$$\eta(r) = \int_r^{\infty} (x-r) D_{ltd}(x) dx \tag{6}$$

Managers often estimate the D_{ltd} from empirical data by observing demand over multiple replenishment periods. Statistically, if mean and standard deviation deviation of both demand and lead-time are known, $\mu_{ltd} = \mu_m \mu_d$; and $\sigma_{ltd} = \sqrt{\mu_L \sigma_d^2 + \mu_d^2 \sigma_L^2}$. The shape of lead-time demand is typically assumed to be normal for fast moving consumer goods (Tyworth and O'Neill, 1999). Researchers use the Gamma distribution for medium to slow moving goods or when lead-times have a long tail. This is often true when using slower modes of transport – chances that shipments are delayed during transit are higher and therefore can result in lead-time demand distributions with longer tails. The Poisson distribution is often used for slow moving items. Table 1 shows how $\eta(r)$ can be computed for different stochastic environments. The lead-time demand (D_{ltd}) can take any of the three forms and the corresponding characteristics of the pdf and computational formulas for $\eta(r)$ are available in the Table (see Boone and Ganeshan, 2001; Silver and Pyke, 1998; Tyworth and Ganeshan, 2001).

Table 1: **Table: Calculating $\eta(r)$ for different Stochastic Environments**

Demand	Normal	Gamma	Poisson
pdf	$g(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$	$\gamma(\alpha,\beta) = \frac{x^{\alpha-1}e^{-x/\beta}}{\beta^{\alpha-1}\Gamma(\alpha)},\ \alpha,\beta \geq 0$	$P(x=k) = e^{\lambda x}(\lambda x)^k/k!, x \geq 0$
Mean	μ	$\alpha\beta$	λ
Standard Deviation	σ	$\alpha\beta^2$	λ
$\eta(r)$	$[f(z) - z(1 - F(z))]\sigma$	$\alpha\beta(1 - G_1(r) - r(1 - G_2(r))$	$\lambda(1 - E_1(r-1) - r(1 - E_1(r))$
Notes	$f(.)$ and $F(.)$ are the pdf and cdf of the standard Normal distribution. $z = (r - \mu)/\sigma$	$G_1(.)$ and $G_2(.)$ are the cdfs of $\gamma(\alpha,\beta)$ and $\gamma(\alpha+1,\beta)$, respectively	$E_1(.)$ is the cmf of $P(.)$

2.2. Calculating Carbon Emissions

For the purposes of this paper, the total emissions are the sum of the emissions from the burning of fuel by thevehicles used for transporting freight; and the emissions from warehousing activities. The emissions are typically reported as carbon -di-oxide equivalents (CO_2e) in weight units (lbs., Kgs., tones, etc). While there is not one universal standard to calculate emissions, most are based on the Green House Gas (GHG) Protocol. The GHG Protocol is a common approach to emissions reporting developed by the World

Resources Institute (WRI) and the World Business Council for Sustainable Development (WBCSD).

Emission of Freight

The most direct method to calculate emissions from freight transport is to measure the fuel that was consumed and multiply it by the emission factor for that particular kind of fuel. If direct fuel usage is unavailable, indirect approaches are used to estimate fuel use. These include estimating fuel use from fuel cost (by using average cost of unit of fuel); or from statistics that most freight operators log – distance and load carried, and then using them in combination with efficiency measures that estimate fuel use from this data. In this paper we assume that the shipper logs distance and load data; and we estimate fuel use using efficiency measures[5]. Once fuel use is known, the emissions can be computed by using the appropriate emission factor for that fuel. Fuel efficiency measures can vary significantly depending on the product being hauled, the equipment hauling it, the geographical location, and load (percent empty and back hauls). In our experience, firms use averages, by mode, over all shipments made in preceding months or years. Table 2 gives average values of efficiency measures for common freight mode-types; and emission factors for common fuels (See IFC International, 2009; EIA, 2014).

