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The Competitive Time Guarantee Decisions Via Continuous Approximation of Logistics Systems

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연속적 근사법에 의한 물류시스템의 경쟁적 시간보장 의사결정 최적화에 관한 연구

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We show how a supplier can peg cost measures to the reliability of his time guarantees via the penalty costs considered in the framework. The framework also enables us to study the connections between the logistics network and the market. In this context, we show that even when the market base increases significantly, the supplier can still use the logistics network designed to satisfy lower demand density, with only a marginal reduction in profit. Finally we show how the framework is useful to evaluate and compare various logistics system improvement strategies. The supplier can then easily choose the improvement strategy that increases his profit with the minimal increase in his logistics costs.

Keywords : Time Guarantee Decisions, Logistics System, Continuous Approximation, Logistics Network

1. Introduction

In this era, the major trends in business include shortened product lifecycle, mass customization, production in low-cost country, globalization to name a few. The fast changing sophistication of consumer needs as well as the rapid advancement of new technologies has led to the constant evolution of competitive paradigms in the market. Among many factors of competitive power the response speed or faster delivery time might be one of the most important factors as long as the price and the quality are in a competitive range. In their book on time-based competition, Stalk and Hout [24] said that

> Generally, if a time-based competitor can establish a response three or four times faster than its competitors, it will grow at least three times faster than the market and be at least twice as profitable as the typical industry competitor. (p.98)

Recently, in December 2013 Amazon CEO Jeff Bezos announced the company's drone delivery plans which would let customers receive packages they ordered on Amazon website in as little as 30 minutes. The benefits of being faster include increased demand consequently larger market share, reduced unit handling cost, lower carrying cost, shorter forecast horizon, reduced inventories, improved customer service level and better market position etc. Consequently, many firms in various industries have been using delivery time guarantee strategies to their customers. See Benson [1], Blackburn et al.

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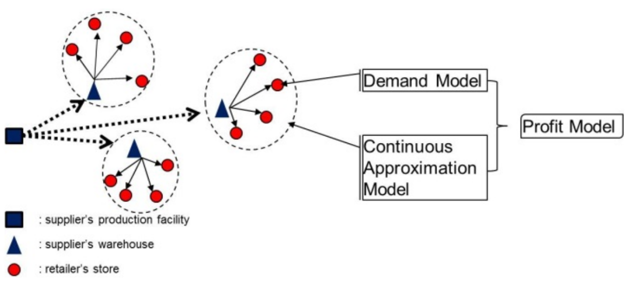
[2], Daniels and Essaides [3], Tucker [26] for various successful delivery time guarantee business cases. In this research we focus on the use of logistics time guarantees in a retail environment with a single supplier and many retailers. And since the ability to fulfill the time guarantees depends on the logistics network and the various parameters that control logistics speed of the distribution system, we explicitly consider these issues in our modeling. In this context the supplier was interested to answer questions such as what are the optimum time guarantees it should offer under various market conditions. What would be the impact of adopting such a time guarantee strategy on its existing logistics system? What changes should be made to the logistics system? Should additional warehouses be added and should the warehousing performance be improved in order for the supplier to meet the promised time guarantees? How should the supplier evaluate various logistics strategies to choose the most beneficial one? What will be the impact of implementing such a strategy on its market share? These are some of the research questions, which will be investigated in this paper. We next review the relevant literature and use that to further motivate, define and situate our research.

