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Models for Cost Efficient and Environmentally Friendly Inventory Replenishment Decisions for Perishable Products

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Abstract

This study presents a bi-objective, mixed-integer programming model in support of inventory replenishment decisions for age-dependent perishable products. The bi-objective optimization model minimizes costs and emissions due to inventory replenishment-related decisions in the supply chain, such as transportation mode selection, supplier selection, and inventory management. The model captures the tradeoffs 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. We use two different approaches to solve the bi-objective model, a modified weighted sum approach and an ε-constraint method. Our experimental results show the tradeoffs that exist between costs and emissions as well as the impacts of lead time and deterioration rates in the performance of the supply chain of perishable products.

Keywords
Perishable inventory, economic lot-sizing, carbon emissions, transportation, supply chain operations.

1. Introduction
This paper proposes a mathematical model that aids inventory replenishment decisions for deteriorating products, such as agricultural and dairy products, human blood, photographic film, etc. Deterioration refers to spoilage, dryness, vaporization, etc., which results in value lost during the storage period. These products are known as perishable products. The model we propose is a multi-objective, mixed-integer linear programming model which minimizes costs and environmental impacts due to supply chain activities including transportation and inventory. The cost objective of this model minimizes 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.

Inventory replenishment decisions for perishable products are more challenging as compared to non-perishable products. This is due to the fact that these products lose value with time, and consequently have a limited shelf life. Therefore, inventory replenishment decisions are impacted not only by the tradeoffs that exist between replenishment and inventory holding costs, but also by the remaining value and shelf life of perishable products. The remaining shelf life of a perishable product can be increased by using refrigerated trucks and storage areas. These activities increase energy consumption and consequently carbon emissions. We live in an environment where public awareness about environmental issues has been increasing. Companies cannot afford to ignore the public, and thus are faced with replenishment decisions which are not easy to make. The goal of this research is to provide tools that can be used by companies in order to make (cost and environmentally conscious) inventory replenishment decisions for perishable products.

One of the main motivations for this research is the public concern about the increased emission levels and the impact of emissions on the quality of our lives. Many countries and governments have accepted that there is an urgent need to put policies into action that set reduction targets for total emissions. For example, through its European Climate

Change Program, the European Union aims to reduce its carbon emissions by at least 20% by 2020 as compared to 1990 levels [1]. As a consequence, many companies are required to take 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.

The model presented below captures the tradeoffs that exist between transportation lead time and remaining shelf life of perishable products. 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, say a 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 limiting pool of suppliers than can be reached and, therefore, less competitive prices. Using refrigerated trucks, refrigerated rail cars and airplanes results in higher transportation costs as compared to using trucks and rail cars.

The model presented below also captures the tradeoffs that exist between costs and emissions in the supply chain. For example, using refrigerated trucks and refrigerated storage areas for dairy products increases products' shelf life. Longer product shelf life reduces the fixed inventory replenishment costs since less frequent replenishments are necessary. On one side, using refrigerated trucks and storage areas increases energy consumption and, as a consequence, GHG emissions. Reducing the number of replenishments saves transportation-related energy.

Experimentations with the environmental objective helps the reader gain insights about the impacts that green initiatives (such as reducing the carbon footprint of the supply chain) have on transportation mode selection decisions, costs and overall emissions levels in the supply chain. The results presented from the numerical analysis help the reader make important observations with respect to the tradeoffs that exist between costs and emissions and identify the mechanism that has the greatest impact on GHG emission reductions on the supply chain. Environmentally conscious companies can use these models and the corresponding solution algorithms as sub-modules within their MRP systems to account for requirements planning when multiple modes, perishable products, and multi-supplier replenishment options exist.

2. Literature Review

The model presented in this paper is an extension of the classical Economic Lot Sizing (ELS) model. The classical ELS model identifies inventory replenishment schedules for non-perishable products which have deterministic and time-varying demand [2]. The classical ELS model assumes that one supplier and one transportation mode can be used to replenish inventories. Replenishment costs are assumed to contain a fixed charge for placing an order. We extend the ELS model by allowing multiple suppliers and transportation modes to be used to replenish inventories. Each supplier uses a particular transportation mode, and has a fixed transportation lead time. Each transportation mode is characterized by its cost and emission functions. The model identifies an inventory replenishment schedule which minimizes total system costs, which include transportation, inventory and purchasing costs. The model also minimizes emissions due to transportation and inventory.

