Proceedings of the 2010 Winter Simulation Conference
B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, and E. Yücesan, eds.

INVESTIGATING THE IMPACTS OF DYNAMIC PRICING AND PRICE-SENSITIVE DEMAND ON AN INVENTORY SYSTEM IN THE PRESENCE OF SUPPLY DISRUPTIONS

Yuerong Chen
Shengyong Wang

Department of Mechanical Engineering
University of Akron
Akron, 44325, USA

ABSTRACT

Supply disruptions have attracted a lot of attention due to the huge detriments they might cause. Supply disruptions have various forms, including machine breakdowns and natural disasters. As an effective marketing tool, dynamic pricing has been helping sellers enhance their profits. In addition, price-dependent demand is common in practice. This paper studies a single-product inventory system that consists of a supplier, a retailer, and customers. The supplier is subject to disruptions. The retailer adopts a periodic review inventory policy, under which an appropriate inventory replenishment order is sent to the supplier every a fixed period of time. Price is adjusted according to inventory level at each inventory review point. Customer demand variation based on price is also considered. In this paper, we simulate the concerned inventory system and investigate the impacts of supply disruptions, dynamic pricing, and price-sensitive demand on the retailer's annual profit.

1 INTRODUCTION

With the globalization of today's market, supply disruptions have caught more and more attention due to the tremendous impacts they may have on today's increasingly complicated supply chain networks. Supply disruptions could be resulted from natural disasters, equipment breakdowns, labor strikes, political instability or terrorism, and so forth (Chopra and Sodhi 2004). Numerous examples have reflected catastrophic results supply disruptions cause. Let us look back at the 2000 lightning incident in Albuquerque, New Mexico (Eglin 2003). This incident severely destroyed Ericsson Company's semiconductor plant. At that time, this plant was Ericsson's single supplier. Therefore, as subsequent results of the incident, the plant had to shut down after the fire, and Ericsson had no other sources of microchips and ultimately lost $400 million. Another famous example of supply disruptions is the 1999 Taiwan earthquake. At that time, Taiwan was the third largest supplier of computer accessories in the world. This earthquake resulted in a two-week global semiconductor shortage, and countless companies all over the world were deeply impacted. For more examples about the destruction supply disruptions may result in, the readers are referred to the literature (Hopp and Yin 2007).

Pricing is a powerful marketing strategy (Nagle and Holden 2001). It plays an important role in achieving a company's high sales figure. An effective pricing strategy can make a significant difference in a company's profit. Thus, pricing has been highly emphasized by companies. One popular pricing model is price differentiation, where different customers are charged different prices for the same good. For instance, some museums sell different tickets for adults, children, senior people, and students. It is also known that auto insurance companies charge premiums based on age, location, driving experience, and other relevant information. A second pricing model is dynamic pricing, where the price of an item changes over time. Dynamic pricing can be employed to manage variability in product supply or in customer demands. It can also be used as a reaction to competitors' marketing strategies. Due to the rapid development of science and technology, sellers are able to easily change an item's price, which makes dynamic pricing effortless and popular. In this paper, dynamic pricing is the pricing model that we take into account.

Inventory management has been widely studied (Hadley and Whitin 1963, Axsäter 2006) since World War II when the military logistics officers tried to find good approaches to manage the supply of arms, ammunition and rations to where they are needed. In recent years, with increasing attention being paid to supply disruptions, inventory management problems have been investigated in the presence of supply disruptions. See the literature (Gupta 1996, Parlar 1997, Mohebbi 2003) for example. On the other hand, much research has been conducted on the coordination of inventory control and pricing strategies. Whitin (1955) starts this work and analyzes the classic newsvendor problem with price dependent demand. However, to the best of our knowledge, no one has studied inventory management problems with the consideration of both supply disruptions and pricing strategies. The aim of this paper is to address such a challenge through simulation techniques. The inventory system we are concerned with is composed of an unreliable supplier, a retailer, and customers. Same as (Whitin 1955), customer demands are deemed to be price dependent. This is consistent with the observations in our daily life. Customers would abort the purchase if a good is too expensive, while customers might buy ahead in the situation where a good is on sale or in promotion. In this paper, the influences of supply disruptions, dynamic pricing, and price-dependent demand will be investigated on the inventory system under study.

The remainder of the paper is organized as follows. Section 2 reviews the literature on inventory system management with supply disruptions and on the coordination of inventory control and pricing. Section 3 states the adopted inventory policy and the considered problem. Section 4 describes the simulation model in detail. Section 5 sets up the experiments for investigating the impacts of supply disruptions, dynamic pricing and price-sensitive demand on the inventory system. Section 6 illustrates the results and provides some managerial insights to the retailer. Concluding remarks are given in Section 7.