2. Literature Review

There is a substantial amount of research work that looks at the impact of time performance on the behavior of a firm. Dewan and Mendelson [4], Mendelson and Whang [18], and Stidham [25] are some of the earliest papers that took into account users' delay cost to study the internal pricing and capacity selection for the internal service operations of a firm. Hill and Khosla [12] used a deterministic model for expressing demand as a function of delivery lead-time and price to study the impact of lead-time reduction of a firm' s revenues and costs. Several researchers have also studied the delivery time performance in a competitive environment, using queuing theory to model a firm's operations and game theoretic frameworks to model competition. Kalai et al. [13] studied the role of processing capacity in a competitive environment, where two firms compete for a stream of customers via their choice of processing speed. Li [16] developed a model to examine the use of inventory for superior delivery time by firms to compete for orders in a market. Li and Lee [17] developed a queuing model to study price competition between two firms, where a stream of customers consider both price and delivery speeds in selecting a service. Lederer and Li [15] extended the above work to develop a queuing model 4 where firms compete by choosing different prices and service rates for multiple types of customers with different delay costs. Their results support Stalk and Hout's [24] basic contention that firms that can establish faster responses than the competitors will grow faster, i.e., have a larger market share as well as be more profitable. There are a few research papers, which have studied the issues of firms quoting uniform delivery times in the closely related service areas. So and Song [23] developed a single firm queuing model to study the optimal selection of price, delivery time guarantee and capacity expansion to maximize the profit of a firm in a service sector. The demands are assumed to be log linear in both price and delivery time. Palaka et al. [20] also study these issues using a very similar queuing model. Their model uses a demand function that is linear in price and time. They also consider congestion costs and lateness penalty costs in the queuing system. So [22] extends So and Song's [23] paper to a multi firm setting and study the equilibrium solution in a multi firm game. Hill et al. [11] study delivery time guarantees more generally using an expected profit model. They approximate the delivery behavior of the firm using exponential distribution and provide a closed form expression for the optimal delivery time quote. Our work is distinct from the above research in two important ways. Firstly this research was focused on strategies such as quoting lead-times or offering some kind of delivery time guarantee in the context of firms operating in service or manufacturing sector. On the other hand we study the component with a significant effect on a firm's competitive capability in the retail sector : logistics time. Secondly in all of the above papers, the firm's operation was modeled using queuing theory, usually as a M/M/1 queue. However such queuing models are not a good representation of firms' logistics systems, which are usually modeled using mathematical programming. In our research, we seek to extend the time based competition to logistics systems, to understand how kind of firms should tailor time guarantees to their logistics systems and vice versa, in order to compete under various market conditions. Such research is critical given the increasing emphasis that retailers are placing on their logistics response. Indeed such efforts by firms to improve their logistics response have already been reported in practice.

Dekhne [7] provides the example of an USCO Logistics (a 3PL logistics provider) project where a large consumer products and electronics supplier restructured its logistics network in order to meet customer requirements that 95 deliveries be made via ground within three days. Similarly Dignan [8] reports that Lowe's, the No 2 home improvement retailer in the US, requires its suppliers to be on time 98% the best of our knowledge, there is no research that clearly examines the link between time based competition and a firm's logistics response. Thus we develop an analytical framework that jointly considers approximate logistics models and demand models to answer those questions.

This paper focuses on the situation where a supplier promises a logistics time guarantee to a retail market. Also the demand faced by the supplier is influenced by the time guarantee. Delay costs are used to quantify the 'opportunity costs' associated with long logistics times. The logistics network of the supplier is modeled using continuous approximation theory. The actual logistics time is obtained from this model. Then the supplier based on the delay costs, the market conditions and the actual logistics time determines the optimal logistics time guarantee, which maximizes his profit. It should be highlighted at the outset that our emphasis when developing mathematical models will be on simplicity and tractability rather than on accuracy of the models. The focus is on developing approximate models that are easy to solve and that provide qualitative managerial insights. Thus we use continuous approximation (CA) methods to model the supplier's logistics system, and consequently the logistics response as shown in <Figure 1>.



<Figure 1> Basic Model

The rest of paper is organized as follows. In Section 3 we present our model. We then present a numerical analysis in Section 4 and use this to derive insights for the firm's decision making. Section 5 concludes this research by summarizing the results and providing future research directions.

3. Model Formulation and Analysis

The supplier offers a logistics time guarantee, within which he promises delivery to the retail market. We assume that retailers in the market are sensitive to these time guarantees and prefer a more responsive supplier, i.e., a supplier who offers a shorter logistics time guarantees. Thus the demand faced by the supplier is influenced by the logistics time guarantee, t_G. This is the decision variable. The actual logistics time, T_l, depends on the logistics system and is a random variable. Also the supplier is expected to compensate the retailers whenever the logistics time guarantee is not met. Thus the objective is to determine the optimal logistics time, t_G^*, which maximizes the supplier's expected profit.