Nahmias [3], and Goyal and Giri [4] present extensive reviews of inventory replenishment models for perishable products. Nahmias distinguishes between perishable products with fixed versus random lifetime. Our article considers perishable products that deteriorate with time and therefore have a random lifetime. The literature discusses deterministic inventory replenishment models for perishable products with random lifetime. These are extensions of the Economic Order Quantity (EOQ) model [5, 6], and Economic Lot Sizing model [7]. For inventory replenishment models for perishable products with fixed lifetime see Eksioglu and Jin [8], Ahuja et al. [9], Zhang and Eksioglu [10], and Onal [11].

Analyzing the impact of operational decisions (such as, inventory management, transportation mode selection, etc.) on a product's carbon footprint has been the focus of a number of recent studies. Some of these studies propose methods to measure and quantify carbon emissions in the supply chain due to processes such as transportation and inventory [12]. Other studies propose optimization models to minimize the carbon footprint of a supply chain through changes in supply chain design and operations. For example, Hoen et al. [13] investigate the effect of two regulatory mechanisms on transportation mode selection in the supply chain under stochastic demand. Benjaafar et al. [14] extend classical ELS model to capture the impact of carbon regulatory policies on inventory replenishment decisions.

The work presented in our paper falls in this latter stream of research, which identifies changes on the operational decisions (such as, inventory replenishment schedules, transportation modes and supplier selection) that impact costs and emissions in the supply chain. Different from the literature, our model also identifies tradeoffs that exist between lead time, remaining shelf life and product perishability in the supply chain.

There is an extensive existing literature in the field of multi-objective programming (MOP) [15]. The purpose of MOP models is to optimize systematically and simultaneously a collection of conflicting objectives. Solving an MOP problem means identifying the set of Pareto optimal solutions which are solutions that are nondominated in the sense that no subset of objectives can be improved without making at least one objective worse. MOP models have been used to optimize green supply chains. For example, Wang et al. [16] uses a bi-optimization model to design a supply chain network which optimizes costs and emissions. This paper extends the classical facility location model to consider transportation-related costs and emissions when making facility location decisions. Neto et al. [17] propose an algorithm to solve an MOP model with three objectives: minimize costs, cumulative energy demand and waste in a reverse logistics network. This paper is consistent with this work since it uses an MOP to optimize costs and emissions in a supply chain.

3. Model Formulations

In this study we assume that the product replenished deteriorates during transportation lead time and storage at the facility. We assume that the product is shipped as soon as it is produced. We denote the deterioration rate from period t to period τ for a replenishment from supplier i, 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 fraction of inventory from supplier i sent in period t that has not perished in period l. We define $k_{itt} = 1$ and $k_{itl} = \prod_{j=t}^{l-1}(1-\alpha_{itj})$ for $1 \leq t \leq l \leq T$. 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 cost-objective of the bi-objective optimization model we propose minimizes the total inventory holding and replenishment costs required by a facility in order to satisfy demand in period t, denoted by b_t, during a planning horizon of length T ($t = 1,\ldots,T$).

One of the decision variables we use is $q_{it\tau}$ which represents the amount shipped by supplier i which arrives in period t to satisfy demand in period τ. Using $q_{it\tau}$ allows us to calculate the age of a product and corresponding inventory replenishment costs.

Inventory holding costs are due to using the storage area, and using refrigerated storage. The unit inventory holding costs in period t is denoted by h_t. We expect inventory holding costs to change with time due to fluctuations in the price and consumption of electricity. However, these costs are not a function of the age of the inventory. Letting $H_t(q_{it\tau})$ denote the inventory holding cost function in period t, then $H_t(q_{it\tau}) = h_t \sum_{i=1}^{I}\sum_{s=1}^{t}\sum_{\tau=t+1}^{T} q_{is\tau}$.