2 LITERATURE REVIEW

Recognizing the critical influences of supply disruptions, many researchers such as Chao (1987), Gupta (1996), Parlar and Berkin (1991), Song and Zipkin (1996), Lewis (2005) have addressed inventory management problems with respect to supply disruptions. In literature, inventory systems are generally divided into two categories: continuous-review based and periodic-review based. Most of previous work considers the continuous-review setting, see (Parlar 1997, Gürler and Parlar 1997, Arreola-Risa and DeCroix 1998, Mohebbi 2003, Mohebbi 2004, Chen and Li 2009). Parlar (1997) addresses a continuous-review stochastic inventory problem with random demand and random lead-time in the situation where supply may be disrupted. Under a (Q,r) policy, the average cost function is derived by using the renewal reward theorem. Gürler and Parlar (1997) extend the above problem (Parlar 1997) by adding one more randomly available supplier. Arreola-Risa and DeCroix (1998) study inventory management in the presence of random supply disruptions and partial backorders, with an (s,S) policy being considered. Mohebbi investigates two continuous-review inventory systems with compound Poisson demand, with one having Erlang distributed lead time (Mohebbi 2003) and the other having hyperexponentially distributed lead time (Mohebbi 2004). Chen and Li (2009) consider a continuous-review inventory system where a single supplier is subject to disruptions. They study the effect of customer segmentation on the system. As to periodic-review inventory systems, due to the intricate nature, little work has been conducted on them. The representative literature includes (Parlar, Wang, and Gerchak 1995, Özekici and Parlar 1999, Li and Chen 2010). Parlar, Wang, and Gerchak (1995) analyze a finite-horizon periodic-review inventory model with backlogging. Under their specific settings, the optimal inventory policy is proven to be of an (s,S) type. Özekici and Parlar (1999) consider infinite-horizon periodic-review inventory models with unreliable suppliers. It is shown that an environment-dependent order-up-to level policy is optimal when the order cost is linear in order quantity. Li and Chen (2010) investigate the impacts of supply disruptions and customer differentiation on a partial-backordering inventory system in the periodic-review setting of (r,S).

As for pricing, it is a crucial marketing tool for companies. It has been well studied by some authors (Nagle and Holden 2001, Mohammed 2005). In recent years, the importance of coordinating inventory control and pricing strategies has been acknowledged by both industrial practitioners and academic researchers. Whitin (1955) initiates the work by formulating a newsvendor model with price effects. In his model, selling price and stocking quantity are set simultaneously, and demand depends on the unit selling price. Feng and Chen (2003) address a joint pricing and inventory control problem with setup costs and uncertain demand. Under the assumption that demands follow Poisson processes that are parameterized with price, they demonstrate that a class of pricing and inventory policies is optimal for maximizing the long-run average profit. Chen and Simchi-Levi (2004a) analyze a finite-horizon, periodic-review, single-product inventory model with stochastic demand and fixed ordering cost. They prove that in the situation where the demand is a function of price and an additive random perturbation, an (s,S,p) inventory policy is optimal. However, this policy is not optimal for general demand processes. By employing a novel concept, symmetric k-convexity, Chen and Simchi-Levi (2004b) prove that in the infinite-horizon version of the problem, a stationary (s,S,p) policy is optimal not only for the additive demand process but also for general demand processes. Unlike the above two studies, Chen and Simchi-Levi (2006) consider a continuous-review model, and show that in the infinite-horizon case, a stationary (s,S) inventory policy maximizes the expected discounted or expected average profit under general conditions. For more literature on the coordination of inventory management and pricing, the readers can see the excellent review papers such as (Petruzzi and Dada 1999, Elmaghraby and Keskinocak 2003, Chan et al. 2004).

3 PROBLEM DESCRIPTION

This paper is concerned with a single-product inventory system that includes a supplier, a retailer, and customers. The supplier provides products to the retailer, which in turn sells products to customers. The retailer reviews its stock and sends replenishment orders to the supplier from time to time. The supplier is unreliable, in other words, it is randomly available. It is subject to random disruptions that may result from natural disasters, material shortage, equipment breakdown, insufficient labor, and the like. When a supply disruption occurs, the supplier can not fulfill the incoming orders from the retailer. Only when the disruption issue is resolved, can the orders be processed. We define the time period during which the supplier is available (*i.e.*, under normal condition) as its ON period, and the time period during which the supplier is not available (*i.e.*, under disruption condition) as its OFF period. ON periods reflect supply disruption frequency, while OFF periods represent supply disruption duration. Frequency and duration are two indices for the severity of supply disruptions. The longer the ON periods, the less frequent the disruptions and the slighter the disruptions. Contrarily, the longer the OFF periods, the longer the disruptions last and the more severe the disruptions. In this paper, ON and OFF periods are assumed to follow exponential distributions, and different combinations of mean values of ON and OFF periods are used to represent different supply disruption scenarios.