3.1 Logistics Network Model

The supplier serves stores in a certain retail market with a range of products. Some of the products are produced locally within the country and the others are imported. These products are then transported to various warehouses. When a retailer orders a product from the supplier, it is dispatched from one of the warehouses. There is a time delay involved for the supplier to process the order and for the inventory system to ready it for shipment. The products are shipped from the warehouse to the stores using trucks. For the purpose of this study, we treat all these products as a single homogenous product. We also assume that all the shipments are direct, i.e., they are one to one. We now develop a logistics network model to represent this operation. Usually such production-distribution networks are modeled using discrete mathematical programming. While these models provide managers with optimal solutions, data and computational requirements increase tremendously as models become more realistic. In addition, data reliability and hence model accuracy decrease. Further, sensitivity analysis and incorporation of uncertainty can lead to countless computational requirements. Also, as Geoffrion [10] pointed out, mathematical programming models do not provide insights into the 'why' of a solution other than deriving 'what' the solution is. However for our analysis the 'why' is what matters. To remedy these weaknesses, we propose to model the supplier's logistics network model using continuous approximation methods. The idea of applying continuum mechanics techniques to finite-dimensional operations research problems was first demonstrated by Newell [19]. For continuous approximation, problems are formulated as continuous functions that are amenable to solution by elementary calculus. The logistics literature appears to be a forerunner in utilizing this method. Daganzo [5] addresses different logistics problems and presents a number of continuous approximation models while Langevin et al. [14] present a taxonomy of continuous approximation models for freight distribution problems. The continuous approximation approach uses a somewhat simplified analysis that focuses on issues of partitioning the market

into roughly circular regions to be served by warehouses under somewhat restrictive assumptions about topology and demand density, leaving the decision of precise locations for subsequent analysis. We call these regions consolidation areas. This concept of consolidation areas is also analogous to Erlenkotter's [9] General Market Areas and Dasci and Verter's [6] Service Regions. These two papers also consider similar logistics network planning problems and use continuum approximation methods. Assume that the supplier wants to open new warehouses in a market area (the entire region where the supplier operates) where each warehouse serves a single consolidation area. Decision variables are the number of warehouses, their location, and respective consolidation areas. The warehouses can be located anywhere in the market area. Hence, let A_M denote the market area. The approximation model then makes the following simplifying assumptions and uses the notation defined therein to characterize the system :

A1 : The retail stores, distributed over A_M, are modeled as the realization of a slowly varying spatial Poisson process with rate $\delta_S(X)$ (stores per square mile). Thus $N_S = \int_{X \in A_M} \delta_S(X) dX$, gives the number of stores in A_M

A2 : All the retail stores are alike, i.e., they face the same demand. Thus we define a slowly varying demand rate, $\lambda_S(t)$ (units per day) over the time horizon T_H, at each store. Also T_H represents considerably longer time frame than other times we consider in the model. For example T_H = 3 months, can be thought of as the time period in which a retailer signs a contract with the supplier.

A3 : The supplier transports product to the store from the warehouse, using a fleet of homogeneous vehicles with shipments of size C units. The cost of transportation per mile is c_d (\$/mile). Pipeline inventory costs and holding costs are ignored in this model.

A4 : The trucks travel from the warehouse to the store at a speed of ρ (hour/mile). We assume that speed is normally distributed, i.e., $\rho \sim N(\mu_\rho, \sigma_\rho^2)$

A5 : The cost opening and operating each warehouse is c_f (\$/day), prorated over the time horizon of its operation. We assume that all warehouses are identical and relocate able. There are also no throughput limits on the warehouses.

A6 : The time to process the order at the warehouse is T_O. We assume that this time, which depends on the decisions, such as the type of inventory policy, the type of warehouse operation taken during the tactical design phase of operation, can be modeled as a normal distribution, i.e., $T_O \sim N(\mu_\rho, \sigma_O^2)$

A7 : The supplier transports product from the manufacturing points to the warehouses in using rail transportation. We assume that this inbound operation doesn't have any effect on the fulfillment of the logistics time guarantees as well as on the logistics cost.

How many warehouses should there be, where and what is the size of their consolidation areas to cover the total market area A_M at the least cost is the strategic question that the supplier answers to determine a cost optimal system. As outlined before, we first determine the optimal consolidation areas and then determine the precise facility locations by subsequent analysis.

All parameters are assumed to vary slowly within a consolidation area but the model allows large differences across areas, which are likely to be served by different facilities. Even if large differences occur in close neighborhoods, continuous approximation still gives good results as pointed out by Daganzo [5]. Given this, the logistics cost prorated per unit in the logistics system is given by :

$$LC(\lambda_S) = \frac{C_f}{\lambda_S \delta_S A_C} + \frac{C_d K \sqrt{A_C}}{C} \tag{1}$$

where K is a constant that depends on the distance metric and the shape of the consolidation area. K $\sqrt{A_C}$ is the average distance from the warehouse to a store in the consolidation area, where the warehouse located is at center of the area. Newell [19] and Erlenkotter [9] have used this well-known result among many other authors. Thus the optimal consolidation area and the corresponding optimal logistics cost are given by :

$$A_C^* = \left[\frac{2cfc}{\delta_S K c_d \lambda_S}\right]^{2/3} \tag{2}$$

$$LC^* = c_1\left(\frac{1}{\lambda_S}\right)^{1/3}\left(\frac{cf}{\delta_S}\right)^{1/3}\left(\frac{KC_d}{c}\right)^{2/3} \tag{3}$$

