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Final Report

Analyzing the Impact of Carbon Regulatory Mechanisms on Supply Chain Management

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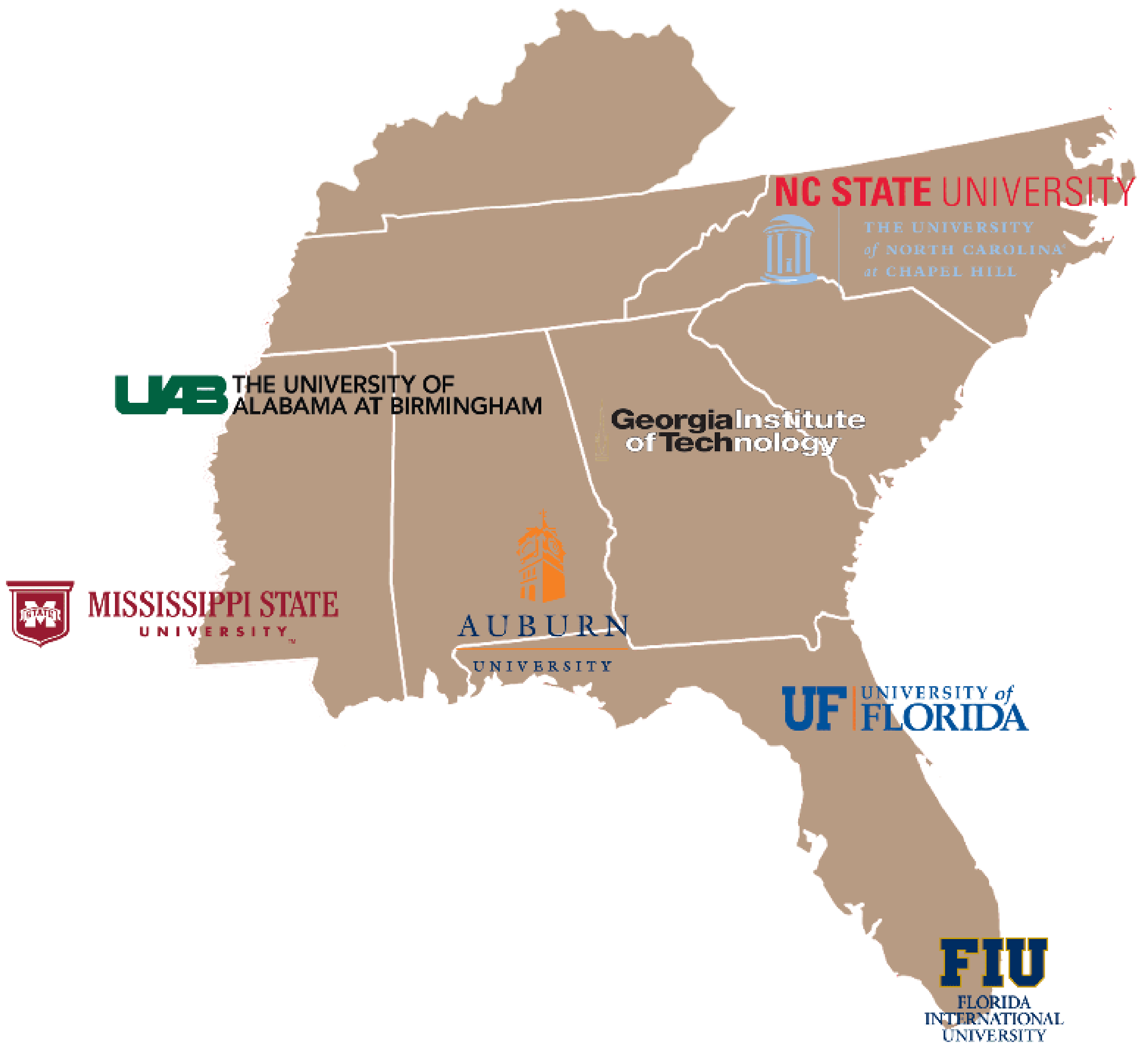
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ABSTRACT

The objective of this research is developing a toolset for designing and managing cost efficient and environmentally friendly supply chains for perishable products.

The models we propose minimize transportation and inventory holding costs in the supply chain, while accounting for carbon emissions due to transportation and other activities. These models are extensions of the classical Economic Lot-Sizing (ELS) model. The ELS model identifies an inventory replenishment schedule for a fixed planning horizon with deterministic and time-varying demand. We extended these models to consider the use of multiple modes of transportation. The models support replenishment decisions for perishable products and capture the impact of inventory replenishment decisions on greenhouse gas emissions. We have used the numerical results to analyze the impact of potential carbon emission regulations on replenishment decisions.

We anticipate that these models will be used to assess the impacts that potential carbon regulatory policies, such as carbon caps, carbon taxes, carbon cap-and-trade, and carbon offsets have on transportation mode selection decisions and overall emissions levels in the supply chain.

The benefits from using these models are twofold. First, policy makers can use these models to evaluate the potential impact on emissions for each regulatory policy. Second, environmentally conscious companies can use these models and the corresponding solution algorithms as sub-modules within their material requirements planning (MRP) systems for requirements planning when multiple modes, multiple products, perishable products, and multiple supplier replenishment options are available.

EXECUTIVE SUMMARY

Concerns have been raised frequently in recent years due to the increased emission levels and the impact of emissions on the quality of air, and consequently, on the quality of our lives. In particular, the burning of fossil fuels for power generation and transportation yields significant amounts of carbon emitted to the environment. Researchers and government entities in different countries note that there is an urgent need to put policies into action and set emission reduction targets. For example, through its European Climate Change Program, the European Union aims to reduce carbon emissions by at least 20% by 2020 as compared to 1990 levels [2]. As a consequence, many companies are taking actions by revising their operations and updating their technologies. Other companies are readily committed to going green since green initiatives not only benefit the environment, but also increase customer goodwill and loyalty and guarantee sustainable operations.

Emissions within the supply chain of a product may result from production, inventory and transportation activities. Freight transportation is a major contributor to greenhouse gas (GHG) emissions as it accounted for 6,800 trillion BTUs (TBTUs) of energy in 2005, and is expected to consume 10,850 TBTUs by 2030, a 60% growth in energy consumption. In addition to developing new technologies, modifications in the way companies manage their day-to-day operations have the potential to reduce carbon emissions. In the context of supply chain management, shifting from one transportation mode to another impacts costs, delivery lead times for shipments and emissions. It is thus important to identify appropriate mode(s) of transportation to use in the supply chain in order to minimize cost while maintaining customer satisfaction by delivering products on-time, and also reducing the carbon footprint of the product delivered.

The research conducted in this study is focused on developing models for designing and managing cost efficient and environmentally friendly supply chains. These mathematical models represent the relationships that exist between costs and emissions in a two-stage supply chain. The models minimize the total of transportation and inventory holding costs in the supply chain, while accounting for carbon emissions due to transportation and other logistics and supply chain-related activities.

These models provide insights and direction to guide companies on making sustainable logistics management and transportation decisions.

CHAPTER 1 BACKGROUND

PROBLEM MOTIVATION

For decades, the main objective of models developed for supply chain optimization, logistics management and transportation systems analysis has focused on minimizing costs. These models have been driven by the needs of different industries to improve cost efficiency and performance. There is a growing interest within the operations research and analytics community to account for "green objectives" in supply chain, transportation and other decision-making related models. This movement has been inspired by our increased awareness of environmental issues and recognition of the need for long-term sustainability. Although some firms may not be in a hurry to "minimize their emissions and carbon footprint," many large companies are now committed to going green. Green initiatives not only benefit the environment, but also benefit the companies that implement them, due to increased customer goodwill and loyalty and sustainable operations. A number of companies such as Walmart, Tesco, and Hewlett Packard [3] are responding to environmental concerns by taking steps toward reorganizing their shipment schedules and using fuel efficient vehicles. These companies have come to realize that reductions in GHG emissions can help to strengthen their brand image and to develop competitive advantages. The expectation is that other companies will join this trend and strive to reduce their carbon footprint.

This research contributes to improving the economic competitiveness of transportation systems, which is one of the three main research themes of STRIDE. From a policy maker's point of view, the outcomes of this research will help identify carbon regulatory policies which have a great impact on reducing transportation related emission at a minimum cost. From a logistics management point of view, the outcomes of this research will help identify transportation schedules that minimize costs while responding to environmental issues and concerns. Overall, this research will contribute to improving transportation-related costs and emissions in the supply chain, and consequently will contribute to the long-term sustainability of transportation systems. We believe that the models we propose have the potential to help companies in the region improve transportation and logistics-related costs and emissions, and therefore, become competitive while mitigating environmental impacts.

RESEARCH OBJECTIVE

The main *objective of this research was to develop a toolset for designing and managing cost efficient and environmental friendly supply chains*. In pursuit of this objective, we extended the classical ELS model to capture the impact of transportation mode selection choices on costs and emissions. These mathematical models minimize total transportation and inventory holding costs in the supply chain, while accounting for carbon emissions due to transportation and other logistics and supply chain-related activities. The goal was to provide insights and guidance for companies to make sustainable logistics and transportation decisions.

This research helps us gain a better understanding of the impact that carbon regulatory mechanisms have on transportation mode selection, transportation schedules, and consequently, on costs and emissions in the supply chain.

PROBLEM STATEMENT

The mathematical models we developed are extensions of the classical ELS model introduced by Wagner and Whitin [4]. Our supply chain consists of a single facility and its suppliers. The facility could be a manufacturing facility, or a retailer making inventory replacement decisions every period within a fixed planning horizon of length T. A "supplier" in our model corresponds to a unique combination of a supply firm and a particular transportation mode. Thus, there may be multiple "suppliers" for a given supply firm- but one for each transportation mode.

A facility can replenish its inventories using local or distant suppliers. Typically, if shipment delivery time is not a concern, a facility can increase the supplier pool size by considering suppliers located further away, which increases the likelihood that the facility will be able to identify suppliers (e.g., wholesalers) that can provide products at a competitive price. Depending on the distance traveled and transportation mode accessibility, barge, rail, or truck can be used to replenish inventories. The facility may, alternatively, replenish inventories using nearby suppliers who can respond in a timely manner. Because of short travel distances, these suppliers tend to use truck shipments. Shipments are initiated depending on the size of a shipment, e.g., full truck load (FTL) or less-than-full truck load (LTL). Somewhat paradoxically, replenishment costs from local suppliers are often higher compared to more distant suppliers, mainly due to frequent LTL shipments, as opposed to the FTL shipments from more distant suppliers. Our goal is to identify suppliers and a replenishment schedule that minimizes total replenishment (purchase and transportation), inventory holding costs and the carbon footprint of this supply chain.