It is common among shippers to report freight movement in weight-distance measure (example tonne-km or ton-mile). If D is the distance, with a chosen lot size Q, the movement $M = QDw$ is the weight-distance statistic per replenishment cycle. $f_{m,T}$ is the efficiency of mode m, given the type of

[5]If fuel usage is available, this step can be bypassed

Table 2: **Table: Efficiency and Emission Factors for Common Freight Modes**

Efficiency		**Emission Factors**	
Rail	Ton-miles/gallon Range	Fuel	Kg CO_2/gallon
Double-Stack	226-512	Diesel fuel	10.15
Box Car	406-469	Kerosene/ Jet fuel	9.57
TOFC	273	Aviation Gasoline	8.32
		Biodiesel (B2)	9.94
Truck		Motor Gasoline	8.91
Dry Van	82-110		
Flatbed	112-133		
Container	68-100		
Barge	576		
Ocean Container	575-1043		

fuel T used. It is usually expressed in weight-distance per unit of fuel (for example, tonne-km/liter or ton-mile/gallon). $M/f_{m,T}$ simply computes the total fuel usage per replenishment cycle. The fuel consumption per replenishment cycle is therefore $M/f_{m,T}e_T$. Since there are λ/Q cycles, the yearly emissions related to freight movement is $M/f_{m,T}e_T * \lambda/Q$.

Carbon Emissions of Inventory

The inventory that is delivered from the supplier is assumed to be warehoused. We have assumed that this warehouse is of sufficient size to accommodate inventory from any of the freight modes under consideration. We also assume that the emissions related to inventory is proportional to the energy use – direct or indirect – to maintain the warehouse. This would include electricity, climate control, and moving operations such as fork lifts within the warehouse. We have assessed an emission factor per unit of inventory – as the inventory increases, energy related to maintaining and servicing it also raises proportionally. For many firms, the emissions resulting from transportation operations far outweighs the emissions from warehousing – unless significant energy is expended on warehousing (for example, a large proportion of freezers and special handling circumstances), this component typically has a small impact on mode choice.

The choice of Q and r determines the average inventory in the warehouse. An emission factor e_I is applied to each unit of cycle inventory $(Q/2)$ and the safety stock $(r - \mu_{ltd})$ to compute the emissions related to inventory: $[Q/2 + (r - \mu_{ltd})]e_I$.

2.3. Transport Cost

Freight cost are a function of the mode, class of product, distance, weight, and volume. In this paper, we model transportation as a function of the lot size Q, the weight w, and distance d. For less-than-truckload, rates per unit weight of the product decrease as the total weight that is shipped increases. We model the rate (in \$/cwt) as $R = m+nln(Qw)$ (see Arcelus and Rowcroft, 1991). The cost of LTL shipments is then $R(in\$/cwt)*Qw(incwt)$. For truck load, carload, and containerized freight, the rates are typically quoted as full-loads (rates to ship Q_m) between origin and destination. Intermodal rates are tailored, and are usually a function of the weight, the equipment being used (TOFC/Double Stack, etc.), the origin and destination. Our model is flexible to handle any freight cost scheme as long as it depends on weight and distance traveled.

Solution procedure

Equation (1) is discontinuous in m as each mode has it's own restrictions on Q and a transport rate and carbon-related efficiency that is idiosyncratic to the mode. For a given m, however, Equation (1) is continuous but non-linear in Q, and r – Equation (1) can therefore be solved using well-known non-linear optimization methods such as Newton's or conjugate gradient algorithms. The typical procedure to solve for m to compute the optimal Q, r, and $ETAC$ for each m and choose the mode with the least cost. Since at any given level of λ, only a subset of modes are usually considered (For example, for small volumes, the choices are typically LTL , TL, or inter modal. As volumes grow, the choices shift towards modes with a larger capacity like rail and waterways), the solution procedure is often computationally less intensive than an entire grid search.

3. Observations on how m impacts carbon emissions

A1. For a given mode m, the emission from transportation alone are independent of Q and r.

A2. For a given mode m, the emissions due to warehousing increases linearly with Q and r.

A3. The practical impact of the carbon budget (C_B) constraint is that it may force planners to use a mode with a lower carbon emission (or invest in efficiency improvements) even though it may not be the lowest cost option.