The facility uses a total of I different suppliers to replenish inventories. Each supplier uses one of M transportation modes available. Let $Q_i(q_{it\tau})$ denote the replenishment cost function from supplier i. Then,

$$Q_{it}(q_{it\tau}) = \begin{cases} s_i + A_i\lceil \frac{\sum_{\tau=t}^{T} q_{it\tau}}{C_i} \rceil + p_i \sum_{\tau=t}^{T} q_{it\tau} & \text{if } q_{it\tau} > 0 \\ 0 & \text{otherwise} \end{cases} \quad \text{for } i = 1,\ldots,I; t = 1,\ldots,T, \tag{1}$$

where $\lceil a \rceil$ stands for the smallest integer that is greater than or equal to a. Instead of using a linear or fixed-charge function, we use a non-linear, step-wise function in order to better represent the structure of the transportation costs. Typically, a fixed cost, denoted by s_i, is charged to setup an order from supplier i. The number of cargo containers used depends on the size of the order, denoted by $q_{it\tau}$, and the capacity of the container, denoted by C_i. For each unit of cargo shipped, a fixed cost is charged, denoted by A_i, to account for loading/unloading activities. In Equation (1), p_i denotes the unit replenishment cost. This cost includes the unit procurement cost and unit transportation costs for supplier i. The transportation lead time for supplier i, denoted by L_i, depends on the location and transportation mode used.

We use two decision variables in order to model the step-wise replenishment cost function. These include y_{it}, a binary variable that takes the value 1 if replenishment mode i is used in period t and 0 otherwise; and z_{it}, an integer variable that represents the number of cargo containers used by replenishment mode i in period t. The following is the total cost (TC) objective of our problem.

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

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

The environmental objective minimizes emissions due to inventory and transportation. In this study we consider only CO_2 emissions since this accounts for about 90% of the total GHG emissions. Carbon emissions due to loading and unloading of one cargo container are considered fixed, and denoted by $\hat{A}_{it}$. Variable emissions, denoted by $\hat{c}_{it}$, are due to transportation. Both types of emissions depend on the transportation mode used and the price of fuel in period t. Variable emissions also depend on the distance traveled. Emissions due to holding one unit of inventory in period t are denoted by $\hat{h}_t$. The following is the total emissions (TE) objective of our problem.

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

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

The following is a mixed integer linear programming (MILP) formulation for this inventory replenishment problem.

$$\text{minimize}_{\,q,y,z}\big(TC(q,y,z), TE(q,z)\big)$$

Subject to (P)

$$\sum_{i=1}^{I}\sum_{t=1}^{\tau} k_{i,t-L_i,t}k_{it\tau}q_{it\tau} = b_\tau \qquad 1 \le \tau \le T \tag{2}$$

$$q_{it\tau} - \frac{b_\tau}{k_{i,t-L_i,t}k_{it\tau}}y_{it} \le 0 \qquad i = 1,2,\ldots,I; 1 \le t \le \tau \le T \tag{3}$$

$$\frac{\sum_{\tau=t}^{T} q_{it\tau}}{k_{i,t-L_i,t}} - C_i z_{it} \le 0 \qquad i = 1,2,\ldots,I; t = 1,2,\ldots,T \tag{4}$$

$$y_{it} \in \{0,1\} \qquad i = 1,2,\ldots,I; t = 1,2,\ldots,T \tag{5}$$

$$z_{it} \in Z^+ \qquad i = 1,2,\ldots,I; t = 1,2,\ldots,T \tag{6}$$

$$q_{it\tau} \ge 0 \qquad i = 1,2,\ldots,I; 1 \le t \le \tau \le T \tag{7}$$

Constraints (2) ensure that demand in period τ ($\tau = 1,\ldots,T$) is satisfied. In this constraint, the term $k_{i,t-L_i,t}$ captures product deterioration during transportation lead time, and $k_{it\tau}$ captures deterioration during storage. Constraints (3) 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 $\tau = t,\ldots,T$. Constraints (2) and (3) indicate that replenishment amounts should be larger than the actual demand to compensate for the loss of inventory due to deterioration. Constraints (4) identify the number of units of cargo required to replenish inventories from supplier i in period t. Constraints (5), (6) and (7) are, respectively, the binary, integrality and non-negativity constraints. Figure (1) gives a network representation of a problem with 2 suppliers and 3 periods. This network contains one dummy node for total supply, T nodes for the facility at each time period, and $I * T$ supplier nodes. In each time period t, the facility has a demand equal to b_t. Supplier nodes correspond to each supplier i in every time period t. Replenishment arcs connect suppliers with the facility in each time period. The amount of flow on these arcs ($q_{it\tau}$) represent the amount shipped using supplier i in time period t for time period τ. There are $I * T$ dummy nodes between the dummy supply node and supplier nodes to ensure that total supply equals to the total demand over the planning horizon.