In this problem, operations costs consist of replenishment and inventory holding costs. Replenishment costs from supplier i $(i = 1, \dots, I)$ in period t consist of a fixed order cost (f_{it}) and a variable cost (c_{it}). Recall that a supplier in our model is defined by the combination of a physical supplier and specific transportation mode. Thus, the fixed order cost consists of the costs necessary to process an order as well as to load or unload a shipment. The variable cost consists of the purchasing cost and distance-dependent transportation costs. These costs are a function of quantity shipped. A unit inventory holding cost is charged per unit of inventory held at the facility at the end of each time period (h_t).

We assume that carbon emissions in this supply chain result from transportation activities and holding inventory. We separate transportation related emissions into fixed ($\hat{f}_i$) and variable $(\hat{c}_i)$ emissions. Fixed emissions are mainly due to loading and unloading of a shipment. These emissions depend on the transportation mode used since the equipment required to load and unload a barge, rail car, or truck, is different. Variable emissions depend on the transportation mode used. That is the case because the amount of carbon emitted per ton and per mile traveled by truck is different from that of rail or barge. Our models also consider emissions that may result from holding inventories. For example, the emissions per unit of inventory held in a time period $(\hat{h}_t)$ depend on the heating/cooling system at the facility.

Figure 1-1 provides a network representation of a two-tier supply chain problem with three suppliers and one facility. The time horizon consists of two time periods. This network contains one dummy node, a total of T facility nodes (one node per time period), and $I \times T$ supplier nodes. The dummy node has a supply equal to the total demand over the planning horizon. A facility node t has a demand equal to d_t, which denotes demand in period t ($t = 1, \dots, T$). The supplier nodes correspond to each supplier in every time period. The network has $I \times T$ replenishment arcs, $T \times 1$ inventory arcs and $I \times T$ dummy arcs. Replenishment arcs connect suppliers with the facility in each time period. The cost per unit flow on a replenishment arc is c_{it} ($i = 1, \dots, I;\ t = 1, \dots, T$). There is also a fixed cost for using supplier i in period t equal to $f_{it}(i = 1, \dots, I;\ t = 1, \dots, T)$ which is incurred when using a replenishment arc. Inventory arcs connect the facility nodes in consecutive time periods. The cost per unit of flow on an inventory arc is h_t ($t = 1, \dots, T$). The inventory replenishment models developed are presented in Chapter 2.

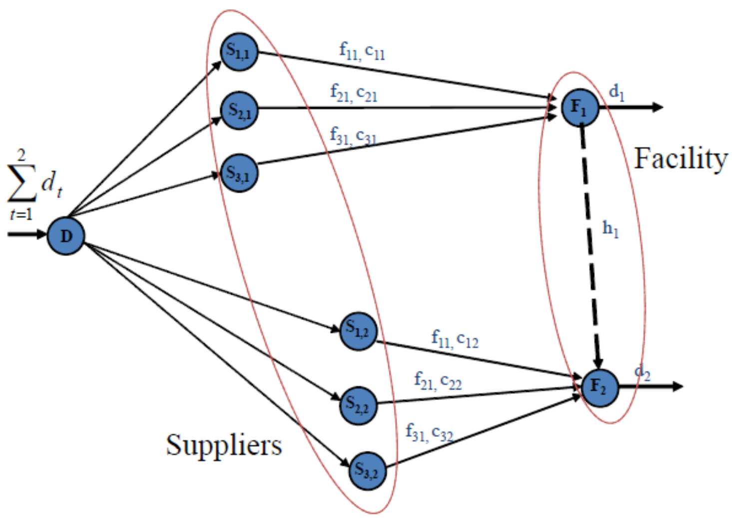


Figure 1-1. The network representation of a two-period, three-supplier problem.

We extend of the models proposed to consider perishable products. We classify perishable products as: products with fixed shelf lifetime and deteriorating products. The former category includes products whose length of lifetime is known a priori, such as, pharmaceuticals, dairy products, and fashion items. The latter category includes deteriorating items. Deterioration refers to spoilage, dryness, vaporization, etc., which results in value lost during the storage period. These are also known as age-dependent perishable products. The objective of inventory replenishment models for these products is to minimize the total system costs associated with replenishment-related decisions. The models developed capture the trade-offs that exist between transportation costs and remaining shelf life of products, transportation and inventory costs, and total costs and CO_2 emissions resulting from transportation and inventory holding. Shorter transportation lead times increase the remaining shelf life for perishable products. This provides companies with more flexibility when making inventory replenishment decisions. For example, if the shelf life of a product is short, such as one day, then the inventories should be replenished daily. If the shelf life of a product is longer, then a company can reduce replenishment costs by ordering less frequently. A company can reduce transportation lead time for perishable products by using local suppliers, or by using transportation modes such as refrigerated trucks and refrigerated rail cars, or airplanes. However, using suppliers located nearby could result on higher replenishment costs, mainly due to a limited pool of suppliers than can be reached and, therefore, less competitive prices. Using refrigerated trucks, refrigerated rail cars and airplanes result in higher transportation costs as compared to using trucks and rail cars.

Inventory decisions are impacted by tradeoffs that exist between replenishment and inventory holding costs, and also by the lead time and remaining shelf life of perishable products. Using refrigerated trucks and storage areas can increase the remaining shelf life of a perishable product. These activities increase energy consumption and consequently carbon emissions.

The models we propose for perishable products are multi-objective, mixed-integer linear programming model which minimize costs and environmental impacts due to supply chain activities including transportation and inventory. The cost objectives of these models minimize the total inventory replenishment costs which consist of transportation, inventory, purchase and fixed order costs. The environmental objective minimizes greenhouse gas (GHG) emissions due to transportation and inventory.

SCOPE OF STUDY

A number of studies propose methods to measure and quantify carbon emissions in the supply chain due to processes such as transportation[5], [6], [7], [8],[9]. Other studies propose optimization models to minimize the carbon footprint of a supply chain through changes in supply chain design and operations. For example, [10] extend the classical ELS model with a single replenishment mode to identify inventory replenishment schedules under different carbon regulatory mechanisms, such as, carbon cap, carbon tax, carbon cap and trade, and carbon offset. [11]and [9] develop extensions of ELS to identify inventory replenishment schedules under a carbon cap and a carbon cap-and-trade mechanism respectively. Studies by[12], [13] , and [14] concentrate on developing larger scale supply chain network design models which take into account carbon emissions.

This study falls into the latter stream of research, which identifies operational policy changes that impact costs and emissions in the supply chain. It specifically contributes to the literature by improving transportation related costs and emissions in the supply chain, and consequently achieving the long-term sustainability of transportation systems. The models proposed have the potential to help companies improve transportation and logistics-related costs and emissions, and therefore, become competitive while mitigating environmental impacts.

Transportation mode selection decisions need to address the trade-offs that exist between costs and emissions in the supply chain. These decisions also need to account for carbon regulatory mechanisms that are in place. In this research we analyzed the impact of four potential carbon regulatory mechanisms, consisting of carbon caps, carbon taxes, carbon cap and trade, and carbon offsets, on supply chain operations. Under a carbon cap mechanism, the amount of carbon emitted due to transportation, production and inventory activities cannot surpass a predetermined cap. Under a carbon tax mechanism, a facility pays a tax per ton of carbon emitted due to its operations. Under a carbon cap-and-trade mechanism, a carbon cap is imposed on the facility, where a carbon market also exists which allows the facility to sell unused carbon credits at a profit, or to purchase carbon credits if needed. Under a carbon offset mechanism, a carbon cap is imposed on the facility. A carbon market may also exist, which allows the facility to purchase carbon credits if needed, but not to sell back unused carbon credits. The models we propose thus consider production and transportation planning decisions for a producer under various assumptions on the costs associated with emissions. Additional distinguishing features of our work include:

- Explicit consideration of transportation cost structures that closely approximate practical transportation pricing terms and costs.

- Consideration of product characteristics such as shelf life and deterioration rate, and how these factors affect replenishment costs and emissions. We expect that emissions in the supply chain, similar to replenishment schedules and costs, are impacted by product type and characteristics.

CHAPTER 2 RESEARCH APPROACH

Below we present mathematical models for optimizing costs and emissions in the supply chain under different carbon regulatory mechanisms. This is an extension of a model proposed by [10]. We add a new dimension to their model that accounts for the availability of different transportation modes to replenish inventories. We also note that this model is an extension of the classical ELS which captures the impact of the following carbon regulatory mechanisms on replenishment decisions: carbon caps, carbon taxes, carbon cap-and-trade and carbon offsets. Depending on the carbon regulatory mechanism, the models we propose require carbon constraints, emissions cost, penalty costs which should be paid per unit of emission, or a combination of both. Description of the different carbon mechanisms and the corresponding objective functions of our models are given below.

To consider perishable products we present two multi-objective optimization models which optimize costs and emissions for perishable products. We describe the cost functions we used in these models. We provide a multi-objective model for perishable products which lose value with time. These are referred to in the literature as deteriorating items. We also provide a multi-objective model for items that have a fixed shelf life.

MODELS WITH ENVIRONMENTAL OBJECTIVES

Consider the two-tier supply chain described in Chapter 1 which consists of a facility and a number of suppliers (Figure 1-1). The facility has the option to use nearby suppliers to replenish its inventories, or use suppliers located further away. In addition to costs, concerns about emissions do impact replenishment decisions of the facility. Transportation related emissions for shipments from local suppliers are typically low due to shorter distances traveled. Unit emissions - given in per ton and per mile - for barge and rail are smaller than unit emissions from trucks. However, depending on the transportation distance, the total emissions for long hauls using rail and barge may be higher. The objective of the models we propose is to identify a replenishment schedule that minimizes the total system costs and the carbon footprint of this supply chain.

Cost Minimization Model

The following is the mixed integer programming formulation of the cost minimization model. We list the model parameters and decision variables.

<u>Model parameters</u>:

- f_{it} , Fixed order cost for supplier *i* (*i* =1,..,*I*) in period *t* (t = 1,…*T*)
- c_{it} , Variable cost per unit shipped from supplier i in period *t*
- h_t , Inventory holding cost in period *t*
- d_t , Demand in period *t*

<u>Decision variables</u>:

- y_{it} Binary variable equal to 1 if supplier *i* is used in period *t*
- q_{it} Amount shipped from supplier *i* in period *t*
- H_t Inventory held in period *t*

We refer to this as model (P).

$$minimize \sum_{i=1}^{I}\sum_{t=1}^{T}(f_{it}y_{it} + c_{it}q_{it} + h_tH_t)$$

s.t. (P)

$$\sum_{i=1}^{I} q_{it} + H_{t-1} - d_t = H_t \qquad t = 1, \dots, T \qquad (1)$$

$$H_0 = 0 \qquad (2)$$

$$q_{it} \leq \left(\sum_{\tau=t}^{T} d_\tau\right) y_{it} \qquad i = 1, \dots I; t = 1, \dots, T \qquad (3)$$

$$y_{it} \in \{0,1\}; q_{it} \geq 0;\ H_t \geq 0 \qquad i = 1, \dots, I; t = 1, \dots, T \qquad (4)$$

The objective function of (P) minimizes total costs. Constraints (1) are the inventory balance constraints. These constraints ensure that demand is met. Constraints (2) set the initial inventory to zero. Constraints (3) connect continuous and binary variables, and ensure that no flow is shipped from supplier i in period t, unless $y_{it} = 1$. The remaining constraints are the binary and the non-negativity constraints, respectively.