A1. The emissions due to transportation $QDw/f_{m,T}e_T * \lambda/Q$ can be rewritten as $\lambda Dwf_{m,T}e_T$. An increase in Q increases the movement M per shipment, but there are fewer shipments to be made, balancing out the total emissions. For a given mode, the choice of equipment and the fuel that powers it determines $f_{m,T}$ and e_T. The annual movement of freight in weight-distance determines the emissions due to transportation. For an annual demand λ and a fixed shipping lane distance d, a change is emissions from transportation for a given mode would require either improving the efficiency of the current equipment or changing the fuel used. Examples include skirts on trucks to improve fuel efficiency; or using electric or hybrid locomotives to power trains with significantly increased efficiency.

A2. For any given mode m, increasing lot size Q increases the cycle stock $(Q/2)$ proportionally. As r, increases, so does the safety stock which the stock held in excess of the lead-time demand. So as lot size increases, so does the emissions due to the increased inventory in the warehouse. As more safety stock is held (for a higher level of service), the level of emissions increase. The practical impact is that when using slower modes (with more uncertain lead-times), the carbon emissions from inventory will increase. This will have to be offset potentially with more efficiency in carrying larger loads.

A3. For illustrative purposes, lets assume that there are two modes, 1 and 2. Let $Q_1^*, r_1^*, Q_2^*, r_2^*$ be the optimal lot size and reorder point for each mode when the carbon constraint is relaxed. Say that $ETAC(Q_1^*, r_1^*, 1) \geq ETAC(Q_2^*, r_2^*)$, i.e., mode 1 is the more expensive option. Let $F_e^1, I_e^1, F_e^2, I_e^2$

are the emissions due to freight and inventory of each of the modes respectively. Let $F_e^1 + I_e^1 \leq C_B \leq F_e^2 + I_e^2$. In this case, although mode 1 is more expensive, it is the mode that satisfies the carbon emission constraint, and hence the optimal choice for Equation (1). The planners, can plan to bridge the carbon gap $F_e^2 - F_e^1 + I_e^2 - I_e^1$ by either increasing efficiency or changing fuel or by operational efficiencies to retain the cheaper mode in the longer term or move to the more expensive mode but use different mean such as renegotiating rates to bring the cost down. Over long distances 1000 miles or above such situations are rare – modes that can carry more load like rail, barge or intermodal are typically cheaper and have lower carbon emissions than faster modes (a win-win situation!). However for shorter distances of 500 miles or lower, such situations can be quite common. For example truckload quantities (TL) are often quoted lower prices then COFC for the same load for the distance. This is simply because it is easier to load a TL along a shipping lane. However, COFCs have significantly lower carbon emissions since they are part of a train and hence transported with higher efficiencies. In such cases, the planner will have use the intermodal to satisfy the constraint or make improvements to the TL fleet to bridge the gap between TL and COFC.

4. Numerical Illustration & Discussion

Consider a firm selling the product that costs \$30 and weighs 2 lbs. The annual demand is 100,000 units and daily demand is uncertain with a mean $\mu_d = \lambda/d$ of 273.97 units and a standard deviation σ_d of 50 units. Other relevant input parameters to the model are given in Table 3. The supplier is at a 500 mile distance and four choices for freight mode are available – less-than-truckload (LTL), truckload (TL), intramodal option of trailer-on-flat-car (TOFC), and rail carloads. Table 3 also gives the rates, lead-time characteristics, capacity, and fuel efficiency of these mode choices. In this example, the LTL rates are quoted per cwt and is given by $67 - 6ln(Qw)$ – so as the weight shipped increases, the rate decreases. This is multiplied by the weight in cwt Qw to compute the cost of shipping each replenishment cycle. For TL, TOFC, and Carloads, the shipper has quoted per shipment rate[6]– for ease of exposition, we assume that the firm will use the entire capacity of the mode when used. We have also chosen the lead-time demand distribution as a Gamma random variable.