4. Solution Approach

MOP 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 an MOP deals with approximating or computing all or a representative set of Pareto optimal solutions. The two main approaches used in the literature in order to calculate the Pareto set of solutions for this bi-objective optimization problem are the weighted sum and the ε-constraint method.

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 [18]. The ε-constraint method minimizes one individual objective function with an upper level constraint imposed on the other objective function [19]. The Pareto frontier is approximated by solving this single-objective problem for different values of the upper bound imposed on the other objective function.

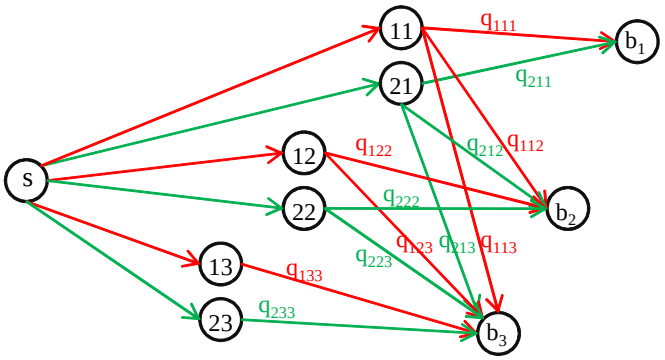


Figure 1: Network Representation for a 2-supplier, 3-period Problem (P)

4.1 Weighted sum method

The weighted sum method minimizes a weighted sum of the two objectives $\lambda_1 TC + \lambda_2 TE$. Typically, the values of λ_1 and λ_2 are selected such that $\lambda_1 + \lambda_2 = 1$ and $\lambda_1, \lambda_2 \geq 0$. The Pareto frontier is then created by solving the single-objective problem for different values of λ_1 and λ_2.

The following is the objective function of the single-optimization problem under the weighted sum approach.

$$Z(q,y,z) = \lambda_1 \sum_{i=1}^{I}\sum_{t=1}^{T}[\sum_{\tau=t}^{T} c_{it\tau}q_{it\tau} + s_i y_{it} + A_i z_{it}] + \lambda_2 \sum_{i=1}^{I}\sum_{t=1}^{T}[\sum_{\tau=t}^{T} \hat{c}_{it\tau}q_{it\tau} + \hat{A}_{it} z_{it}].$$

In this study, the sum of λ_1 and λ_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.

4.2 ε-constraint method

The ε-constraint method approximates the set of Pareto solutions by solving a series of instances of the following single-objective problem (R) for different values of the parameter ε.

$$\text{minimize: } TC(q,y,z)$$
$$\text{Subject to: } (2)\ to\ (7)$$
$$TE(q,z) \leq \varepsilon$$
$$\underline{\varepsilon} \leq \varepsilon \leq \overline{\varepsilon}$$

Model (R) identifies 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 are obtained from the optimization of each separate objective function as follows:

$$\text{minimize: } TE(q,z)$$
$$\text{subject to: } (2)\ to\ (7)$$

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

$$\text{minimize: } TC(q,y,z)$$
$$\text{subject to: } (2)\ to\ (7).$$

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

solution to the problem.

5. Results

This section summarizes the results of the computational experiments performed. We solved our model using the ILOG/CPLEX commercial solver. 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. Delivery lead time for shipments from this supplier is 1 day since the LTL service provider, in order to minimize its costs, serves a number of customers in each route. The lead time from supplier 2 is 2 days. This supplier is a wholesaler who provides the product at a discount price. This supplier sends shipments using dedicated, non-refrigerated trucks. The third supplier is also a wholesaler who uses dedicated, refrigerated trucks for delivery. The delivery time for this supplier is 3 days. We assume that products do not perish during delivery time if shipped by refrigerated trucks. Replenishment costs from this supplier 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. Table 1 summarizes the input data.