3.1 The Adopted Inventory Policy

The retailer adopts a periodic-review inventory policy (r,S), where r is an inter-review period and S is an order-up-to level. This policy means that, every a period of time r, the retailer reviews its inventory position and orders an appropriate quantity of products from the supplier such that inventory position is increased to the order-up-to level S. Figure 1(a) shows a standard (r,S) inventory policy that does not consider supply disruptions. Time points t_1, t_2 and t_3 are inventory review points when inventory position is reviewed and an order of appropriate quantity is placed to the supplier. t_4, t_5 and t_6 are time points when the ordered products are received by the retailer. Time periods $t_4 - t_1$, $t_5 - t_2$ and $t_6 - t_3$ are three realizations of stochastic replenishment lead time L. In Figure 1(a), the solid line represents net inventory level, which is defined as on-hand inventory minus backorders (Hadley and Whitin 1963). In this paper we assume that there are no backorders and all unsatisfied demands are lost. Thus, net inventory level in this paper actually stands for on-hand inventory which is non-negative. We here address it by inventory level for simplicity. When inventory level is positive, the retailer incurs holding cost that is proportional to holding duration and the quantity of held products. The dotted line in the figure represents inventory position, which by definition is equal to the corresponding net inventory level plus the quantity of products in the currently outstanding orders (Hadley and Whitin 1963, Hopp and Spearman 2008). Outstanding orders stand for the orders that have been placed to the supplier but have not yet been received by the retailer.

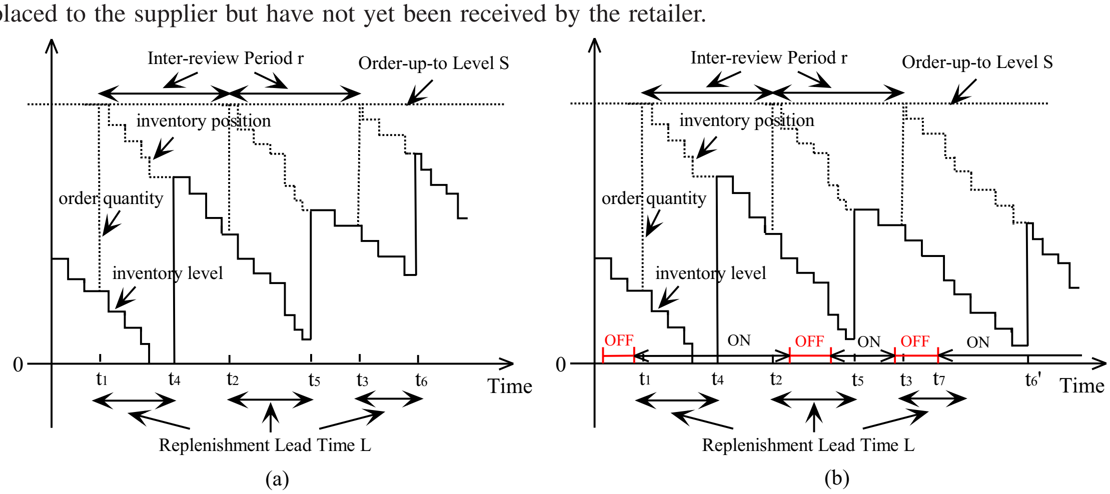

Figure 1: (a) A standard (r, S) inventory policy. (b) An (r, S) inventory policy with supply disruptions.

Figure 1(b) shows an (r,S) inventory system where supply disruptions are taken into account. As seen in this figure, the red line segments on 'Time' axis represent OFF periods of the supplier, and the other line segments on the horizontal axis represent ON periods. Similar to those in Figure 1(a), time points t_1, t_2 and t_3 are three review points. However, the orders placed at these time points receive different treatments. At time points t_1 and t_2, the supplier is available (*i.e.*, in ON periods) and the orders are processed and shipped out immediately. The retailer receives the products at time points t_4 and t_5, respectively. However, at time point t_3, the supplier is in an OFF period (*i.e.*, under disruption status), so the order can not be processed until the supplier restores to its normal status. Hence, the order is processed and shipped out after the end of the OFF period, which occurs at time point t_7. The retailer finally receives the products at time point $t_6{}'$. Similarly, time periods $t_4 - t_1, t_5 - t_2$ and $t_6{}' - t_3$ are three realizations of stochastic replenishment lead time L. Comparing Figure 1(b) with Figure 1(a), it is obvious that supply disruptions delay order replenishment.

3.2 The Considered Inventory Problem

This paper assumes that customer demand is pertinent to the selling price of the product. Specifically, the average customer inter-arrival time is assumed to increase with price. That is, higher price leads to less customer purchase, which is common in real life. Demand size of a customer, however, is assumed to be irrelevant to price and follow a fixed probability distribution. All unsatisfied customer demands are deemed to be lost. The retailer incurs lost-sale cost accordingly. The retailer also incurs holding cost for inventory. Moreover, when the retailer places an inventory replenishment order, it is subject to the ordering cost which includes both a fixed setup cost and a variable cost proportional to the amount ordered. The number of outstanding orders is allowed to be more than one and the replenishment lead time is assumed to be stochastic. In addition, this paper considers dynamic pricing. Price is changed at each inventory review point, and the change is dependent on the inventory level at that time point. If the inventory level is high, price is decreased to attract customer demands. Contrarily, if the inventory level is low, price is increased to make more profit. The reason to adopt such a pricing policy is that, inventory level reflects if the price is set at the right place or not. For instance, low inventory level indicates that the product with the current price is popular in customers. In this case, the retailer can appropriately raise the price.