Carbon Cap Mechanism

We now discuss a mathematical model which optimizes replenishment decisions under a carbon cap mechanism. Due to the carbon cap, the total amount of carbon emitted during the planning horizon cannot surpass this cap. To express this cap mathematically, we add constraint (1) to the model. This constraint limit the total emissions in the supply chain to *C*. *C* denotes the carbon cap level over the planning horizon. We refer to this as model (P-Cap).

<u>Model parameters</u>:

- $\hat{f}_{it}$ Fixed emissions for supplier *i* (*i* =1,..,*I*) in period *t* (t = 1,…*T*)
- $\hat{c}_{it}$ Variable emissions per unit shipped from supplier i in period *t*
- $\hat{h}_t$ Inventory holding emissions in period *t*

The following is the MIP formulation of the problem.

$$minimize \sum_{i=1}^{I}\sum_{t=1}^{T}(f_{it}y_{it} + c_{it}q_{it} + h_tH_t)$$

s.t. (P-Cap)

(1) – (4)

$$\sum_{i=1}^{I}\sum_{t=1}^{T}(\hat{f}_i y_{it} + \hat{c}_{it} q_{it} + \hat{h}_t H_t) \leq C \qquad (5)$$

The objective function minimizes total costs, subject to ELS constraints as well as the carbon cap constraint, *C*. This model, in addition to costs, keeps track of emissions from inventory holding, transportation and loading/unloading activities. While the firm still minimizes supply chain related costs, it must ensure that the carbon constraint is not violated. This additional constraint can potentially increase total costs and impact supplier and transportation mode selection decisions.

Carbon Tax Mechanism

Under a carbon tax mechanism, a facility pays a fee/tax for each unit of CO_2 emitted. Let α denote the tax charged per unit of CO_2 emitted. The following is the corresponding optimization model, which we refer to as (P-Tax):

$$minimize \sum_{i=1}^{I}\sum_{t=1}^{T}(f_{it} + \alpha\hat{f}_i)y_{it} + (c_{it} + \alpha\hat{c}_{it})q_{it} + \left(h_t + \alpha\hat{h}_t\right)H_t$$

s.t. (P-Tax)

(1) - (4)

The objective function minimizes the total of replenishment costs, inventory costs, and emission taxes.

Carbon Cap-and-Trade Mechanism

A carbon cap is imposed on the facility under a carbon cap-and-trade mechanism. However, a carbon market also exists, which allows the facility to sell unused carbon credits at a profit, or to purchase carbon credits if needed to satisfy customer demand (the European Union Emissions Trading system was the first large emission trading scheme in the world). Let e_t^+ be the amount of carbon credits purchased in period *t*, and let e_t^- denote the amount of carbon credits sold in period *t*. We denote the market price per unit of carbon by p. The following is the corresponding optimization model, which we refer to as (P-CT):

$$minimize \sum_{i=1}^{I}\sum_{t=1}^{T}(f_{it} y_{it} + c_{it} q_{it} + h_t H_t) + p\sum_{t=1}^{T}(e_t^+ - e_t^-)$$

s.t.: (P-CT)

(1) - (4)

$$\sum_{i=1}^{I}\sum_{t=1}^{T}(\hat{f}_i y_{it} + \hat{c}_{it} q_{it} + \hat{h}_t H_t) + \sum_{t=1}^{T} e_t^- \leq C + \sum_{t=1}^{T} e_t^+ \tag{6}$$

Carbon Offset Mechanism

A carbon cap is imposed on the facility under a carbon offset mechanism, and a carbon market also exists that allows the facility to purchase carbon credits. However, under a carbon offset mechanism, a facility cannot sell unused carbon credits. Let e_t^+ be the amount of carbon credits purchased in period *t*. The following is the optimization model, which we refer to as (P-CO):

$$minimize \sum_{i=1}^{I}\sum_{t=1}^{T}(f_{it} y_{it} + c_{it} q_{it} + h_t H_t) + \sum_{t=1}^{T} p e_t^+$$

s.t.: (P-CO)

(2) - (4)

$$\sum_{i=1}^{I}\sum_{t=1}^{T}(\hat{f}_i y_{it} + \hat{c}_{it} q_{it} + \hat{h}_t H_t) \leq C + \sum_{t=1}^{T} e_t^+ \tag{7}$$

Experimental results have provided us with some interesting insights about the impacts of carbon regulatory mechanisms on supplier and transportation mode selection decisions. We discuss some of our findings in the following section.

REPLENISHMENT MODELS FOR PERISHABLE ITEMS

In this section, we present the economic lot sizing model with multiple replenishment modes for perishable products. The objective of this problem is to identify a replenishment schedule for perishable products which minimizes costs and emissions during a planning horizon of length *T*.

Transportation Cost Functions with Multiple Setup Cost Structure

The fixed-charge transportation cost structure assumes there is a fixed cost as well as a variable cost per unit shipped using a particular transportation mode. The multiple setup cost structure (Equation (8)) assumes a fixed order cost (f_i), a unit variable cost charged for each unit shipped (p_i), and a fixed cargo container cost (A_i), which is charged for each container used. The following corresponds to a multiple setup transportation cost function.

$$TrCost_i(q_{it}) = \begin{cases} f_i + p_i q_{it} + A_i \left\lceil \frac{q_{it}}{U_i} \right\rceil & if\ q_{it} > 0 \\ 0 & otherwise. \end{cases} \tag{8}$$

In Equation (8), U_i is the cargo capacity. Different from most of the literature that uses a linear or fixed-charge cost structure, we use a non-linear, step-wise function in order to better represent the structure of the replenishment costs. Figure 2-1 illustrates a multiple setup cost function for two different replenishment modes. This cost structure allows us to more accurately represent both the costs and the emissions associated with a given mode as a function of the quantity shipped.

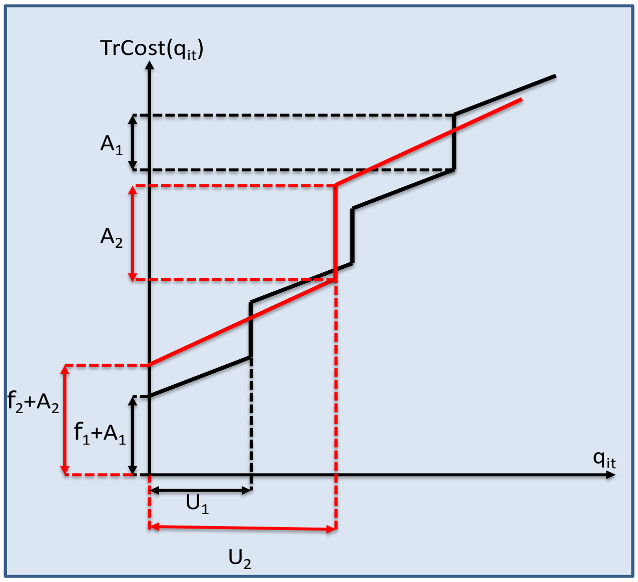


Figure 2-1. A multiple setup cost function.

In Equation (8), p_i is the unit replenishment cost. This cost includes the unit procurement cost and unit transportation costs for replenishment mode i.

Replenishing Age-Dependent Deteriorating Items via Multiple Transportation Modes

We start by defining a new set of decision variables, denoted by $q_{it\tau}$. Let $q_{it\tau}$ represent the amount of demand on period τ satisfied by a replenishment that used mode i and arrived in period t. Using $q_{it\tau}$ allows calculating the age of a product and corresponding inventory replenishment costs. Let p_i denote the unit procurement cost for replenishment mode i, and A_i denote the fixed cost of a replenishment mode i. We now present the multiple setup cost function presented in equation (7) using these newly defined variables.

$$TrCost_i(q_{it\tau}) = \begin{cases} f_i + p_i \sum_{\tau=t}^{T} q_{it\tau} + A_i \left\lceil \frac{\sum_{\tau=t}^{T} q_{it\tau}}{U_i} \right\rceil & if\ q_{it\tau} > 0 \\ 0 & otherwise. \end{cases} \tag{9}$$

The model considers product deterioration during delivery time and during storage at the facility. We assume that the product is shipped as soon as it is produced. The transportation lead time for replenishment mode i, denoted by L_i, depends on the location of the supplier and the transportation mode used. We denote the deterioration rate for a replenishment using mode i from period t to period τ by $\alpha_{it\tau}$. The deterioration rate is not constant; instead, it depends on the duration of product storage. Typically, deterioration rate increases with time, and thus, $\alpha_{it\tau} \leq \alpha_{itj}$ for $1 \leq t \leq \tau \leq j \leq T$.

Let k_{itl} represent the percentage of inventory from replenishment from supplier i which arrived in period t that has not perished until it is used in period l. The order of this replenishment is released at time $t - L_i$ to count for the transportation lead time. If transportation lead time is assumed to be zero, replenishment in time period t for the same time period is received without a loss. This means that $\alpha_{itt} = 0$ and 100% of the replenishment is delivered. Thus, we define $k_{itt} = 1$. The remaining k_{itl} for $1 \leq t \leq l \leq T$ are calculated as: $k_{itl} = \prod_{j=t}^{l-1}(1 - \alpha_{itj})$. Based on the assumption stated above, we can see that $k_{itl} \leq k_{i\tau l}$ for $1 \leq t \leq \tau \leq l \leq T$.

The formulation of the lot-sizing problem with multi-mode replenishment and age dependent perishable inventories is presented below. We refer to this as formulation (Q). Next we present the new variable and parameters used in this formulation.