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). The 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.

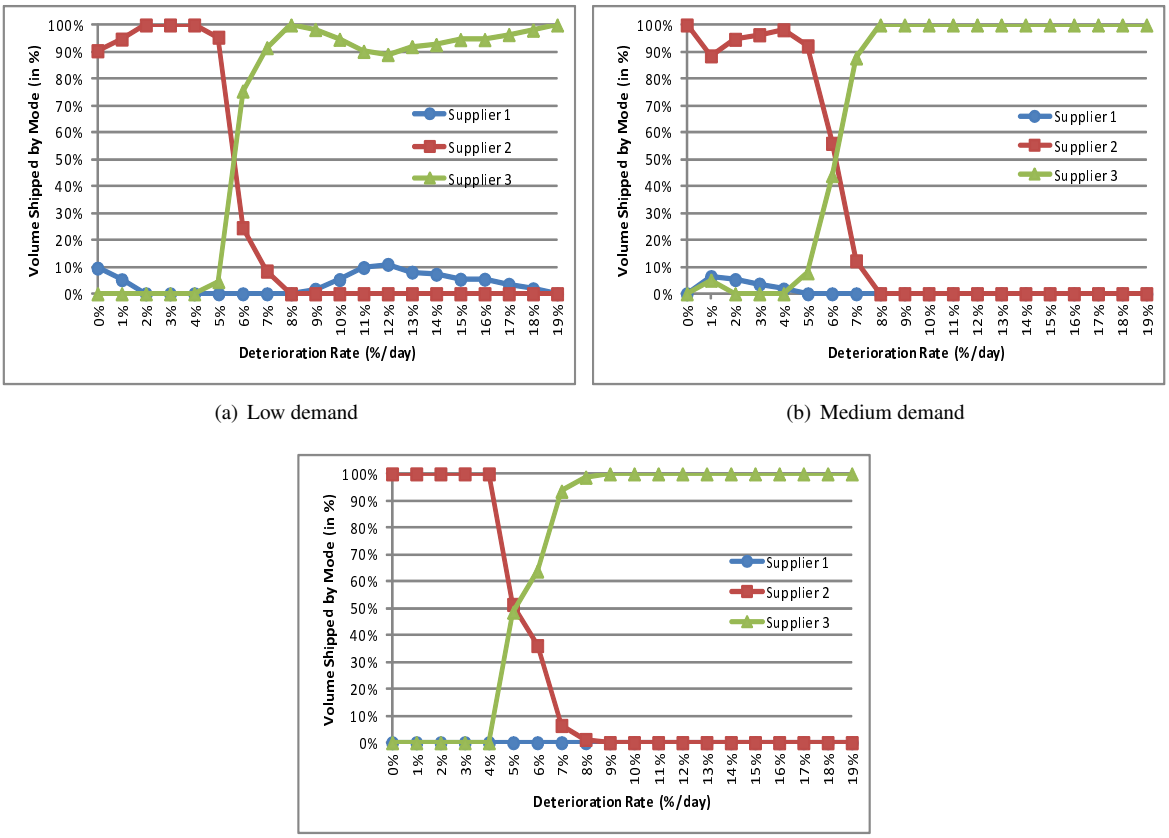
Table 1: Problem Parameters

Supplier	s_i	A_i	p_i	C_i	$\hat{A}_i$	$\hat{p}_i$	L_i
1	50	0	15		30	1	1
2	50	U[45,55]	10	25	50	1	2
3	50	U[45,55]	12	25	50	1.5	3

In order to generate the results presented in Figures 2 to 4 we used the ε-constraint method and set the value of $\bar{\varepsilon}$ 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. Each point in a graph represents the average results from solving 10 different randomly generated problem instances.

Figure 2 presents the relationship between supplier selection decisions and the product's deterioration rate for different levels of customer demand. We make two major observations from these graphs. First, as demand increases, the volume shipped from a local supplier decreases. This finding makes sense since high demand levels justify the use of full truckloads. Therefore, the retailer makes use of wholesalers who provide discounted prices. Second, as the deterioration rate increases, the volume shipped using refrigerated trucks increases (supplier 3). When daily deterioration rate is 8% or higher, supplier 2 is not used, despite the fact that supplier 2 provides a smaller unit replenishment cost as compared to supplier 3. This is because the lead time from this supplier is 2 days, and therefore, the remaining shelf life for the product delivered decreases dramatically.