Dasci and Verter [6] and Geoffrion [10] have also obtained similar results. The geometry of consolidation area is not crucial to the analysis because it only affects K values. Also the actual logistics time, T_l, can be expressed as the sum of two random variables, i.e., $T_l = T_m + T_O$, where $T_m \sim N(\mu_\rho K\sqrt{A_C}, (\sigma_\rho K\sqrt{A_C})^2)$, is the time in transit from the warehouse to the store and

$T_O \sim N(\mu_O, \sigma_O^2)$ as previously defined in A6, is the time from the placement of an order to its shipment from the warehouse. Thus

$$T_i \sim N(\mu_\rho K\sqrt{A_C} + \mu_O, (K\sqrt{A_C})^2\sigma_\rho^2 + \sigma_O^2) \tag{4}$$

The supplier uses this distribution in his profit model to determine the optimal logistics time guarantee, t_G^*, that he should offer to the market.

3.2 Demand Model

The supplier serves a market in which retailers are responsive to the logistics time guarantee offered, i.e., his demand is influenced by the time guarantee. From the notation developed in A2, Section 3.1, this demand is defined by the store level demand rate, λ_S. Thus $\lambda_S(t_G)$ decreases monotonically with t_G. Given that the shortest guarantee given by express mail companies like UPS is one day, we assume the least logistics time guarantee the supplier can offer is one day. Under this guarantee the supplier will capture all of the market demand. Similarly if the supplier offers a very long guarantee he will capture almost none of the market. Also since the supplier under consideration is in a very stable market, we assume that the market is perfectly competitive in price, i.e., all the suppliers offers the same price to the retailers. So the only way in which the suppliers can attract retailers is by offering a reduced time guarantee. We assume the following log linear function for the demand rate:

$$\lambda_S(t_G) = M_R(t_G)^{-b} \tag{5}$$

where b is a positive constant representing 'logistics time guarantee elasticity of demand', M_R is the total time sensitive demand rate of the market. So and Song [23] as well as Hill and Khosla [12] use similar functions to relate demand and time. Rust and Metters [21] also present a number of such mathematical models that connect consumer behavior to service management variables such as delivery time.

3.3 Supplier's Profit Model

After the supplier promises a logistics time guarantee of t_G, the retailers would expected to be compensated in some way if the promises are not met on time. The supplier would also face a loss of goodwill as well might not be chosen in future by the dissatisfied retailer. For example Dignan [8] reports how at Lowe's for a late shipment, the supplier is hit with a fine of 20% of the invoice value of the late shipment and that goes up to 30% in the next month, and so on. Thus we assume that the supplier is charged a penalty of c ($/unit) per unit of product that the retailers receive later than t_G. We also assume that the penalty paid by the supplier to the retailers is high enough to keep their entire market share, i.e., the market share remains unaffected by late deliveries. Thus the total penalty cost paid by the supplier is given by

$$PC(t_G) = cP(T_l > t_G)\lambda_S(t_G) \tag{6}$$

where $P(T_l > t_G)$ is the probability that the actual logistics time taken the supplier's logistics system, T_l , is greater than the logistics time guarantee, t_G and $\lambda_S(t_G)$ is the time sensitive demand as given by (5). Also given (4), we can rewrite $P(T_l > t_G)$ as

$$P(T_l > t_G) = 1 - \phi\left(\frac{t_C - [\mu_\rho K\sqrt{A_C} + \mu_O]}{\sqrt{(K\sqrt{A_C})^2\sigma_\rho^2 + \sigma_O^2}}\right) \tag{7}$$

Letting p be the average gross margin per unit of product, we can thus write the profit function as :

$$\max_{t_C} \pi(t_G) = p\lambda s(t_G) - LC(t_G)\lambda s(t_G) - PC(t_G) \quad (8)$$

where

$$\lambda s(t_G) = M_R(t_G)^{-b} \quad (9)$$

$$LC(t_G) = c_1\left(\frac{1}{\lambda_S}\right)^{1/3}\left(\frac{cf}{\delta_S}\right)^{1/3}\left(\frac{KC_d}{C}\right)^{2/3} \quad (10)$$

$$PC(t_G) = cP(T_l > t_G)\lambda_S(t_G) \quad (11)$$

The above non-linear program represents the profit model. The objective is to find the optimal logistics time guarantee, t_G^*, so that the supplier can maximize the expected profit per period.