The firm has allocated a voluntary budget of 10000 Kg. of CO_2 for yearly operations. Emissions are measured for both transportation and warehousing. LTL, for example, using diesel fuel can on average haul 100 tons a mile with one gallon of fuel. One gallon of diesel fuel equates to about 10.21 Kg of CO_2. Warehousing each unit accounts for 0.01 Kg CO_2. For LTL, therefore, most of the GHG emissions are from transportation. For Carloads, on the other hand, 90000 lbs. are shipped at a time with a fuel efficiency of 500 ton-mile per gallon. When combined with the relatively longer lead-times, the emissions from warehousing for carloads can be significantly higher than that of LTL. LTL and TL have similar emission levels, but TL is faster and less expensive. TL and TOFC have similar capacities; TOFC is slower but also has significantly less emissions. TOFC and Carloads have similar emission

[6]Irresective of how much is shipped a constant rate is charged. The model is flexible however to incorporate a tiered shipping rate if shippers do offer the option

Table 3: **Input Parameters**

Product Characteristics			
Expected annual demand	λ	100000	per year
Number of days in a year	d	365	
Mean demand per day	μ_d	273.97	items
Std Dev. Of Demand per day	σ_d	50	items
Cost per item	C	\$30	per item
Weight per item	w	2	lb. per item
Emissions from inventory	e_I	0.01	per item
Cost of placing an order	S	\$500	per order
Inventory carrying charge	h	\$0.15	per \$ per year
Backorder cost	π	\$10	per unit
Service Level	ρ	95%	
Carbon Cap	C_B	10000	$KgCO_2$ per year

Mode Characteristics				
Name (m)	LTL	TL	TOFC	Carload
Rate ($TC_m(Q, D)$, per shipment)	$67 - 6ln(Q) * Qw$	\$3031	\$2500	\$1750
Mean Lead time (μ_m, days)	6	3	7	10
Distance (D, in miles)	500	500	500	500
Standard deviation (σ_m,days)	0.6	0.3	0.7	1
Capacity (Q_m, lbs.)	40000	40000	40000	90000
Fuel Efficiency ($f_{m,T}$, ton-mile/gallon)	100	100	400	500

levels but carloads are cheaper and carry significantly more product.

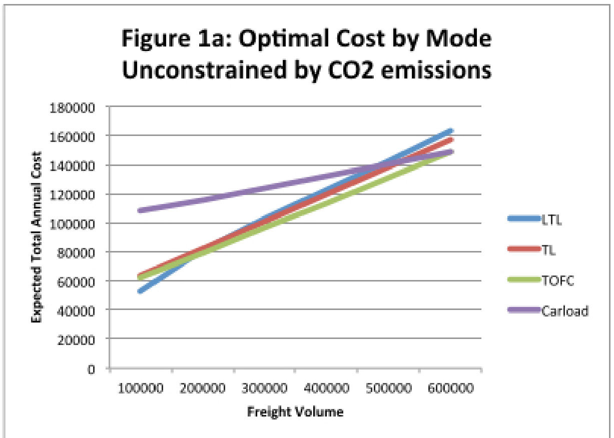
Table 4 gives the results of the optimization model. In this case, LTL is the mode that minimizes cost, given the constraints on service (95% availability), mode capacity (40000 lbs.), and GHG emissions (capped at 10000 Kg of CO_2). The firm optimally would order 8227.53 units (to be shipped by LTL) when the inventory goes below 2028.06 units. The transport costs are significant (almost 50% of total costs) and 98.8% of the emissions are from transportation.

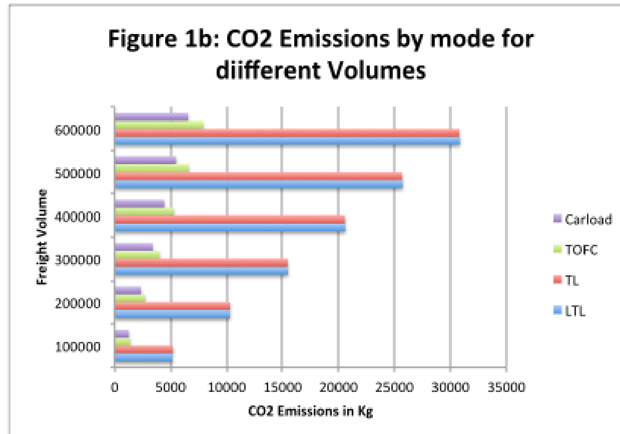
Figure 1 shows how the mode choice varies with volume. Figure 1a shows the optimal cost as freight volume increase but without the carbon constraint (it is the minimization of (1) without constraint (3)). In the unconstrained problem, when $\lambda = 100000$, LTL is the cheapest mode. When $20000 \leq \lambda \leq 500000$, TOFC is the cheapest mode. When $\lambda \geq 600000$, Carload is the cheapest. When $C_B = 10000$ and $\lambda = 100000$, LTL is still the choice as the total GHG emission is less than 10000. However if $C_B = 5000$, this firm will have to move away from LTL, the cheapest mode and choose TOFC – an example where the carbon constraint impacts mode choice. Alternatively, we know the total CO_2 emissions is 5166.42 Kg – so the firm can undertake efforts to improve efficiency or switch fuels to get under the carbon cap. TOFC costs $9422 more than LTL so if the improvements to LTL shipments (such as skirts on trucks, installing battery packs, etc.) cost less than this price premium, it may be a worthwhile experiment.