Figure 3 helps understand the relationship that exists between deterioration rate and (a) replenishment and inventory holding costs ($\sum_{i,t,\tau} c_{it\tau} q_{it\tau}$); (b) order costs ($\sum_{i,t} s_i y_{it}$); and (c) cargo costs ($\sum_{i,t} A_i z_{it}$) for different levels of demand. As the deterioration rate increases, replenishment costs increase due to the fact that the volume shipped using supplier 2 (refrigerated trucks) increases. This supplier is relatively more expensive. As the deterioration rate increases the shelf life of products decreases, and therefore, the retailer chooses orders of smaller size. To satisfy demand, orders are initiated more frequently resulting in higher order costs. Similarly, as the deterioration rate increases, the facility moves away from using the local supplier who sends LTL shipments that do not incur cargo container costs. As a consequence, cargo costs increase with the deterioration rate. The increase in costs (due to increasing deterioration rate) becomes greater as the demand for the product increases.



(a) Low demand

(b) Medium demand

(c) High demand

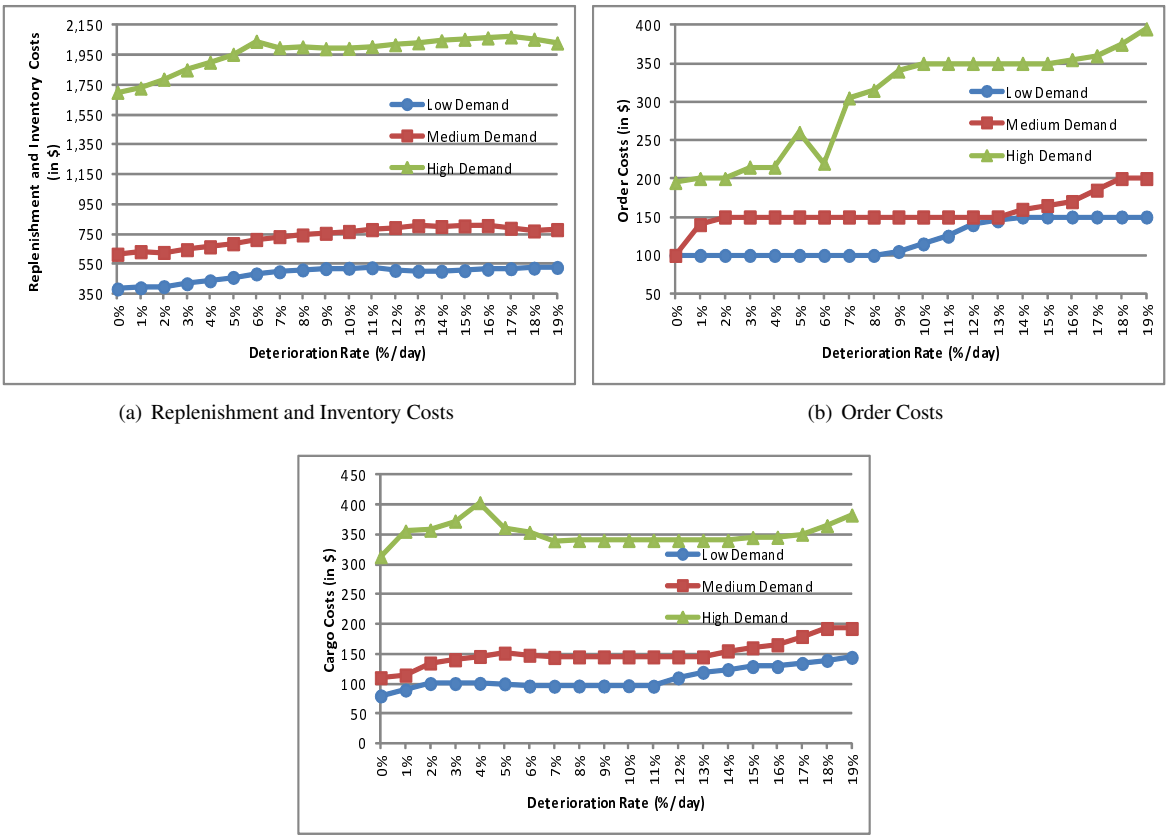
Figure 2: Transportation Mode Selection

Figure 4 presents the total unit cost versus deterioration rates for low, medium and high demand. We make two observations here. First, as demand increases, the total unit cost decreases. This decrease is due to the economies of scale achieved from using full truckload shipments. Second, as the deterioration rate increases, the total unit cost increases. As deterioration costs increase (see Figure 2), the volume shipped from supplier 3 increases. The increase in costs is due to the higher replenishment costs of supplier 3.

Figure 5 displays the set of Pareto solutions (costs versus emissions) for the bi-objective optimization problem. The three Pareto frontiers presented are generated for low, medium and high deterioration rates. We make the following observations from the graphs. First, as the deterioration rate increases, both costs and emissions required to satisfy demand increase. The increase in costs is due to using refrigerated trucks and due to increasing the number of orders required because of the limited shelf life of these products. The increase in emissions is due to increasing the volume shipped by refrigerated trucks. Second, decreasing emissions in this two-stage supply chain comes at a cost. For example, when the deterioration rate is 4% and $\bar{\varepsilon} = 260$kg, a decrease in emissions from 260 to 225 increases costs from \$960 to \$993. In other words, a 13.5% improvement in emissions comes at a 3.3% increase in costs. For this particular problem, experimental results indicate that great reductions in emissions can be achieved in a supply chain with minimum impact on costs.