4. Analysis

To begin the analysis, we first study the properties of the objective function of $\pi(t_G)$, by first studying the component parts that are functions of t_G.

Proposition 1 *For all b > 0, LC(t_G) is strictly increasing in t_G.*

Proof. From (9) and (10) we can rewrite $LC(t_G)$ to be $C_2 M_R^{-\frac{1}{3}} t_G^{\frac{b}{3}}$, where $C_2 = C_1\left(\frac{cf}{\delta_S}\right)^{1/3}\left(\frac{KC_d}{C}\right)^{2/3}$ is a positive constant. Q.E.D.

Proposition 2 *If b > 3, LC(t_G) is convex in t_G and if 0 < b < 3 LC(t_G) is concave in t_G.*

Proof. The first and second derivatives of *LC(t_G)* can be expressed as

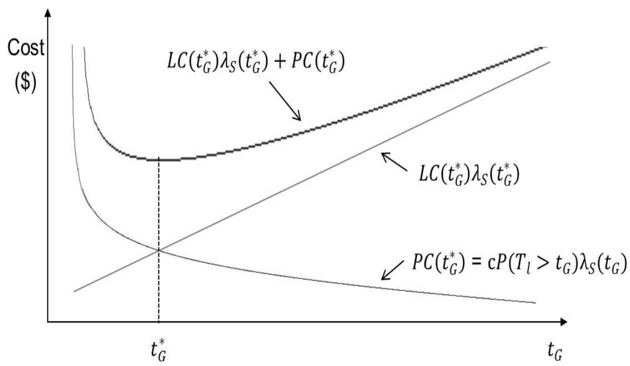
$$\frac{\partial LC(t_C)}{\partial t_G} = \frac{bc_2}{3} M_R^{-\frac{1}{3}} t_G^{\frac{b-3}{3}},$$

$$\frac{\partial^2 LC(t_C)}{\partial t_G^2} = \frac{b(b-3)c_2}{9} M_R^{-\frac{1}{3}} t_G^{\frac{b-6}{3}}$$

respectively, where $C_2 = C_1\left(\frac{cf}{\delta_S}\right)^{1/3}\left(\frac{KC_d}{C}\right)^{2/3}$ is a positive constant. If *0 < b < 3* then the second derivative is negative, i.e., LC(t_G) is concave and if b > 3 then the second derivative is positive, LC(t_G) is convex. Q.E.D.

Proposition 3 $\pi(t_G)$ has the maximum value of $\pi(t_G^*)$ when t_G^* minimizes $LC(t_G^*)\lambda_S(t_G^*) + PC(t_G^*)$.

Proof. $\pi(t_G)$ has two components, the revenue and the cost. The first term in equation (8) represents revenue part. And the last two terms of (8) represents cost part. <Figure 2> illustrates the shape of the cost function has only one minimum at t_G^*. And if we notice that the revenue part is monotonically decreasing function in t_G then $\pi(t_G)$ has it's minimum at t = t_G^* while t_G^* minimizes the cost part of the model. Q.E.D.



<Figure 2> Shape of the Cost Function

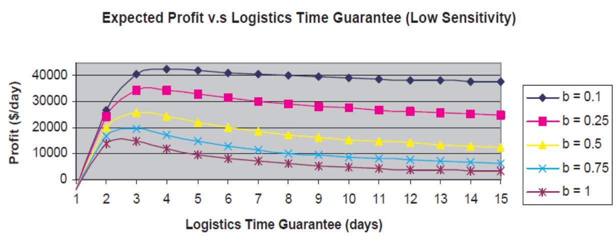
Since T_l is normally distributed, *PC(t_G)* don't have a clear functional form in t_G. This means that we can't find a closed form solution for t_G^* analytically. Thus the objective function and the optimal solution have to be solved by numerical methods. We proceed to do that using a realistic example. Geoffrion [10] outlined a series of 'auxiliary models', similar to the logistics model of Section 3.1. In this section, we use the parameter values of Geoffrion's study to model the supplier's logistics system. This is then used to study the properties of $\pi(t_G)$ and to find the optimal solution numerically. Thus we simulate the above system over a range of values for the parameters, given in <Table 1> and study the response.