Model parameters:

- $\hat{A}_{it}$: GHG emissions due to loading and unloading of one cargo container mode i in period t
- C_i: Capacity of a cargo container for replenishment mode i
- k_{itl}: Percentage of inventory from replenishment mode i that arrives in period t that has not perished until it is used in period

Decision variables

- $q_{it\tau}$: The amount received from replenishment mode i in period t to satisfy demand in period τ ($\tau \geq t$)
- z_{it}: Number of cargo containers of replenishment mode i used in period t

The following is the mixed integer programming formulation of the problem.

$$\boldsymbol{minimize\ z} = \sum_{i=1}^{I}\sum_{t=1}^{T}[\sum_{\tau=t}^{T} c_{it\tau}\, q_{it\tau} + f_{it}y_{it} + A_i z_{it}],$$

St. (Q)

$$\sum_{i=1}^{I}\sum_{t=1}^{T} k_{it\tau}q_{it\tau} = d_\tau \qquad 1 \leq \tau \leq T \qquad (10)$$

$$q_{it\tau} - \frac{d_\tau}{k_{it\tau}} y_{it} \leq 0 \qquad i = 1, \dots, I; 1 \leq t \leq \tau \leq T \qquad (11)$$

$$\sum_{\tau=t}^{T} q_{it\tau} - C_i z_{it} \leq 0 \qquad i = 1, \dots, I; t = 1, \dots, T \qquad (12)$$

$$y_{it} \in \{0,1\}; q_{it\tau} \geq 0;\ z_{it} \in Z^+ \qquad i = 1, \dots, I; t = 1, \dots, T \qquad (13)$$

Where, $c_{it\tau} = p_i + \sum_{s=t}^{\tau-1} h_s k_{its}$.

Constraints (9) ensure that demand in period τ ($\tau = 1, \dots, T$) is satisfied. In this constraint the term $k_{it\tau}$ captures product deterioration during both transportation lead time and storage. Constraints (10) relate the continuous variables $q_{it\tau}$ to the binary variables y_{it}. When $y_{it} = 0$, this implies no replenishment of inventories in period t, as a consequence $q_{it\tau} = 0$ for $\tau = t, \dots, T$. Constraints (9) and (10) indicate that replenishment amounts should be larger than the actual demand to compensate for the loss of inventory due to deterioration. Constraints (11) identify the number of units of cargo required to replenish inventories from replenishment mode i in period t. Constraints (12) are, respectively, the binary, integrality and non-negativity constraints.

A Multi-Objective Optimization Model for Age-Dependent Deteriorating Items

Multi Objective Programming models are used when optimal decisions need to be taken in the presence of tradeoffs between two or more conflicting objectives. Typically, there does not exist a single solution that simultaneously optimizes each objective. Thus, solving a multi-objective optimization model means approximating or computing all or a representative set of Pareto optimal solutions. We describe two approaches to calculate the Pareto set of solutions for the bi-objective optimization problems we present below. The approaches are the weighted sum and ε-constraint methods.

The multi-objective optimization model presented next aids with replenishment decisions for perishable products. The goals are to identify inventory replenishment modes and build a schedule which minimizes the total costs and emissions. In these models we consider only CO_2 emissions, since they account for about 90% of the total GHG emissions. We consider products which have a fixed shelf life as well as products that deteriorate gradually.

The total cost (TC) objective is the following:

$$TC(q;\ y;\ z) = \sum_{i=1}^{I} \sum_{t=1}^{T} [\sum_{\tau=t}^{T} c_{it\tau}\, q_{it\tau} + f_{it} y_{it} + A_i z_{it}], \tag{20}$$

where, $c_{it\tau} = p_i + \sum_{s=t}^{\tau-1} h_s k_{its}$.

The following is the total emissions (TE) objective function.

$$TE(q, z) = \sum_{i=1}^{I} \sum_{t=1}^{T} [\sum_{\tau=t}^{T} \hat{c}_{it\tau}\, q_{it\tau} + \hat{A}_{it} z_{it}], \tag{21}$$

where, $\hat{c}_{it\tau} = \hat{c}_{it} + \sum_{s=t}^{\tau-1} \hat{h}_s k_{its}$.

The following is a multi-objective, mixed integer linear programming formulation for this inventory replenishment problem, which we refer to as (M-P).

$$minimize_{q,y,z}(TC(q,y,z), TE(q,z))$$

s.t. (M-P)

$$(10)-(13)$$

A Multi-Objective Optimization Model for Perishable Items with Fixed Shelf-Life

The model considers that items have a fixed shelf life which we denote by *k*. In this case, the product can stay on the shelves for at most *k* time periods, after which, the product is disposed at no cost. We consider that the planning horizon of length T is a typical one and repeats itself over time. All problem data are assumed cyclic with cycle length equal to T ($d_{T+1}=d_1; d_{T+2}=d_2;...,$ where d_t is the demand in period *t*). As a result, the inventory pattern at the facilities will be cyclic as well. We model this by letting the initial inventory be equal to the last period inventories. The decisions to be made in each time period are which supplier to select and mode of transportation to use, and how much to order.

The total cost objective is the following:

$$TC(q,y,z) = \sum_{i=1}^{I}\sum_{t=1}^{T}[\sum_{\tau=t}^{t+k}(c_{it}\, q_{it[\tau]} + h_t q_{it[\tau+1]}) + f_{it}y_{it} + A_i z_{it}] \qquad (22)$$

The following equation represents the total emissions due to storage and transportation:

$$TE(q,z) = \sum_{i=1}^{I}\sum_{t=1}^{T}[\sum_{\tau=t}^{t+k}(\hat{c}_{it}\, q_{it[\tau]} + \hat{h}_t q_{it[\tau+1]}) + \hat{A}_{it} z_{it}] \qquad (23)$$

The following is a mixed integer linear programming formulation for this inventory replenishment problem, which we refer to as (M-D).

$$minimize_{q,y,z}(TC(q,y,z), TE(q,z))$$

s.t. (M-D)

$$\sum_{i=1}^{I}\sum_{t=[\tau-k]}^{\tau} q_{it\tau} = d_\tau \qquad 1 \le \tau \le T \qquad (24)$$

$$\sum_{\tau=t}^{t+k} q_{it[\tau]} \le \sum_{\tau=t}^{t+k} d_{[\tau]}y_{it} \qquad i = 1, \dots, I; 1 \le t \le T \qquad (25)$$

$$\sum_{\tau=t}^{t+k} q_{it[\tau]} - C_i z_{it} \le 0 \qquad i = 1, \dots, I; 1 \le t \le T \qquad (26)$$

$$y_{it} \in \{0,1\} \qquad i = 1, \dots, I; 1 \le t \le T \qquad (27)$$

$$q_{it\tau} \geq 0 \qquad i = 1, \dots, I; 1 \leq t \leq \tau \leq T \qquad (28)$$
$$z_{it} \in Z^{+} \qquad i = 1, \dots, I; 1 \leq t \leq \tau \leq T \qquad (29)$$

For our convenience, in this formulation we have used the notation $[t] = (t+1) \bmod T+1$ i.e., $d_{[t-1]}=d_{t-1}$ for $t=2,..,T$. This objective function minimizes costs and emissions due to inventory replenishment decisions. The cost function includes production, setup, inventory holding, and transportation costs. The emission objective includes transportation, loading/unloading and storage related emissions. Constraints (24) ensure that demand in the period τ ($\tau =1,\dots T$) is satisfied. Constraints (25) indicate that if a shipment is initiated from supplier i in period t, then, the amount shipped could be as big at the total demand in the following k periods. Constraints (26) identify the number of cargoes required to replenish inventories from supplier i in period t. (27) are the binary constraints. (28) are the non-negativity constraints, and (29) are the integer constraints.

CHAPTER 3 SOLUTION APPROACH

In Chapter 2 we proposed four extensions of the ELS model which capture the impact of carbon regulatory mechanisms on supplier and transportation mode selection decisions in the supply chain. The mechanisms we investigate are the following: carbon cap, carbon tax, carbon cap-and-trade and carbon offset. The models for carbon tax (P-Tax) and carbon cap-and-trade (P-CT) mechanisms are easily solvable. We present two dynamic programming algorithms which solve these problems in polynomial time. The models for carbon cap (P-Cap) and carbon offset (P-CO) mechanisms are NP-hard [16]. In our numerical analysis, we use CPLEX to solve small instances of these problems. The two NP-hard models imply that solution times, when the problems are solved using standard MILP solvers, will be impractical as the problem sizes grow. Both models include a single carbon cap constraint. In the absence of this constraint, the problems are shown to be polynomially solvable. Thus, relaxation of this constraint leads to easily solvable subproblems. Considering this fact, one can develop Lagrangian relaxation-based algorithms to generate good lower and upper bounds for these difficult problems. It is also possible to generate upper bounds for these models by removing the carbon cap constraint, and changing the objective to minimizing the total carbon emissions. However, we do not provide details for these algorithms since this is beyond the scope of this project, which focuses on demonstrating how carbon regulatory mechanisms influence costs and emissions in a biofuel supply chain.

In order to solve the multiple-objective models (M-P) and (M-D) we use the weighted sum and the ε-constraint methods described below.

SOLVING MODELS WITH ENVIRONMENTAL OBJECTIVES

In this section we provide a dynamic programming algorithm to solve model (P). The following proposition presents the properties of an optimal solution to model (P). This knowledge is then used in developing the algorithm presented below.

Proposition 1: *There exists an optimal solution to (P) such that*:

$$q_{it}^{*} q_{lt}^{*} = 0, \qquad for\ i, l = 1, \dots, I, \quad i \neq l, \quad and, \quad t = 1, 2, \dots, T$$

$$q_{it}^{*} H_{t-1}^{*} = 0, \qquad for\ i = 1, \dots, I, \quad t = 1, 2, \dots, T$$

Proof: This indicates that an optimal solution satisfies the zero-inventory ordering property and uses at most one supplier for replenishment in each period. This proposition is adapted from [17]. Model (P) is a special case of the ELS problem with multi-mode replenishment costs and cargo capacity constraints discussed by Eksioglu [18]. In that study, Eksioglu proposes an extension of the dynamic programming algorithm of Wagner and Whitin [4] that solves the ELS model with multi-mode replenishment and fixed-charge cost functions, model (P).

Theorem 1: *There exists a dynamic programming algorithm that solves problem (P) in* $O(IT^2)$.