Table 4: **Results of Optimization**

Derived Elements			
Expected demand during lead time	μ_{ltd}	1643.83	units
Expected backorders	$\eta(r)$	3.57	per replenishment cycle
Total number of trips	λ/Q	12.15	per year
Ship weight	Qw	16455.06	lbs per replenishment cycle
Cost of shipping	$TC_m(Q,D)$	\$2124.11	per replenishment cycle
Average Inventory	$Q/2+r$	6141.83	in warehouse + in transit
Decisions			
reorder point	r	2028.06	units
order quantity	Q	8227.53	units
Mode	m	LTL	
Costs			
ordering	$S\lambda/Q$	\$6077.15	per year
Inventory Carrying	$(Q/2+r)h$	\$20240.99	per year
Backorder Costs	$\eta(r)\pi\lambda/Q$	\$434.80	per year
Transport Costs	$TC_m(Q,D)\lambda/Q$	\$25817.10	per year
Expected total annual cost	$ETAC(Q,r,m)$	\$52570.05	per year
Carbon Computations			
Transportation	$M/f_{m,T}e_T * \lambda/Q$	5105	Co2 Kg per year
Inventory	$Q/2+(r-\mu_{ltd})e_I$	61.41	Co2 Kg per year
Total		5166.41	Co2 Kg per year
Budget	C_B	10000	Co2 Kg per year

Figure 1: How the Optimal Solution Varies with Volume





5. Summary & Conclusion

The clarion call for action against climate change has many firms reexamining traditional supply chain decisions under this new lens of GHG emission mitigation. In this paper, we provided a model that helps planners choose the appropriate freight mode, when voluntary carbon constraints are in place.

Our model uses a continuous-review reorder-point stochastic inventory control context to compute the optimal lot size, reorder point, and mode choice for a given set of product and freight mode characteristics. Our model assumes a voluntary emissions constraint on total emissions from transportation and warehousing activities. The decisions are made comprehensive inventory-transportation cost framework that includes all relevant costs of the order management cycle - ordering; holding cycle, safety and in-transit inventory; and finally the cost of transportation. Our model is flexible to accommodate a wide variety of stochastic environments, product, and freight mode characteristics.

The key finding, other than the methodology to evaluate mode-choice, of the paper is that firms with voluntary constraints on emissions may be forced to choose modes of freight that do not have the lowest overall cost (because they violate carbon constraints). This either forces the firm to spend more on a mode with lower emissions or invest in trying to lower the emissions of the lowest priced mode. There are multiple strategies for improving efficiency (the $f_{m,T}$) – better designed vehicles that use less fuel, optimizing transport network, and by efficient load planning that increases weight and cube utilization and reduces number of trips. A second strategy is to switch fuels – moving to hybrid vehicles or those that run on bio diesel also reduce the e_T. A third strategy – to reduce the warehousing emissions (e_I) is to build energy efficient warehouses that run on renewable fuel such as solar; and by making improvements that improve the energy efficiency of these buildings. These three strategies can have a significant impact on the freight and warehousing emissions. Fourth, firms can also gain by lobbying for emission cap legislation – any savings below the cap can then be "traded" for revenue.

Finally, further research can focus on the following questions:

- When multiple sources are used often across different parts of the globe, how can a firm manage emissions by managing these multiple modes of supply?

- How will "cap and trade" mechanism impact mode choice and warehousing?

- How does the differentiated cost of carbon emissions in different countries play a part in managing freight in the supply chain?

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