All the above considerations, combined with the complex nature of a periodic-review inventory system, make it very difficult to investigate this inventory management problem in an analytical way. In this paper we will utilize simulation techniques (Kelton, Sadowski, and Sturrock 2007) to study the concerned inventory system, seeking to derive some insights about this system and to provide managerial suggestions to the retailer. The used measure of performance is the annual profit of the retailer, which is equal to annual revenue minus annual ordering cost, annual inventory holding cost, and annual lost-sale cost. We denote the to-be-used notation by the following:

r: inter-review period
S: order-up-to level
$\lambda(t)$: the average customer arrival rate at time point t
D: stochastic demand size of a customer
L: replenishment lead time
T: a year, *i.e.*, 365 days
$IL(t)$: inventory level of the retailer at time point t
$IP(t)$: inventory position of the retailer at time point t
$P(t)$: unit selling price of the product at time point t
$NS(t)$: the number of products sold to customers at time point t
OQ_i: the order quantity at the i-th inventory position review, $i = 1, 2, \ldots, \lfloor T/r \rfloor$
u: the mean duration of ON periods
v: the mean duration of OFF periods
m: the average price when inventory level is zero
k: the slope of the function of price versus inventory level
ε_p: the random variable that influences price variation
a: the intercept of the function of λ versus price
b: the slope of the function of λ versus price
ε_λ: the random variable that influences the average customer arrival rate variation
A: setup cost for each order placement
c: unit ordering price of the product
h: unit holding cost per time unit
l: unit lost-sale cost
NLS: the number of lost sales
ARN: annual revenue
AOC: annual ordering cost
AHC: annual holding cost

ALC: annual lost-sale cost
AP: annual profit

It is easy to derive the calculation formulas for annual ordering cost, annual holding cost, annual lost-sale cost, annual revenue and annual profit of the retailer. They are as follows:

$$AOC = \sum_{i=1}^{\lfloor T/r \rfloor} [A \cdot \delta(OQ_i) + c \cdot OQ_i], \quad (1)$$

$$AHC = \int_0^T h \cdot \max(IL(t), 0) dt, \quad (2)$$

$$ALC = l \cdot NLS, \quad (3)$$

$$ARN = \sum_t P(t) \cdot NS(t), \quad (4)$$

$$AP = ARN - AOC - AHC - ALC. \quad (5)$$

where

$$\delta(x) := \begin{cases} 1 & \text{if } x > 0, \\ 0 & \text{otherwise.} \end{cases}$$

4 THE SIMULATION MODEL

The considered inventory system is too complicated to study analytically. Thus, we construct a simulation model for it, which is composed of two processes: customer demand process and inventory replenishment process. The customer demand process is as follows. When a customer arrives, the retailer checks its inventory level. There are three situations. The first situation is that, the current inventory level is positive and is enough to satisfy the customer demand. Under this situation, the customer makes purchase with satisfaction. The retailer then reduces its inventory level and inventory position by the customer's demand size accordingly. The revenue is calculated as well. The second situation is that, the current inventory level is positive but there is no enough stock for the customer demand. In this case, the customer only takes the available products without placing a backorder, since we assume that all unsatisfied customer demands are lost. The retailer thus incurs lost-sale cost that is proportional to the unsatisfied quantity. The inventory position decreases by the quantity of the products the customer takes. The inventory level is subsequently set to be zero. The revenue is calculated accordingly. The third situation is that, there are no products available at all. Under this situation, the customer just leaves and maybe go for other competitors. The retailer is therefore subject to lost-sale cost proportional to the demand size of the customer. Inventory position and inventory level keep unchanged since no purchase is made. There is no revenue for this case.

The inventory replenishment process works as below. At each inventory review point, the retailer reviews its inventory position and determines how many products to replenish. According to the adopted (r,S) inventory policy, inventory position needs to be increased to the order-up-to level S. Therefore, the needed product quantity (*i.e.*, order quantity) is equal to S minus the current inventory position. The corresponding ordering cost is then calculated as the fixed order setup cost plus the product of order quantity and unit ordering price for the product. The inventory position is updated to S. In addition, unit selling price of the product and the average customer arrival rate are both adjusted at each inventory review point. The unit selling price is a non-increasing function of the inventory level at the review point, while the average customer arrival rate is a non-increasing function of the unit selling price just set. When an order is placed, the availability of the supplier needs to be checked. If the supplier is in its normal condition, it processes the order immediately. If the supplier encounters a disruption at that time, the order has to wait for being processed until the supplier restores to its normal status. After being processed, the order is shipped out. Going through the transportation process, the order arrives at the retailer and the inventory level is increased correspondingly.

5 EXPERIMENTAL SETUP

We first consider a base model for the inventory system. In this base model, the parameters for supply disruptions, the price-inventory level function, and the demand-price function are set to reflect a mild situation. For this base model, we use OptQuest in Arena to derive an optimal inventory policy (r^*, S^*) which maximizes the annual profit of the retailer. Then the parameters for the above three factors are adjusted to comprise experiments. Under the derived optimal policy, the experiments are conducted to investigate the impacts of supply disruptions, dynamic pricing, and price-dependent demand on the inventory system.