We use the weighted sum method to generate Figure 6 which presents emissions versus λ_2 for different deterioration rates. The amount of CO_2 emitted decreases as the value of λ_2 increases. This is understandable since, when the model is solved using the weighted sum method, each unit of CO_2 emitted is penalized by an amount λ_2. Total emissions also increase with deterioration rate due to the increase in the volume shipped by refrigerated trucks.

In our problem setting, we have considered different lead times (1 to 3 days long) for each supplier. In order to observe the effects of lead time on costs and emissions, we re-ran the experiments for different values of lead time. To simplify



(a) Replenishment and Inventory Costs

(b) Order Costs

(c) Cargo Costs

Figure 3: Total Cost Distribution

the experiments and observe the impact of lead time only on costs and emissions, we assume that each supplier has exactly the same lead time. Figures 7 and 8 summarize the results. As deterioration rate and lead time increase, both costs and emissions in this supply chain initially increase. After some point, the lines remain flat and do not change with lead time. Recall that products shipped using refrigerated trucks do not deteriorate during delivery. Therefore, the breakpoint where the lines become flat corresponds to using only refrigerated trucks for inventory replenishment.

This breakpoint of lead times decreases as the deterioration rate increases. For example, a rate of 4% requires 4 days of lead time for the costs to remain constant whereas 15% can only afford 1 day of lead time. Figure 8 shows the level of emissions for increasing lead times. Emissions keep increasing up to the breakpoint in lead times and stay constant with the usage of refrigerated trucks.

6. Conclusions

This paper proposes a bi-objective mathematical model that aids inventory replenishment decisions for perishable products, such as agricultural and dairy products, human blood, photographic film, etc. This is a mixed-integer linear programming model which minimizes costs and environmental impacts due to supply chain activities such as transportation and inventory. The cost objective of this model minimizes the total inventory replenishment costs, including transportation, inventory, purchase and fixed order costs. The environmental objective minimizes greenhouse gas (GHG) emissions due to transportation and inventory.

We propose two solution procedures to solve this problem, a weighted sum method and a ε-constraint method. The weighted sum method minimizes a series of single-objective problems. The objective function represents the total supply chain costs as well as penalties due to CO_2 emissions necessary to maintain supply chain operations. The ε-constraint method minimizes one individual objective function with an upper level constraint imposed on the other