Proof: Problem (P) is also a special case of the lot sizing problem with substitutions with a single end-product and multiple substitutable components. Based on the Zero Inventory Property, an optimal replenishment schedule exists such that if period t is a replenishment period, the corresponding replenishment quantity equals $\sum_{\tau=t}^{t'-1} d_\tau$ for some $t \le t' \le T+1$ (where t' is the next replenishment period after period t, and we use the dummy period $T+1$ as a final replenishment period in any solution by convention). Based on the Single Source Property of (P) the minimum cost associated with periods t through $t'-1$ equals

$$g_{t,t'} = \{min_{i=1,\ldots,I}(f_{it} + c_{it}d_{t,t'-1})\} + \sum_{\tau=t}^{t'-1} h_\tau d_{\tau+1,t'-1}. \qquad (30)$$

Where $d_{k,j} = \sum_{\tau=k}^{j} d_\tau$ and $k = 1, \ldots, T$ and $0 < k \le j \le T$. Because any solution contains a sequence of setup periods, we can solve problem (P) by solving a shortest path problem in an acyclic network. That is, we create a graph G, where the total number of nodes in G is $T+1$, with one node per time period plus a dummy node $(T+1)$. Traversing arc $(t, t') \in G$ represents the choice of satisfying demand for periods $t, \ldots, t'-1$ using a replenishment in period t. The cost of arc (t, t') is $g_{t,t'}$, and the supplier used for replenishment in period t is the one that gives the minimum in (30). The goal is to find the shortest path from node1 to $T+1$ in G.

The same dynamic programming algorithm can thus be used to solve the problem of (P-Tax) in $O(IT^2)$ time in the worst case.

In an optimal solution of (P-CT), constraints (6) are necessarily binding. For any solution such that the left-hand side is less than the right-hand side, we can decrease the objective (assuming $p > 0$) by increasing the value of one or more e_t^- variables. We can thus re-write constraint (6) as follows:

$$\sum_{i=1}^{I}\sum_{t=1}^{T}(\hat{f}_i y_{it} + \hat{c}_{it} q_{it} + \hat{h}_t H_t) - C = \sum_{t=1}^{T}(e_t^+ - e_t^-) \qquad (31)$$

We can then substitute $\sum_{t=1}^{T}(e_t^+ - e_t^-)$ out of the objective function of (P-CT) as follows:

$$\textbf{\textit{minimize}} \sum_{i=1}^{I}\sum_{t=1}^{T}(f_{it} y_{it} + c_{it} q_{it} + h_t H_t) + p\sum_{i=1}^{I}\sum_{t=1}^{T}(\hat{f}_i y_{it} + \hat{c}_{it} q_{it} + \hat{h}_t H_t) - C \qquad (32)$$

Next, we can re-arrange the terms in the objective function to obtain:

$$\textbf{\textit{minimize}} \sum_{i=1}^{I}\sum_{t=1}^{T}(\tilde{f}_{it} y_{it} + \tilde{c}_{it} q_{it} + \tilde{h}_t H_t) - pC \qquad (33)$$

Where $\tilde{f}_{it} = f_{it} + p\hat{f}_i, \tilde{c}_{it} = c_{it} + p\hat{c}_{it}$, and $\tilde{h}_t = h_t + p\hat{h}_t$ for all $i = 1, \dots, I$ and $t = 1, \dots, T$.

Note that in this objective function, pC is a constant, and so we can remove it from the objective without loss of optimality. After this transformation, the feasible regions of (P) and (P-CT) are identical, as is the mathematical structure of the objective function in both cases. Therefore, we can use the dynamic programming approach detailed above to solve this problem in $O(IT^2)$ time.

SOLVING COST MINIZATION MODELS FOR PERISHABLE ITEMS

In this section we present approaches which solve the cost minimization, inventory replenishment models with multiple setup cost structures.

An optimal solution to the inventory replenishment problem with multiple setups cost structure - described in here using model (Q) - does not satisfy the Zero Inventory Order property. This is due to the fact that the items considered do deteriorate with time. Therefore, in an optimal solution to this problem, demand in a time period can be satisfied through the inventory from a previous period and an FTL replenishment during the current time period. However, a few feasible solutions - which may not necessary be the optimal solution -to the problem, do satisfy the Zero Inventory Order policy. We rely on this in order to develop a dynamic programming algorithm which assumes that the Zero Inventory Order policy holds. For this reason, the solutions found when using this algorithm, are not necessary the optimal solutions to the problem modeled using (Q). We also develop a second dynamic programming algorithm that takes into account the multiple setups cost structure of the cost function. This algorithm is updated from [19] to consider age-dependent perishable inventories. Through extended numerical analysis we calculate the error gap that exists between the dynamic programming algorithm and the optimal solution generated using CPLEX. The maximum error gap observed was 0.1%. The maximum running time for the dynamic programming algorithm was 0.12 CPU seconds, and for CPLEX 596 CPU seconds.

A Dynamic Programming Algorithm for Zero Inventory Order Policy

Based on the Zero Inventory Order Policy, an order is placed at time period t only if $I_{t-1} = 0$. Also, demand of period t cannot be satisfied from both replenishment in period t and inventory from period $t - 1$. Consider that a replenishment schedule exists which, such that: period t is a replenishment period and the corresponding replenishment quantity equals $b_{t\tau} = \sum_{\gamma=t}^{\tau-1}({}^{b_\gamma}/_{k_{t\gamma}})$ for some $t \le \tau \le T+1$ where $1 \le t \le T$, and τ represents the next replenishment period after period t. Let $T + 1$ be a dummy period with demand equal to zero. The number of cargo containers for the replenishment in period t equals $M_{t\tau} = \left\lceil {}^{b_{t\tau}}/_{C} \right\rceil$. The cost associated with satisfying demand from period t through $\tau - 1$ is denoted by $f(t, \tau)$ and equals:

$$f(t,\tau) = s = \sum_{\gamma=t}^{\tau-1} C_{t\gamma} {}^{b_s}/_{k_{t\gamma}} + AM_{t\tau}$$

We created an acyclic network where each $f(t, \tau)$ represents an arc cost on the graph and we solved the shortest path problem to find the optimal solution. We create graph G - as shown in Figure 3-1 – which has T +1 nodes are; one for each of the T time periods in addition to the dummy node T +1. Each arc (t, τ) in G represents a shipment that satisfies demands from t through $\tau - 1$. The cost of each arc $(t, \tau)$is equal to $f(t, \tau)$. The dynamic programming algorithm finds the shortest path from node 1 to T + 1 in graph G.

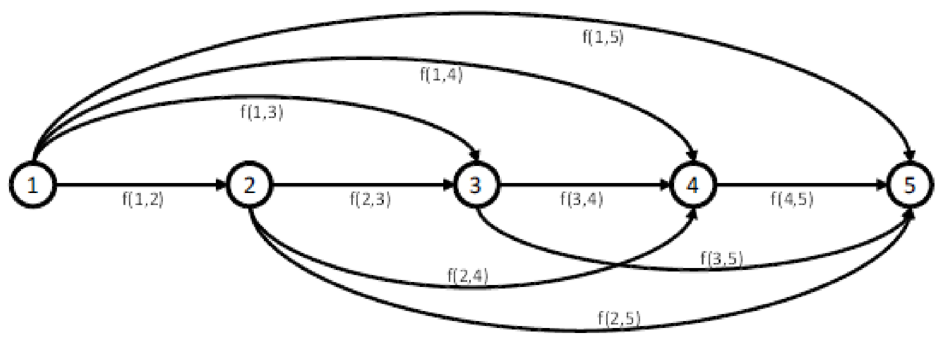


Figure 3-1- Network representation for dynamic programming algorithm (T = 4).

A Dynamic Programming Algorithm for Multiple Setups Cost Structure

Hwang [19] proposes a dynamic programming algorithm to find the optimal solution for the problem with a single replenishment mode, stationary cargo costs and a no speculative cost structure. We proposed a dynamic programming based heuristic by modifying this algorithm to consider age-dependent perishable inventories. We again assume $t - 1$ and$\tau - 1$ $(1 \leq t < \tau \leq T + 1)$ be two consecutive regeneration points. Let the (t, τ) problem be finding the minimum cost (denoted by $f(t, \tau)$) of satisfying total demand from period t through $\tau - 1$. Once all $f(t, \tau)$ values are determined, the shortest path on Figure 3-1 finds the minimum solution to the model.

Finding $f(t, \tau)$ values are more challenging in this case, as there may be FTL shipments within the (t, τ) problem.

Let $g(m, \tau)$ be the minimum cost of (m, τ) problem using only FTL shipments. Thus, $f(t, \tau)$ is calculated as a function of $g(m, \tau)$. It calculates the minimum cost of satisfying the demand in (t, τ) problem with a possible LTL shipment only in period t and FTL shipments in the remaining periods. The procedure uses a backward dynamic programming approach.

SOLVING MULTI OBJECTIVE MODELS FOR PERISHABLE ITEMS

The two methods used to solve the bi-objective optimization models described above are the weighted-sum and ε-constraint methods. The weighted sum method is a traditional, popular method which transforms a bi-objective problem into a series of single-objective problems. This method generates a number of single-objective problems by changing the weights assigned to each objective function. The solutions to these problems approximate the Pareto frontier for the bi-objective problem. The ε-constraint method minimizes one individual objective function with an upper level constraint imposed on the other objective function. The Pareto frontier is approximated by solving this single-objective problem for different values of the upper bound imposed on the other objective function.

A weighted sum method: The weighted sum method minimizes a weighted sum of the two objectives $\boldsymbol{\lambda_1 TC + \lambda_2 TE}$. Typically, the values of $\boldsymbol{\lambda_1}$ and $\boldsymbol{\lambda_2}$ are selected such that $\boldsymbol{\lambda_1} + \boldsymbol{\lambda_2} = 1$ and $\boldsymbol{\lambda_1, \lambda_2} \geq \mathbf{0}$. The Pareto frontier is then created by solving the single-objective problem for different values of $\boldsymbol{\lambda_1}$ and $\boldsymbol{\lambda_2}$. The following is the objective function of the single-optimization problem under the weighted sum approach.

<u>Deteriorating items:</u>

$$minimize_{q,y,z} \lambda_1 TC(q,y,z) + \lambda_2 TE(q,z)$$

Subject to: (10) – (13)

$$\lambda_1, \lambda_2 \geq 0$$

<u>Fixed-shelf life items:</u>

$$minimize_{q,y,z} \lambda_1 TC(q,y,z) + \lambda_2 TE(q,z)$$

Subject to: (14) – (17)

$$\lambda_1, \lambda_2 \geq 0$$

In this study, the sum of $\lambda_1 + \lambda_2$ is not equal to 1. We set the value of $\lambda_1 = 1$ and change the value of λ_2. One can think of the values of λ_2 as the cost of per unit of CO_2 emissions. In this case, the objective function calculates the total costs due to replenishment and emissions in the supply chain. This approach helps us test for changes in the total costs by increasing in the relative importance of λ_2 to λ_1. λ_2 could as well be considered as the tax a facility would pay per unit of emission under a carbon tax mechanism. Carbon regulatory mechanisms, such as carbon cap, carbon tax, carbon cap-and-trade, and carbon offset do not exist at the federal level. However, a few actions have already been enacted. For example, policies articulated by executive order in California set statewide GHG emission reduction targets for 2010, 2020, and 2050**.**

An $\boldsymbol{\varepsilon}$ -constraint method: The ε-constraint method approximates the set of Pareto solutions by solving a series of instances of the following single-objective problem for different values of the parameter ε.