5.1 Input Parameters for the Experiments

Customer inter-arrival time is assumed to follow an exponential distribution with a mean of $1/\lambda(t)$ days, where $\lambda(t)$ is the average customer arrival rate and changes at each inventory review points. $\lambda(t)$ is assumed to be a non-increasing function of unit selling price. Specifically, $\lambda(t) = a - b \cdot P(t) + \varepsilon_\lambda$, where t's values are review points only and ε_λ is a random variable of normal distribution. In the base model, we let $a = 18, b = 0.4$, and $\varepsilon_\lambda \sim N(0, 0.05^2)$. Besides, each customer's demand size D is assumed to take values of {1, 2, 3} with probability of {0.85, 0.1, 0.05}, respectively. Unit selling price is assumed to be a non-increasing function of inventory level: $P(t) = m - k \cdot IL(t) + \varepsilon_p$, where t's values are review points only and ε_p is a random variable with normal distribution. For the base model, $m = 30, k = 0.3$ and $\varepsilon_p \sim N(0, 0.1^2)$. In addition, two indicators of supply disruption severity magnitude (ON periods and OFF periods) are assumed to follow exponential distributions with respective mean values of $u = 60$ and $v = 2$. Without loss of reasonability, we set other parameters as follows. The setup cost for each order placement is $A = \$10$; unit ordering price of the product is $c = \$10$; unit holding cost per time unit is $h = \$1$; unit lost-sale cost is $l = \$5$. The transportation duration of each order is assumed to follow a normal distribution with a mean of 2 days and a standard deviation of 0.1 days.

The initial inventory level and initial inventory position of the retailer are arbitrarily set to be $IL(0) = IP(0) = 20$. The initial unit selling price and initial average customer arrival rate are set to be $P(0) = 30, \lambda(0) = 5$. Such settings prevent the initial inventory status, initial price, and initial customer arrival rate from being unrealistically "empty and idle". Later we will warm up the simulation model to remove the influences these initial settings may bring about.

5.2 Experimental Design and Simulation Settings

We first investigate the influence of supply disruptions on the inventory system by considering different combinations of u and v to represent different supply disruption scenarios. Specifically, as the indicator of supply disruption frequency, u takes values of {10, 60, 200}, standing for severe, moderate, slight disruptions, respectively. Similarly, as the indicator of supply disruption duration, v takes three values {0.5, 2, 10}, denoting slight, moderate, severe supply disruptions, respectively. Therefore, there are 9 scenarios, for each of which the annual profit of the retailer is calculated via simulation. These experiments are conducted under the optimal inventory policy $(1, 38)$ which is obtained from the base model.

As for the impact of dynamic pricing, we fix the value of m and adjust k's value only to reflect the sensitivity extent of price changing with inventory level. According to the optimal solution for the base model, we estimate the range of inventory level and let k take values of {0.05, 0.3, 0.7}. These three values correspond to insensitive, moderate, and sensitive price variation with inventory level, respectively. Likewise, regarding the impact of the price-sensitive customer demand, we take into account three combinations of a and b to represent different sensitivity extents of the average customer arrival rate changing with price. These three combinations are listed in Table 1, standing for insensitivity, moderateness, and sensitivity, respectively. We also consider three supply disruption scenarios as shown in Table 1. Under each disruption scenario, the effects of different k values and the influences of different combinations of a and b are explored via simulation. In addition, the impacts of three supply disruption scenarios on the inventory system are looked into based on different k values and different combinations of a and b.

Table 1: The design for experiments

Parameter	Values
(u, v)	(10, 10); (60, 2); (200, 0.5)
k	0.05; 0.3; 0.7
(a, b)	(12, 0.1); (18, 0.4); (30, 0.9)

The warm up period for the simulation is determined by observing the moment when the average daily profit begins to stabilize. In the experiments, the warm up period is obtained to be equal to 30 days. For each experiment, we run $n = 50$ replications such that the half width of a 95% confidence interval of annual profit is reasonable. The average annual profit of the retailer from these 50 replications is recorded as the result of each experiment.

6 RESULT ANALYSIS

The experimental results are illustrated in Figures 2-7. Figure 2 shows the impact of disruption frequency indicator u on the inventory system, based on different scenarios of disruption duration indicator v. We can see that, for each v, the average annual profit of the retailer increases with u. Moreover, the increase magnitude augments with v. These findings indicate that, given a fixed mean value of disruption duration, less frequent disruptions lead to bigger average annual profit. Furthermore, when disruptions last longer, the above effect is more obvious. In addition, from the fact that when $v = 0.5$ the average annual profits differ not much for different u values, we can infer that short enough disruption duration buffers the impact of high-frequency supply disruptions.

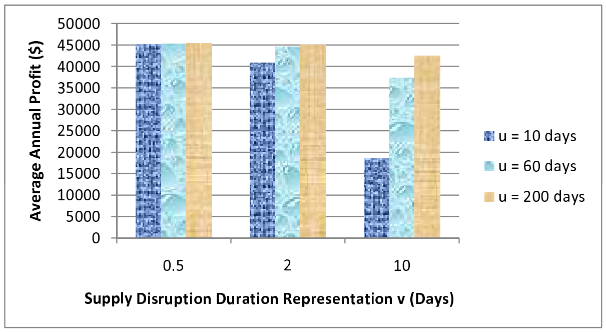

Figure 2: The impact of u on the inventory system under different scenarios of v

Figure 3 illustrates the impact of disruption duration indicator v on the inventory system, based on different scenarios of disruption frequency indicator u. It is obvious that, for each u, the average annual profit of the retailer decreases in v. Moreover, the decrease magnitude lessens with u. These observations reveal that, when disruption frequency is given, shorter disruption duration leads to bigger average annual profit; when supply disruptions occur more frequently, the above effect is more clear. Figure 3 also implies that, once supply disruptions are very rare, the effects of different disruption duration scenarios do not differ significantly.