<Table 1> Parameter Values

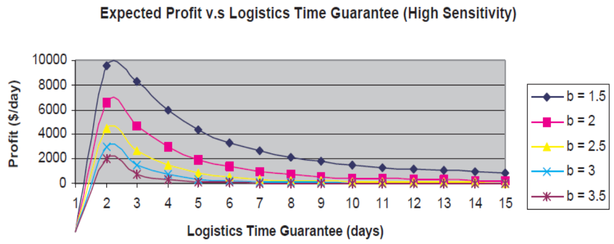
Parameters	Values
b (Demand sensitivity to time guarantee)	0.1, 0.25, 0.5, 0.75, 1, 1.5, 2.0, 2.5, 3.0, 3.5
p (Unit price)	5
c (Penalty cost)	10
t_G *(Delivery time guarantee)*	[1:15]
M_R *(Market Demand Rate (units/day))*	10,000
c_d *(Transportation cost ($/mile))*	5
C (Vehicle capacity (units))	10,000
δ_S *(Store density (stores/sq-mi))*	5×10^{-4}
c_f *(Prorated facility cost ($/day))*	10,000
μ_p *(Mean Pace (hrs/mile))*	2×10^{-2}
σ_p *(Std. Dev. of Pace (hrs/mile))*	2×10^{-2}
μ_O *(Mean Order Processing Time (hrs))*	18
σ_o *(Std. Dev. Of Order Processing Time (hrs))*	18
A_M *(Total Market Area (sq-mi))*	10^6(1 Million)
T_H *(Supply Time Horizon (days))*	90
Working hours in a day (hrs)	18

4.1 Analysis with Respect to t_G

<Figure 3> and <Figure 4> show how the expected profit varies under different market conditions and different logistics time guarantees offered by the supplier. These results support our intuition that as the market becomes increasingly sensitive to the logistics time guarantee (t_G), i.e. as b increases, the supplier's optimal logistics time guarantees (t_G^*) are driven lower in order for him to compete for demand share. Also the supplier's profit declines more steeply under higher b values (b > 1). This is because of two related reasons. First as b > 1, the supplier's demand share decreases very steeply with increasing t_G. For example when b = 2 (an extremely competitive market) and 7 < t_G, the demand share of the supplier nearly halves for each day's increase in t_G. The unit logistics costs also increase rapidly in t_G. Proposition 1 also supports this.

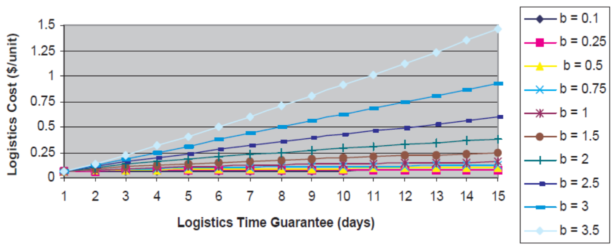


<Figure 3> Low Sensitivity Case



<Figure 4> High Sensitivity Case

In the above example these costs increase by a third for each day's increase in t_G. One reason for this is because when the supplier's logistics system facing a shrinking demand share is used as it is, it will supply fewer and fewer units of the product increasing the cost per unit. This is shown in <Figure 4>. Correspondingly the changes to the supplier's logistics system, under different market conditions and time guarantees are shown in <Figure 5>. It can be seen that as the demand share decreases, it is served by fewer warehouses. This leads to an increase in the average travel distance and consequently increases in travel time, T_m. Also under high time competition, the supplier is forced to offer a low time guarantee in spite of a high probability of the logistics system not meeting that guarantee.



<Figure 5> Logistics Cost vs Logistics Time Guarantee

For example, when b = 2, t_G^* = 2 days, vs. t_G^* = 4 days when b = 0.25, even though the logistics system cannot meet this lower guarantee 22.8% of the time. If t_G^* = 4 days, the guarantee is not only 1% of the time. However the market share reduces from 25% to 4%. Thus the supplier is forced to win retail demand at the cost of poor performance in meeting the logistics time guarantees.