<u>Deteriorating items</u>:

$$minimize_{q,y,z}\ TC(q,y,z)$$

Subject to: (14) – (17)

$$TE(q,z) \leq \varepsilon$$

$$\underline{\varepsilon} \leq \varepsilon \leq \overline{\varepsilon}$$

Fixed-shelf life items:

$$minimize_{q,y,z}\, TC(q,y,z)$$

Subject to: (10) – (13)

$$TE(q,z) \leq \varepsilon$$
$$\underline{\varepsilon} \leq \varepsilon \leq \overline{\varepsilon}$$

These models identify an inventory replenishment schedule which minimizes total costs, subject to, carbon emission constraints. One can think of ε as an emission cap imposed on the facility under the scenario that a carbon cap policy is used.

The lower and upper limits within which the ε parameter must fall in ($\underline{\varepsilon} \leq \varepsilon \leq \overline{\varepsilon}$) are obtained from the optimization of each separate objective function as follows:

Deteriorating items:

$$minimize_{q,y,z}\, TE(q,z)$$

Subject to: (14) – (17)

Fixed-shelf life items:

$$minimize_{q,y,z}\, TE(q,z)$$

Subject to: (10) – (13)

Let (q, z) be the solution to this problem. Then, $\underline{\varepsilon}$ = TE (q, z) represents the minimum level of carbon emissions required to meet demand, without any considerations of costs.

Deteriorating items:

$$minimize_{q,y,z}\, TC(q,y,z)$$

Subject to: (14) – (17)

Fixed-shelf life items:

$$minimize_{q,y,z}\, TC(q,y,z)$$

Subject to: (10) – (13)

Let (q, y, z), be a solution to these models. Then, $\overline{\varepsilon}$ = TE (q, z) represents the emission levels for the cost-optimal solution to the problem.

CHAPTER 4 FINDINGS AND APPLICATIONS

DATA GENERATION

In the following section we summarize the data we generated in order to test our algorithms and validate our models. We start by describing the dataset used to test models with environmental objectives and non-perishable items. The results of these experiments are summarized in Figures 4.1 to 4.3.

The product on which we focus on in this analysis is forest residue. Due to its physical characteristics of bulkiness, barge, rail, and truck may be used for shipping. The choice of the transportation mode depends on the travel distance and the associated level of carbon emissions. Forest residues are raw materials that can be used by biorefineries to produce cellulosic ethanol. We assume that such a biorefinery can meet its demand for forest residues using suppliers located nearby, or other suppliers around the nation. Canada is rich in forest, and therefore Canadian companies can be potential suppliers of forest residues. These suppliers may use rail or barge to ship their products to the US. Table 4.1 summarizes some of the parameters our study used to generate data related to suppliers. We use uniform distributions to randomly generate transportation distances and variable replenishment costs. The selection of purchasing costs (at the roadside) is motivated by the following fact. The US Department of Energy (US DOE) estimates that for a price ranging from $20 to $80 per dry ton at the roadside, quantities of forest biomass currently available for production of biofuels would vary (at the national level) from 33 to 119 million dry tons (MDT) annually. However, for the biofuels industry to thrive, high levels of biomass should be available at lower prices. The US DOE is investigating a number of technology improvements, such as pre-processing of biomass that would reduce these prices in the near future [16]. The data in the table indicates a decrease in purchasing costs as we consider suppliers located further away. This is mainly because the pool of available suppliers increases as we consider suppliers located further away. A larger supplier pool provides the facility with more competitive prices.

Table 4.1 Input data for forest residues

Distance (in miles)	Number of Suppliers	Purchasing Costs (in $)
U[5-25]	5	U[40-42]
U[25-100]	5	U[38-40]
U[100-500]	5	U[36-38]
U[500-1,000]	15	U[34-36]
U[1,000-1,500]	15	U[30-35]

Table 4.2 presents the scheme we use to assign transportation modes to suppliers. We assume that suppliers located within 25 miles of the facility will use truck shipments only. We assume that 50% of the suppliers located between 25 and 100 miles have access only to truck

shipments, and the remaining 50% have access to both truck and rail. We assume that 50% of the suppliers located between 100 and 500 miles have access to truck and rail, and 50% have access to truck, rail and barge. As distance increases, the number of suppliers that have access to all modes of transportation increases. We use this scheme to also capture the reality that some suppliers may not have access to barge or rail due to the limited rail and barge infrastructure.

Table 4.2 Transportation mode assignment scheme

Distance (in miles)	Truck (in %)	Truck & Rail (in %)	Truck & Rail & Barge (in %)
U[5-25]	100	0	0
U[25-100]	50	50	0
U[100-500]	0	50	50
U[500-1,000]	0	30	70
U[1,000-1,500]	0	0	100

Table 4.3 presents the scheme we use to generate variable costs for truck transportation. Variable transportation costs depend on the distances traveled and the quantities shipped; therefore, the unit costs presented in the table are charged per mile and per ton traveled. The intervals that we use to calculate costs were generated by analyzing data made available by the Agricultural Marketing Service (AMS) of the US Department of Agriculture. The AMS publishes quarterly reports which present truck transportation trends for agricultural products in different regions of the US. The data in the table presents the average national rates charged during the last six quarters, beginning in January 2011.

Table 4.3 Variable cost for truck transportation

Distance (in miles)	Unit cost ($/(mile*ton))
[0-25]	U[0.0801 - 0.2401]
[25-100]	U[0.0457 - 0.1857]
> 100	U[0.0346 - 0.1746]

We randomly generated the fixed cost and variable costs for rail shipments. To identify these costs, we investigated the web-sites of Class I railway companies, such as CSX Transportation and BNSF Railway. These companies provide quotes (in $ per rail car) for different products and different origin-destination pairs. We used the data provided for forest products to derive regression equations. The independent variable in these equations is the distance traveled, and the dependent variable is the price charged per rail car. The value of R^2 for these equations was 70% and the p-values of all independent variables were smaller than 0.1%. These values indicate that transportation distance has a great impact on the price charged. Based on these results, we decided to generate the fixed transportation cost using the following uniform distribution U[$2, 500, $3,500] (in$/shipment), and the unit variable cost using the following uniform distribution U[$0.008, $0.2] (in $ /(mile*ton)). We also use data from AMS publications to derive transportation costs for barge. Based on this data, we generated the variable transportation cost using the following uniform distribution U[$0.100, $0.112] (in $ /(mile*ton)).

We also consider the in-transit inventory costs. This is very important as the travel time differs substantially in different transportation modes. To calculate these costs, we first identify the travel time (in number of days) per shipment using information about travel distance and the average speed of the transportation vehicle. We assume the average speed for a truck is 65 mph, for rail 18 mph, and for barge 6.25 mph; vehicles operate for a total of 16 hours per day, and vehicles operate for 350 days per year. The annual unit inventory holding cost (in $ /ton) is set equal to 20% of the unit purchase cost. We then use trip duration and unit inventory holding costs to calculate the inventory holding costs per ton shipped.

The total unit replenishment cost for supplier i, c_i (in $/ton), is the sum of the unit purchasing, transportation and in-transit inventory holding costs. The unit purchasing cost for supplier i is charged per ton of product replenished. Since variable transportation costs are provided in $/(mile*ton), we multiply a supplier's transportation distance by the variable transportation cost in order to calculate a variable transportation cost per ton shipped from supplier i. We consider a time horizon of T = 12 months, with t = 1,…,12. We assume that demand for forest residues in each month is uniformly distributed between 80,000 and 100,000 tons. The conversion rate is estimated to be 60 gallons of ethanol per ton of residues [17]. Thus, the production capacity of the facility ranges between 57.6 and 72 million gallons of year (MGY).

Let us now discuss the approach we used to collect emissions related data. In order to calculate emissions from material handling, we assume that loading and unloading of trucks, rail cars and barge are completed using loaders. The maximum allowable load for trucks (30 tons) is much smaller than rail (100 tons) or barge (1,500 tons) [18]. For a 30 ton truck, the loading time of forest residue bundles takes about 45 to 50 minutes, and unloading takes about 50 to 55 minutes [84]. We assume that a loader with horsepower of 140 and fuel consumption of 0.0217 gals/(hp*hr) is used [19]. It is estimated that the consumption of one gallon of diesel fuel emits 9; 922 grams of CO_2 [20]. We assume that all modes of transportation use the same loading and unloading equipment, and therefore, we calculate the fixed emissions in tons of CO2 per ton loaded and unloaded as follows: (duration of loading and unloading activities) * 0,0217 * 140 * 9,922 * 10^{-6}/30. Loading and unloading times are given in hours.

We also consider emissions due to storage of forest residues. A study by Wihersaari [21] indicates that greenhouse gas emissions from storage can be much greater than emissions from the transportation of forest residues. The study indicates that "Greenhouse gas emissions are probably methane, when the temperature in the fuel stack is above the ambient temperature, and nitrous oxide, when the temperature is falling and the decaying process is slowing down." Following this study, we consider emissions due to storage and inventory to be uniformly distributed between 5 and 10 kg per ton of forest residues held in inventory every month.

We use the method developed by Hoen et al. [22] to calculate emissions from transportation. Hoen et al. [22] provide the following equations to calculate emissions for transportation via truck, rail and barge. In these equations, transportation distance D is in kilometers, the load weight w is in kilograms, v denotes volume, and p denotes density.

$$e_{truck} = v * max(25, p) * (0.0002089 + 0.00003143*D)$$
$$e_{rail} = 2.223 * 10^{-5} * D * w$$
$$e_{barge} = 1.3904 * 10^{-5} * D * w$$

To generate the results in Figures 4.4 to 4.9 we consider the following example. Suppose that a retailer replenishes its inventories for a perishable product using 3 suppliers. Supplier 1 is a local supplier who uses a less-than-truckload (LTL) service provider. Supplier 2 is a wholesaler who provides the product at a discount price. This supplier sends shipments using dedicated, non-refrigerated trucks. Supplier 3 is also a wholesaler who uses dedicated, refrigerated trucks for delivery. Each supplier has its own lead time as shown in Table 4.1. We assume that products do not perish during delivery time if shipped by refrigerated trucks. Replenishment costs from supplier 3 are higher than supplier 2 due to using a refrigerated truck, but smaller than the local supplier. Order set-up and processing costs are the same for each supplier. Cargo container costs, which represent loading and unloading costs, are zero for the LTL service provider since he simply charges a fixed dollar amount per ton of product shipped. The dedicated trucks have a fixed capacity of 25 tons. Unit emissions are higher for shipments that use refrigerated trucks since additional energy is consumed for refrigeration. We consider a time horizon T = 10 days, and a time period equal to 1 day. We assume that inventory holding costs equal $1/(ton*day) and inventory holding emissions are 0.5 kg/(ton*day). Inventory holding emissions are due to using air conditioning in the storage area. We test the performance of this retailer considering different daily demands which vary from low demand levels ($b_t \sim$ [2;4] tons), to medium ($b_t \sim$ [4;6] tons) and high ($b_t \sim$ [14;16] tons.