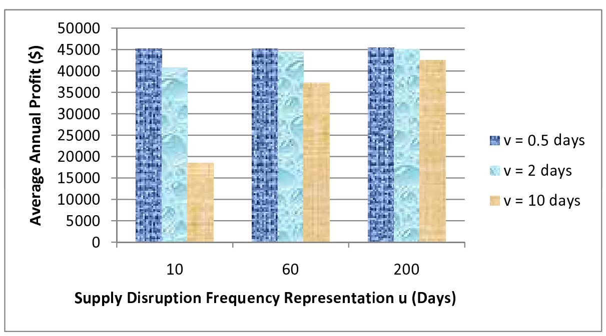

Figure 3: The impact of v on the inventory system under different scenarios of u

Figures 2 and 3 tell the retailer that, in order to acquire bigger annual profit, it should select a supplier with lower disruption frequency and/or shorter disruption duration. Moreover, when one supply disruption magnitude indicator (frequency or duration) suggests low enough disruption magnitude, the effect of the other magnitude indicator (duration or frequency, accordingly) on the inventory system is slight.

Figure 4 shows the effect of the sensitivity extent of price variation k on the inventory system, based on different scenarios of supply disruptions. We find that, regardless of what supply disruptions, the average annual profit decreases with k. Moreover, the decreasing mode is similar among different supply disruption scenarios. These phenomena indicate that, whether supply disruptions are severe or not, the more sensitive the price varying with inventory level, the less the average annual profit. Moreover, the effect of sensitivity extent on the average annual profit is independent on supply disruption magnitude. Figure 4 also shows that, the influences of mild and slight supply disruptions on k's impact are almost the same. Combined with the case of severe supply disruptions, this may indicates that disruption duration has larger impact on the inventory system than disruption frequency.

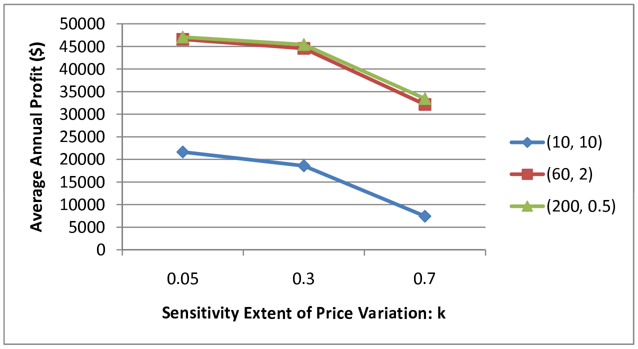

Figure 4: The effect of sensitivity extent of price variation on the inventory system under different supply disruption scenarios

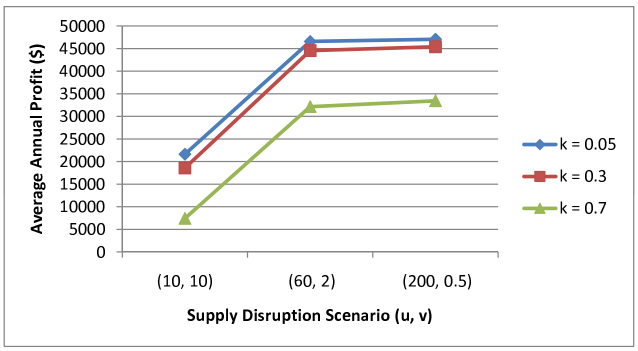

Figure 5: The impact of supply disruption magnitude on the inventory system under different scenarios of k

Figure 5 demonstrates the impact of supply disruption magnitude on the inventory system, based on different k values. It shows that, whatever k value, the average annual profit increases when supply disruption magnitude decreases. Furthermore, the increase mode is almost the same. These reflect that, slight supply disruptions lead to more average annual profit, and the impact of supply disruption magnitude on the inventory system is irrelevant to the sensitivity extent of price variation.

Figures 4 and 5 suggest the retailer that, unit selling price of the product should be adjusted slightly with the specific inventory level at each inventory review point. Both figures also illustrate that, the impact of supply disruption magnitude on the inventory system does not have interactions with the impact of sensitivity extent of price variation on the inventory system.