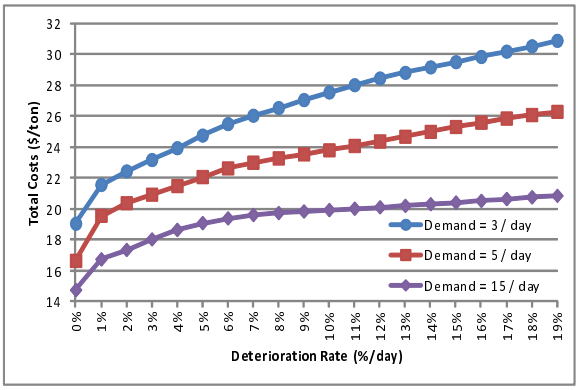


Figure 4: Total Unit Costs

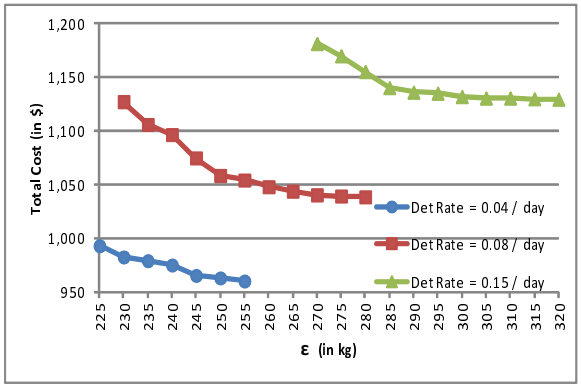


Figure 5: Emissions versus Costs

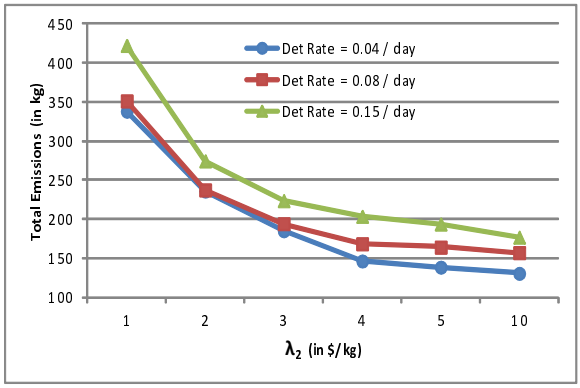


Figure 6: Total Emissions versus λ_2

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. The single-objective problems are solved using CPLEX.

We ran a number of experiments in order to observe the relationships that exist between costs and emissions in the supply chain. The following are some important observations we made. (a) An increasing deterioration rate 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. (b) An increasing deterioration rate increases inventory replenishment costs since often suppliers that have shorter lead times (such as local suppliers) do not necessarily provide the least expensive products. (c) As the deterioration rate increases and 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. (d) An increasing deterioration rate increases emissions due to using refrigerated trucks, and increasing the frequency of shipments. (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 emission reductions and result in relatively small increases in costs.

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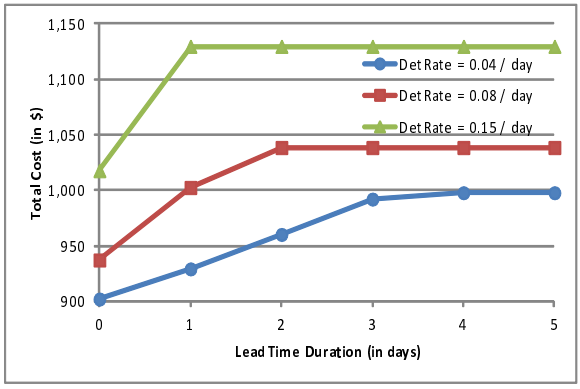


Figure 7: Lead Time Costs

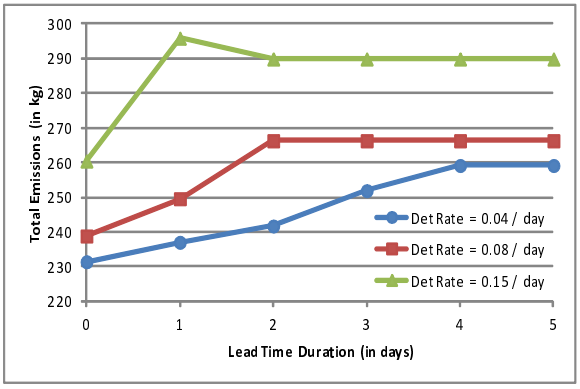


Figure 8: Lead Time Emissions

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