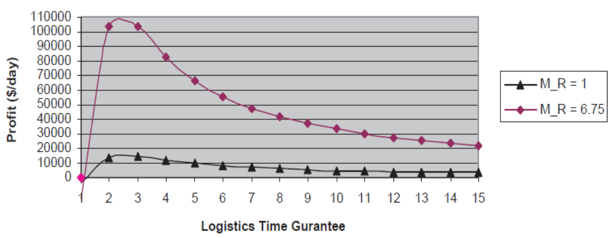
However in reality such poor performance will be unacceptable to most retailers, especially under conditions when the product is time sensitive. This is because such inability to deliver will invariably cause high stock outs. In such a case retailers will charge the supplier higher penalties for not meeting the promised time guarantees. This suggests the need for suppliers to adopt 'flexible' logistics systems and strategies to be able to deliver efficiently under differing time competitive market conditions. For example, when b = 2, the supplier should consider using a more efficient logistics strategy to serve this highly time sensitive market than the one he uses to serves less time sensitive markets. One possible strategy could be the use of a fast third party logistics provider who can guarantee very short logistics times to supply. Even though the logistics costs would be higher, these will be mitigated by lower penalty costs and higher market share.

4.2 Sensitivity Analysis

In this section we would like to study the impact on the optimal values of logistics time guarantee (t_G^*) and expected profit, $\pi(t_G)$, of varying one of the parameters while keeping others constant. This is useful to study the impact of the parameter on the behavior of the supplier as well as to compare two suppliers that are different only in this parameter.

4.2.1 Changing M_R

We first consider the case where the total time sensitive demand rate of the supplier's market increases, i.e., M_R increases. <Figure 6> considers one such case for a moderately competitive market (b = 1) in which M_R increases by 6.75 times. This value, which changes the response of the supplier, was determined using interpolation. The optimal logistics time guarantee changes accordingly from 3 days to 2 days.



<Figure 6> Sensitivity Analysis on MR vs. Time Guarantee

This also means that supplier now commands a larger market share, which goes up to 50% from 33%. The unit logistics costs are also halved, changing from 8.9 cents to 4.1 cents. This is because the supplier's logistics system is correspondingly changed. First the optimal number of warehouses increases from 10 to 47 in order to handle the denser demand. This increase also implies that the average travel distance decreases significantly.

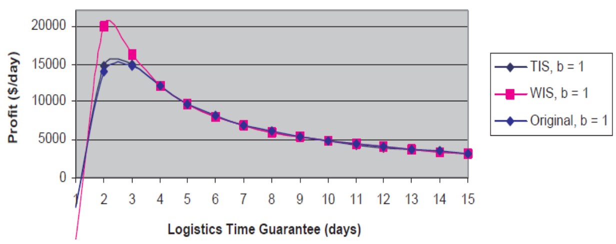
Indeed the travel distance reduces from 119 miles to 55 miles. It is because of this reduction, and the consequent reduction in the motion time, T_m, that the supplier is able to reduce the optimal time guarantee by a day. However one important issue remains. The above change in the supplier's logistics time guarantee is based on the implicit assumption that the supplier is flexible enough to change his logistics system accordingly. But sometimes this may not be possible and the supplier might be constrained to supply the product using a less than optimal logistics system. Our model enables the supplier to easily measure the effect of his response in such a scenario. For example, say in the above case the supplier has to supply the retail market with increased market demand, with the original logistics network comprising of 10 warehouses. In such a scenario, the supplier still has to offer the original optimal time guarantee, i.e., t_G^* = 3 days to maximize his revenue.

<Figure 7> Sensitivity Analysis on MR vs. Profit

But as shown in <Figure 7>, interestingly the difference in the optimal profit between the two cases is very little, amounting to only $4098/day, i.e., a difference of less than 4%. Such little change in the profit is because of two reasons. Firstly the effect of the unit logistics cost on the expected profit is quite minimal. For example in both the configuration of the logistics system, these costs amount to less than 2% of the unit price. While these costs might appear to be quite conservative, unit logistics costs in real logistics systems usually are less than 10% of the unit price. Thus even though the unit logistics costs in the optimal system are 65% of the cost of using the original, and thus non optimal, system, because of the low values of these costs relative to the unit price, the expected profit doesn't change much. The second reason is because of the EOQ like structure of optimal unit logistics cost, LC(t_G^*), it is not sensitive to changes in the values of the parameters. Dasci and Verter (2001) have also pointed this out.