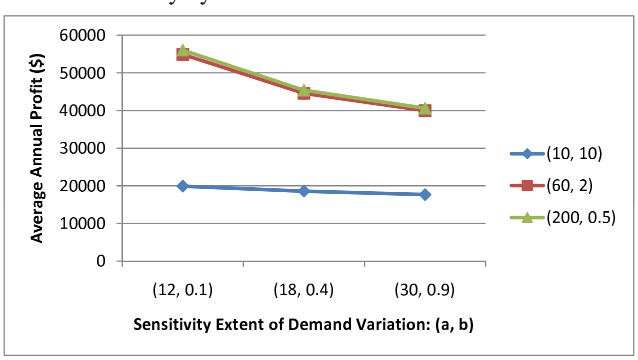

Figure 6: The effect of sensitivity extent of customer arrival rate variation on the inventory system under different supply disruption scenarios

Figure 6 exhibits the effect of the sensitivity extent of customer demand arrival rate variation (a,b) on the inventory system, based on different scenarios of supply disruptions. It is clear that, regardless of what

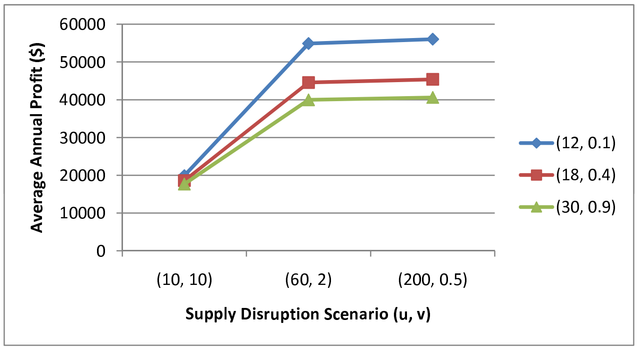

Figure 7: The impact of supply disruption magnitude on the inventory system under different scenarios of sensitivity extent of customer arrival rate variation (a,b)

supply disruption scenarios, the average annual profit decreases when the sensitivity extent of customer arrival rate variation deepens. For the cases of mild and slight supply disruptions, the effect of (a,b) on the system is almost the same. However, when $u = 10$ and $v = 10$, the decrease trend slows down.

Figure 7 discloses the impact of supply disruption magnitude on the inventory system, based on different scenarios of sensitivity extent of customer arrival rate variation (a,b). This figure implies that, whatever sensitivity extent of customer arrival rate varying with price, the average annual profit increases with the decrease of supply disruption magnitude. Furthermore, in the situation of severe supply disruptions, there are no differences regarding the influences of different sensitivity extents of customer arrival rate variation.

Figures 6 and 7 jointly advise the retailer that, it should make sure that the change of customer arrival rate with price is not significant. Moreover, comparing different supply disruption situations, both figures imply that supply disruption duration's effect on the inventory system might be bigger than that of supply disruption frequency.

7 CONCLUSIONS

This paper studies a single-product, periodic-review inventory system which consists of an unreliable supplier, a retailer, and customers. The retailer sells products to customers and replenishes its stock from the supplier which is subject to random disruptions. The retailer adopts a periodic-review inventory policy under which every a period of time, inventory position is reviewed and an order of appropriate quantity is placed to the supplier. Dynamic pricing is considered in this study. Unit selling price is adjusted at each inventory review point, based on the inventory level at that time. This paper is the first work to combine supply disruptions and dynamic pricing to investigate an inventory system. This study also takes into account varying customer demand, which is assumed to be price-dependent. In addition, this paper relaxes some restrictions in previous literature. For example, we permit arbitrary number of outstanding orders and consider stochastic replenishment lead time. All these considerations make the problem more realistic and more complicated to study.

We develop a simulation model for the customer demand process and the inventory replenishment process of the concerned inventory system. We then investigate the impacts of supply disruptions, dynamic pricing and price-sensitive demand on the inventory system. Different supply disruption scenarios, different scenarios of sensitivity extent of price variation, and different scenarios of sensitivity extent of demand variation are considered. Experimental results provide very useful managerial suggestions to the retailer. For example, under the fact that a supplier is more or less subject to random disruptions, the retailer should choose a supplier with low-frequency and/or short-duration disruptions. Moreover, the results show that both insensitive price variation with inventory level and insensitive demand arrival rate variation with price lead to larger average annual profit of the retailer. Therefore, the retailer should keep these variations from overdoing.

In this paper, the adopted inventory policy is (r,S), which is periodic-review based. Future work can be conducted on the continuous-review case with other inventory policies such as (s,S). In addition, combining other factors like customer differentiation into the study would be a possible research direction.

REFERENCES

Arreola-Risa, A., and G. DeCroix. 1998. Inventory management under random supply disruptions and partial backorders. *Naval Research Logistics* 45:687–703.

Axsäter, S. 2006. *Inventory control*. 2nd ed. New York: Springer.

Chan, L., Z. M. Shen, D. Simchi-Levi, and J. Swann. 2004. Coordination of pricing and inventory decisions: a survey and classification. In *Handbook of Quantitative Supply Chain Analysis: Modeling in the E-Business Era*, ed. D. Simchi-Levi, S. Wu, and Z. M. Shen, Chapter 9. Kluwer, Boston.

Chao, H. 1987. Inventory policy in the presence of market disruptions. *Operations Research* 35 (2): 274–281.

Chen, X., and D. Simchi-Levi. 2004a. Coordinating inventory control and pricing strategies with random demand and fixed ordering cost: The finite horizon case. *Operations Research* 52 (6): 887–896.

Chen, X., and D. Simchi-Levi. 2004b. Coordinating inventory control and pricing strategies with random demand and fixed ordering cost: The infinite horizon case. *Mathematics of Operations Research* 29 (3): 698–723.