Table 4.4 Problem parameters

Supplier	Replenishment mode	Replenishment unit cost (p)	Fixed order cost (s)	Fixed cargo Cost (A)	Capacity of mode (W)	Fixed emissions ($\hat{A}$)	Variable emissions ($\hat{c}$)	Lead time (L)
1	LTL	15	50	0		30	1	1
2	Non refrigerated FTL	10	50	U[45,55]	25	50	1	2
3	Refrigerated FTL	12	50	U[45,55]	25	50	1.5	3

The results presented in Figures 4.2 to 4.4 correspond to a product which deteriorates with time. In order to generate these results, we assume daily deterioration rates vary from 0 to 19%. Since deterioration increases with a product's age, we consider the increment to be constant at 1% daily. Deterioration rate during refrigeration is assumed zero. To generate these results we used the ε-constraint method and set the value of ε equal to 325 kg. This is the same as solving the problem by considering the cost objective only. The purpose of these experiments is to observe the impact of perishability on replenishment decisions.

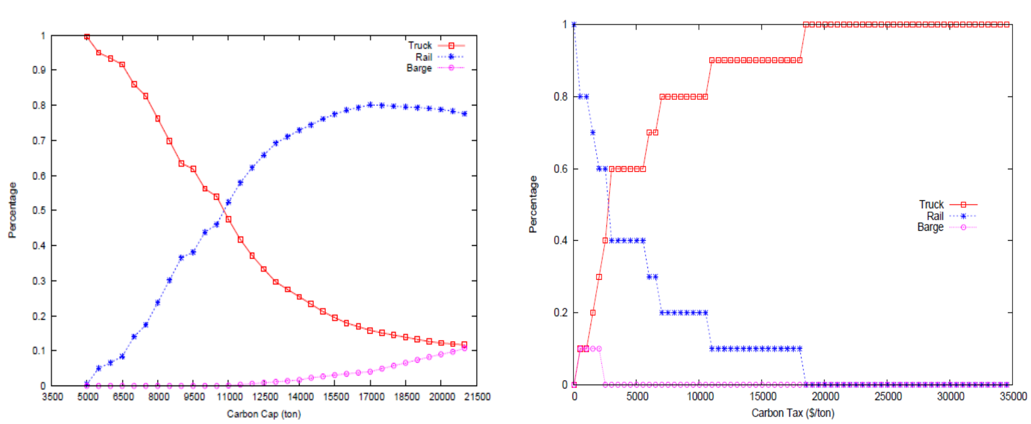
The results presented in Figures 4.5 to 4.7 correspond to products which have a fixed shelf life of *k* periods. The results presented in these graphs are obtained by solving the problem using the weighted sum method. In these experiments we use $\lambda_1 = 1$ and $\lambda_2 = 0.7$. The sum of $\lambda_1 + \lambda_2 > 1$.

Since a number of parameters used in these problems are generated randomly, for each problem solved we generate 10 instances, and present here the average of the results over all instances. The models are solved using the ILOG/CPLEX commercial solver.

FINDINGS AND APPLICATIONS

Models with Environmental Objectives

We investigated the use of the models developed to gain insights on the impacts the potential carbon regulatory policies, such as carbon cap and carbon tax have on transportation mode selection decisions, costs, and emissions in the supply chain. More specifically, the results from our numerical analysis help us to (a) make important observations with respect to the tradeoffs that exist between costs and emissions; (b) analyze the implications that carbon regulatory mechanisms have on supply chain-related costs and performance; and (c) identify the mechanism that has the greatest impact in GHG emission reductions on the supply chain.



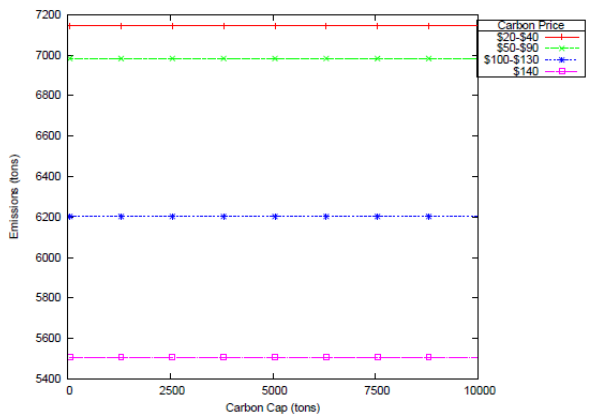
(a) (b)

(a) Carbon cap mechanism (b) Carbon tax mechanism

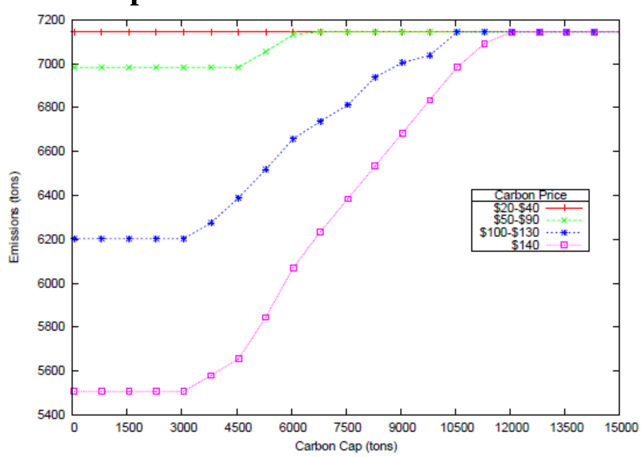
Figure 4-1 Transportation mode utilization.

The graphs in Figure 4-1 present the percentage usage of each mode of transportation for the delivery of forest residues under carbon cap and carbon cap and trade mechanisms. Under a carbon cap policy, decreasing the carbon cap level leads to an increase in the use of truck shipments from local suppliers to replenish inventories. As the carbon cap increases, other modes of transportation are explored. Under a carbon tax policy, similar behavior is observed. However, the shapes of the curves are not continuous, indicating that companies are less responsive to a carbon tax than a carbon cap. Figures 4-1 c and d are based on carbon market and offset price of 20 to 40 $.

A carbon cap and trade mechanism is more efficient than a carbon offset mechanism. The supply chain behaves similarly under the two mechanisms when the carbon cap is tight. However, the supply chain behaves differently under the two mechanisms when the cap is loose. Under loose carbon caps, in a cap and trade mechanism, the unused carbon units can be sold in the market at a profit. This is not the case under a carbon offset mechanism, which punishes companies for going over the cap, but does not reward for emissions below the cap. The shapes of the graphs in Figure 4-2 and Figure 4-3 support this observation.



4-2 Carbon Cap and Trade Mechanism - Total Emissions.



4-3 Carbon Offset Mechanism - Total Emissions.

Replenishment Decisions for Age-Dependent Perishable Items

Using the models presented above we obtained insights about the relationship that exists between costs and emissions, transportation and inventory costs, and transportation mode and inventory holding costs for deteriorating items. More specifically, based on the results from our numerical analysis, we made the following observations.

a) An increasing deterioration rate or short shelf life impacts supplier selection decisions in the supply chain. Suppliers that have shorter lead times are preferred since shorter lead times for perishable products imply longer shelf life. (See graph in Figure 4-4; Suppliers 1 and 2 are local and have zero lead time, while Supplier 3 is a far away wholesaler.)

b) An increasing deterioration rate increases inventory replenishment costs, as suppliers that have shorter lead times (such as local suppliers) do not necessarily provide the least expensive products (see Figure 4-5-a).

c) As the deterioration rate increases and the shelf life of a product decreases, inventories are replenished in smaller quantities. This increases the frequency of shipments and consequently, the fixed order replenishment costs (see Figure 4-5-b).

d) An increasing deterioration rate increases emissions due to using refrigerated trucks, and increasing the frequency of shipments (see Figure 4-6).

e) Decreasing emissions in the supply chain comes at a cost. There are a number of operational changes (such as supplier selection, or transportation mode selection) which result in great emissions reductions and result in relatively small increases in costs (see Figure 4-6).

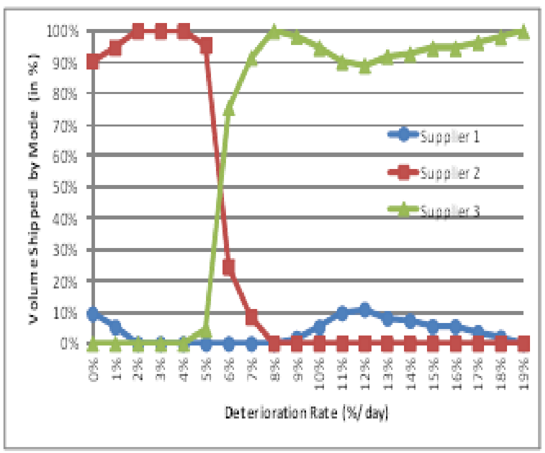
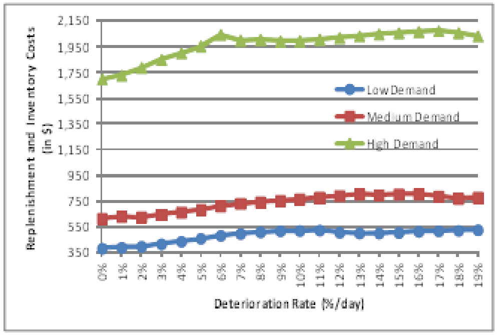
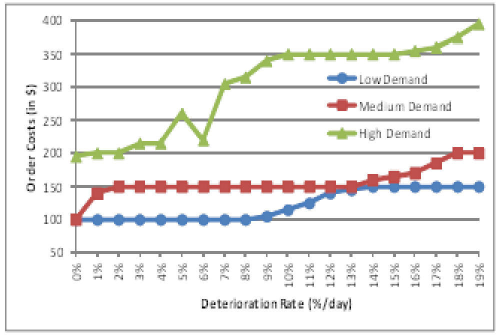


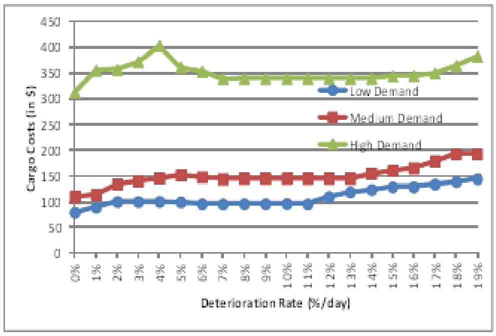
Figure 4-4 Replenishment mode selection for deteriorating products when demand is low.