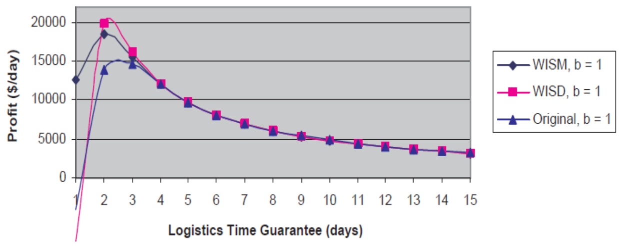
4.2.2 Changing the Supplier's Logistics System

The supplier would seek to improve his logistics time by making changes to his logistics system. Some of the questions that need to be answered include what aspects of the logistics system should be changed, how does the supplier trade off among various improvement solutions, what is the impact of implementing one such solution on the expected profit? Our model enables the supplier to do this very easily. Suppose the supplier wants to reduce the variance of the actual logistics time, T_l. In order to do this he can reduce the variance of either of the two component times, motion time (T_m) or order processing time (T_o). Suppose that the supplier can reduce the variance in either of the two time components if the respective cost parameters are doubled. Assume σ_ρ is halved by paying two times the transportation cost per mile, c_d, i.e., 10/mile instead of 5/mile. This is a reasonable transportation improvement strategy. Similarly assume σ_O is halved by paying two times the warehouse costs per day, c_f, i.e., \$ 20000/day instead of \$10000/day. This also can be a reasonable warehousing improvement strategy. The question that the supplier would seek to answer is which of these two strategies to use and what would be the consequent impact on the expected profit. <Figure 8> below (TIS: transportation improvement strategy, WIS : warehouse improvement strategy) shows the effect of these strategies on the expected profit.



<Figure 8> Warehouse vs. Transportation Improvement Strategies

We see that the warehousing improvement strategy offers the most improvement in the expected profit. Indeed the profit increases by 34% over the profit obtained with the original logistics system. Also this improvement strategy enables the supplier to offer a shorter optimal time guarantee of 2 days. This is because the deviation of the actual logistics time is reduced by 45%, from 1.13 days to 0.64 days. Consequently the supplier's market share also increases from 33% to 50%. In comparison the transportation improvement strategy increases the profit only by 2%. Also since the optimal time guarantee doesn't change from the original time guarantee of 3 days, the supplier's market share doesn't increase. The deviation is reduced only marginally from 1.13 days to 1.05 days. In the transportation improvement strategy the unit logistics costs increased by almost 60%. In contrast, the warehouse improvement strategy causes these costs to go up by only 10%. Thus we can conclude that the supplier would prefer the warehouse strategy for improving his profit as well as his logistics response. Our model can easily evaluate the impact of other similar improvement strategies as well. Suppose that the supplier has two warehousing technology alternatives, one that halves the mean order processing time, μ_O and the other halves the standard deviation, σ_O. Assuming that use of either of these alternatives doubles the warehouse costs per day, c_f, the supplier can easily make his decision.



<Figure 9> Warehouse vs. Transportation Improvement Strategies

<Figure 9> (WISM : warehouse improvement strategy in mean, WISD : warehouse improvement strategy in standard deviation) shows the system response to these two alternatives. Clearly the supplier benefits more by adopting the technology that halves the deviation of order processing time.

5. Conclusion

While there are numerous researches that deal with firms offering time-based guarantees for their services, they model the firm's operation as a queue or using a distribution. Conversely there is no research in the area of logistics system modeling, which explicitly connects a firm's logistics response to its ability to compete in the market. In this paper we tried to fill this gap. Using a stochastic demand function and a continuous approximation model of the supplier's logistics system, we have studied the optimal logistics response under varying market conditions, defined by varying sensitivities to both time and price. We have also demonstrated the impact of changing various parameters of the supplier's logistics system on the optimal profit. This framework in turn is useful for a supplier, aspiring to be a time-based competitor, to choose the best possible logistics improvement strategy. A number of extensions of this research are required to overcome the limitations of the framework. The first limitation is that of the highly simplified nature of the approximate logistics model. Indeed we have assumed that the supplier services the retail market out of a single-tiered network of warehouses. While this maybe still valid, as in the case of Geoffrion's [10] study, most retail logistics networks nowadays consists of usually two or more tiers. We need to extend the continuous approximation models to such cases. A further limitation of the logistics model is the assumption that the supplier always has sufficient inventory on hand to meet the time guarantee. We can extend our model to consider both the optimal inventory level and time guarantee in our subsequent research. Furthermore noticing that in retail markets, where logistics have become quite critical, competing suppliers will respond suitably to prevent loss of market share. A game theoretic multi-firm model could be developed where each supplier can react to other's actions in the future research.

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