Chen, X., and D. Simchi-Levi. 2006. Coordinating inventory control and pricing strategies: The continuous review model. *Operations Research Letters* 34:323–332.

Chen, Y., and X. Li. 2009. The effect of customer segmentation on an inventory system in the presence of supply disruptions. In *Proceedings of the 2009 Winter Simulation Conference*, ed. M. D. Rossetti, R. R. Hill, B. Johansson, A. Dunkin, and R. G. Ingalls, 1610–1621. Pisticaway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Chopra, S., and M. Sodhi. 2004. Managing risk to avoid supply-chain breakdown. *MIT Sloan Management Review* 46 (1): 53–61.

Eglin, R. 2003, Nov. 23. Can suppliers bring down your firm? Sunday Times(London). appointments sec., p. 6.

Elmaghraby, W., and P. Keskinocak. 2003. Dynamic pricing in the presence of inventory considerations: Research overview, current practices, and future directions. *Management Science* 49 (10): 1287–1309.

Feng, Y., and F. Y. Chen. 2003. Joint pricing and inventory control with setup costs and demand uncertainty. The Chinese University of Hong Kong.

Gupta, D. 1996. The (Q, r) inventory system with an unreliable supplier. *INFOR* 34 (2): 59–76.

Gürler, Ü., and M. Parlar. 1997. An inventory problem with two randomly available suppliers. *Operations Research* 45 (6): 904–918.

Hadley, G., and T. M. Whitin. 1963. *Analysis of inventory systems*. Prentice-Hall, Inc., Englewood Cliffs, N.J.

Hopp, W., and Z. Yin. 2007. Protecting supply chain networks against catastrophic failures. under revision for IIE Transactions.

Hopp, W. J., and M. L. Spearman. 2008. *Factory physics*. McGraw-Hill/Irwin.

Kelton, W. D., R. P. Sadowski, and D. T. Sturrock. 2007. *Simulation with arena*. 4th ed. McGraw-Hill.

Lewis, B. 2005. *Inventory control with risk of major supply chain disruptions*. Ph. D. thesis, Georgia Institute of Technology.

Li, X., and Y. Chen. 2010. Impacts of supply disruptions and customer differentiation on a partial-backordering inventory system. *Simulation Modelling Practice and Theory* 18:547–557.

Mohammed, R. 2005. *The art of pricing: How to find the hidden profits to grow your business*. Crown Business.

Mohebbi, E. 2003. Supply interruptions in a lost-sales inventory system with random lead time. *Computers & Operations Research* 30:411–426.

Mohebbi, E. 2004. A replenishment model for the supply-uncertainty problem. *International Journal of Production Economics* 87:25–37.

Nagle, T., and R. Holden. 2001. *The strategy and tactics of pricing: A guide to profitable decision making*. 3rd ed. Prentice Hall.

Özekici, S., and M. Parlar. 1999. Inventory models with unreliable suppliers in a random environment. *Annals of Operations Research* 91:123–136.

Parlar, M. 1997. Continuous-review inventory problem with random supply interruptions. *European Journal of Operational Research* 99:366–385.

Parlar, M., and D. Berkin. 1991. Future supply uncertainty in EOQ models. *Naval Research Logistics* 38:50–55.

Parlar, M., Y. Wang, and Y. Gerchak. 1995. A periodic review inventory model with markovian supply availability. *International Journal of Production Economics* 42:131–136.

Petruzzi, N. C., and M. Dada. 1999. Pricing and the newsvendor problem: A review with extensions. *Operations Research* 47 (2): 183–194.

Song, J., and P. Zipkin. 1996. Inventory control with information about supply conditions. *Management Science* 42 (10): 1409–1419.

Whitin, T. 1955. Inventory control and price theory. *Management Science* 2:61–80.

AUTHOR BIOGRAPHIES

YUERONG CHEN is a post-doctoral research associate at the Department of Mechanical Engineering, University of Akron, USA. She obtained her PhD degree at the Department of Industrial and Information Engineering, University of Tennessee - Knoxville, USA. Her research interests include healthcare system engineering, supply chain management, inventory control, and production planning and scheduling. She received Best Paper Award at the 2007 IIE annual conference. Her email address is <yuerong@uakron.edu>.

SHENGYONG WANG is an Assistant Professor in the Mechanical Engineering Department at the University of Akron (UA). Prior to joining the faculty of UA, Shengyong worked as a Research Assistant Professor in the Department of Systems Science & Industrial Engineering at the State University of New York at Binghamton for three years. He received his Ph.D. in Industrial Engineering from Purdue University in 2006, his M.S. in Innovation in Manufacturing System and Technology from Singapore-MIT Alliance in 2001, and his B.S. in Mechanical Engineering from Beijing University of Aeronautics and Astronautics in 2000. His research focuses on the application of Industrial and Systems Engineering in a variety of domains, including aerospace systems, manufacturing systems, and health systems. He is senior member of IIE and ASQ, member of IEEE, ASEM, and INFORMS. And he is an ASQ certified six sigma black belt. His email address is <wangs@uakron.edu>.