(a) Replenishment and Inventory Costs



(b) Order Costs



(c) Cargo Costs

Figure 4-5 Total Cost Distribution.

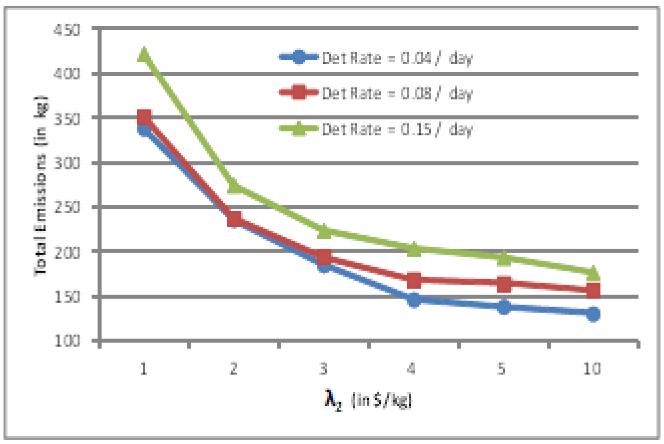


Figure 4-6 Total Emissions versus λ_2 (multiplier we use for emissions in the objective function when implementing the weighted sum method.).

Replenishment Decisions for Perishable Items with Fixed Shelf-Life

The following are some important observations about products with a fixed shelf life.

a) As the length of the shelf life of a product increases, the use of full-truckload shipments increases. As the value of *k* increases, the facility has the flexibility to use local suppliers as needed, or use discounted full-truckload shipments (see Figure 4-7).
b) As the product shelf life increases, purchasing costs decrease. Long product shelf life provides more flexibility for inventory replenishment decisions. For example, as shelf life increases, the plant has the option to order not only from local suppliers, but also from suppliers located further away. As a result, purchasing costs decrease due to increasing the pool of suppliers (see Figure 4-8-a).
c) Order costs decrease when *k* increases. (See Figure 4-8-b) This is due to the fact that, as product shelf life increases, orders are placed less frequently. Each order is of a larger size, which justifies the use of full truckload shipments. Thus, cargo container costs increase with *k* (see Figure 4-8-c).
d) Inventory holding costs increase due to the increase in product shelf life and, consequently, due to the increase in order size (see Figure 4-8-d).
e) For products with a very short shelf life ($k = 1$), increasing the value of λ_2 does not impact total emissions. When product shelf life is short, the facility has less flexibility in replenishment decisions. In our example, the facility replenishes its inventories using the local supplier. As the value of *k* increases, the facility has more options to explore. In this case, the multiplier λ_2 plays a greater role in reducing emissions in the supply chain. Increasing the value of λ_2 impacts replenishment decisions and reduces emissions. One can think of λ_2 as a penalty multiplier for emissions in the objective function, or as an emissions tax, which is charged per unit of CO_2 generated in the supply chain. Thus, as the value of this tax increases, the amount of CO_2 emitted decreases (see Figure 4-9)

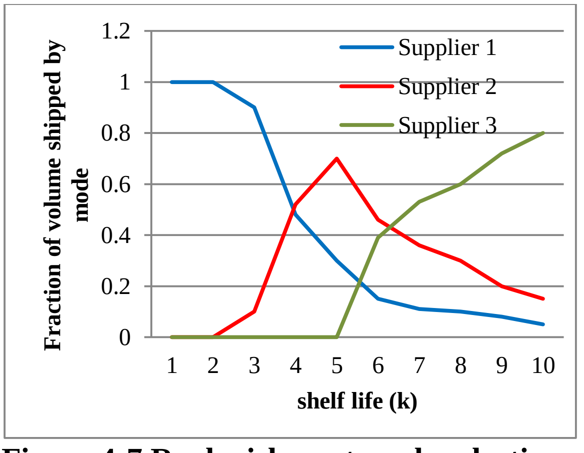
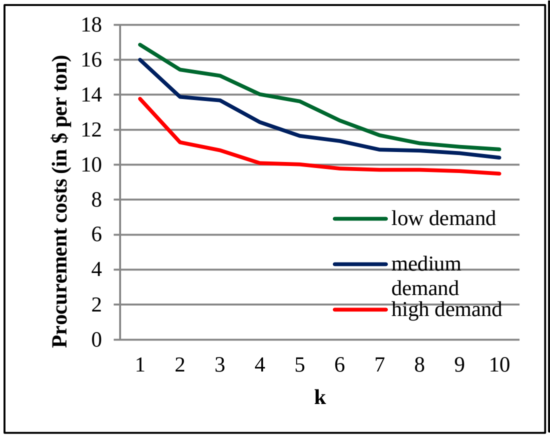
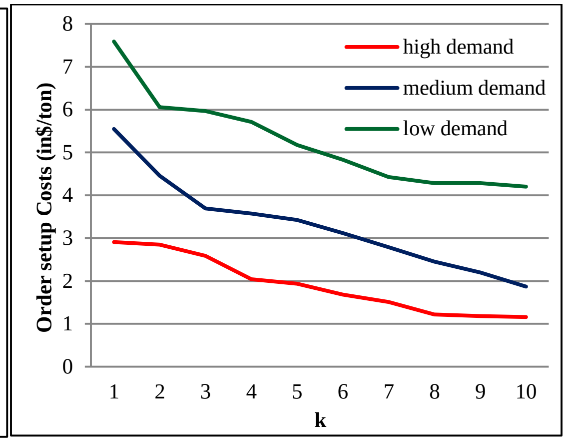
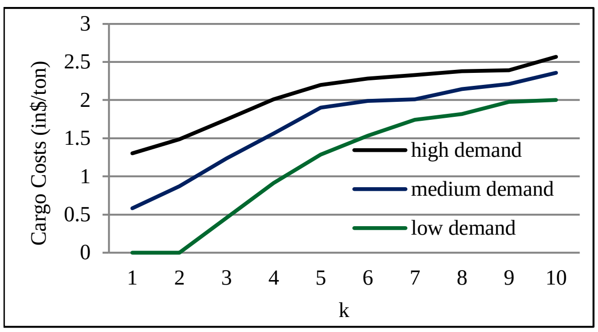


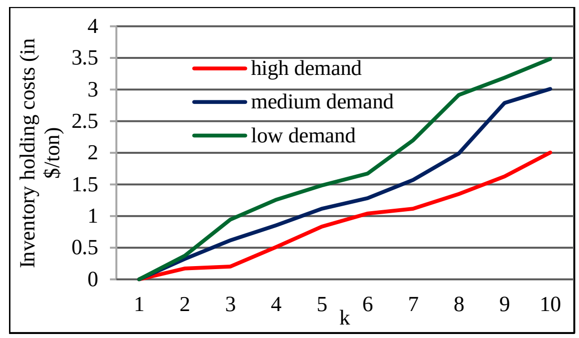
Figure 4-7 Replenishment mode selection.





(a) (b)





(c) (d)

Figure 4-8 Replenishment-related costs versus product shelf life.

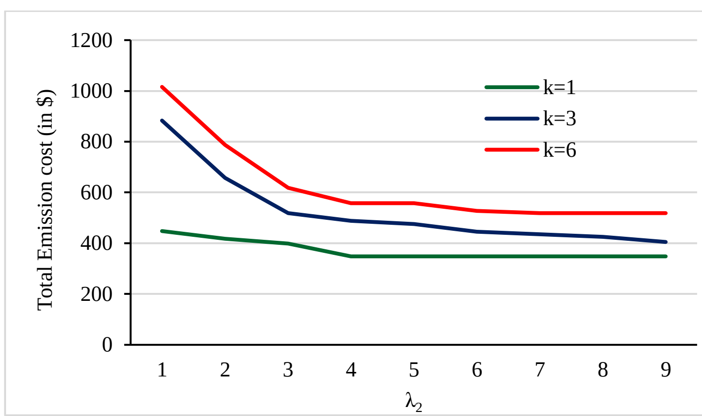


Figure 4-9 Total emissions versus λ_2.

CHAPTER 5 CONCLUSIONS AND SUGGESTED RESEARCH

CONCLUSIONS

This research studies extensions of the ELS models to capture the environmental impacts of replenishment decisions in the supply chain. These models are further extended to consider perishable products with either a fixed shelf-life or products which deteriorate with time. We also investigate the impact of multiple replenishment modes to costs and emissions in the supply chain of perishable products.

Replenishment decisions for perishable products are challenging due to shorter lifetime in the shelves. Replenishment decisions for perishable products are subject to a variety of tradeoffs. We investigate the trade-offs that exist between transportation costs and remaining shelf life of products, transportation and inventory costs, and total costs and CO_2 emissions resulting from transportation and inventory holding. The objective of the models proposed is to satisfy the demand for perishable products over the time horizon using different replenishment modes such that the total costs and total emissions of the supply chain are minimized. Experimental results provide some interesting insights about the impacts of carbon regulatory mechanisms on supplier and transportation mode selection decisions in the supply chain.

We provide a number of mathematical models and solve these models using algorithms which were developed based on the knowledge we created about the properties of optimal solutions to these problems. For example, we developed dynamic programming algorithms to solve some special cases of the cost-minimization models for products which deteriorate with time. One of the algorithms solves the problem assuming that the Zero Inventory Order policy holds. The other algorithm solves the problem with a single replenishment mode, stationary cargo costs and a no speculative cost structure. The bi-objective optimization models are solved using the ε-constraint and the weighted sum methods.

The following are some important observations for replenishment decisions for perishable products: deterioration rate and product shelf life impacts the supplier selection decisions in the supply chain, the frequency of shipments, emissions and costs in the supply chain.

SUGGESTED RESEARCH

A possible extension to this research is to consider the joint replenishment decisions of different products types which use the same replenishment modes. In this case, replenishment decisions should address additional tradeoffs that exist between replenishment costs, required delivery time, shelf life of multiple products, and lead time of each replenishment mode. Consolidating replenishment decisions of different products may lead to fewer order setups, but may increase total inventory holding costs. Thus, this problem requires an extended analysis to understand the impact of joint replenishment decisions on the total costs and emissions.

Another extension of these models is to capture the impact that disposing of perishable products has on costs and emissions. Perishable products go to waste due to expiration date or deterioration. While some customers are willing to purchase products of high quality at a higher price, others, may be willing to purchase a product of lower quality when supplied at a low price. The lower quality is due to keeping a perishable product on the shelves for some time. Therefore, one could develop models to capture the tradeoffs that exist between price and quality of perishable products.

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