THE IMPACTS OF DATA INACCURACY ON RETAILER'S PERISHABLE INVENTORY

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ABSTRACT

Since perishable products such as fresh produce, dairy and meat have a finite usable lifetime and constitute more than a third of the worldwide sales at grocery retailers, controlling the inventories of these products is increasingly important. Without alignment of physical inventory and information system inventory, inventory information becomes inaccurate due to product spoilage and the retailer cannot take efficient inventory decisions. The purpose of this research is to investigate how the data inaccuracy affects the retailer's inventory performance for different levels of product lifetime, uncertainty of demand and lead time. Using a simulation model, the lost sales, product spoilage, average inventory and order quantities are calculated to investigate the retailer's performance over a 365 day period and ANOVA analysis is performed to examine the results.

Keywords: Perishable, Product lifetime, Inventory, Simulation, Data inaccuracy.

1. INTRODUCTION

Perishable products such as fresh produce, dairy and meat constitute more than a third of the worldwide sales at grocery retailers (Broekmeulen and Donselaar, 2009). The life of perishable product is a function of the product's characteristics and the environment in which the product is stored. An efficient cold chain is very essential to ensure that the product remains fresh for the expected duration. Beside the safety, timely production and delivery of perishable goods are very important. The rapid and continuous decaying characteristic of perishables makes the suppliers postpone the time to produce and deliver the product as fast as possible. However, a lot of perishable items exceed the expiration date in retailer's inventory. If the retailer doesn't track the items in real time, inventory data will become inaccurate. Therefore, inventory decisions will be taken with inaccurate data and the lost sales will increase.

According to Kendall and Lee (1980), the critical objectives of perishable product inventory management are (i) satisfiying demand by carrying sufficient inventories (ii) holding down inventory carrying costs (iii) keeping the amount of product spoilage (outdating) at an acceptable level, and (iv) maintaining quality by using the product while it is still fresh, and (v) keeping the cost rotation low.

Efficient inventory management is very critical for the retailer to increase the profitability. However, due to the discrepancy between physical inventory and information system inventory, the retailer cannot take efficient inventory decisions.

This study focuses on data inaccuracy of the retailer's perishable inventory and investigates the impacts of this inaccuracy on retailer's perishable inventory for different levels of product lifetime, demand and lead time uncertainty. Using a simulation model, the lost sales, product spoilage, average inventory and order quantities are calculated to investigate the retailer's performance.

This paper starts with the review of the relevant literature. Section 3 and 4 describe the simulation model and the experimental design respectively. Section 5 analyzes and evaluates the simulations results. Finally, Section 6 presents the conclusions and outlines further research.

2. LITERATURE REVIEW

Most of the existing inventory models in the literature assume that items can be stored indefinitely to meet the future demands. However, certain types of commodities deteriorate in the course of time and hence are unstable. Inventory problems for deteriorating items have been studied extensively by many researchers from time to time. There are several literature reviews on perishable inventory system (Nahmias, 1982; Raafat, 1991; Goyal and Giri, 2001). Most publications focus on pricing and lot sizing models (Ferguson et al., 2007; Li et al., 2007; Dye, 2007; Teng et al., 2007; Elmaghraby and Keskinocak, 2003; Chu et al., 1998), or with 2 echelon systems (Wee et al., 2007, Zanoni and Zavanella, 2007; Ferguson and Ketzenberg, 2006; Sarker et al. 2000).

Research in this area started with the work of Within (1957) who considered fashion goods deteriorating at the end of prescribed storage period. One of the focuses of the research on perishable products is interaction and coordination in supply chains (Song et al., 2005). For example, Goyal and Gunasekaran (1995) developed an integrated production- inventory-marketing model for determining the economic production quantity and economic order quantity for raw materials in a multi-stage production system. Yan and Cheng (1998) studied a production-inventory model for perishable products, where they assumed that the production, demand and deterioration rate are all time-dependent. They gave the conditions for a feasible point to be optimal. Arcelus et al. (2003) modeled a profit maximizing retail promotion strategy for a retailer confronted with a vendor's trade promotion offer of credit and/or price discount on the purchase of regular or perishable products. Kanchanasuntorn and Techanitisawad (2006) investigated the effect of product deterioration and retailers' stockout policies on system total cost, net profit, service level, and average inventory level in a two-echelon inventory-distribution system, and developed an approximate inventory model to evaluate system performance. Li, Cheng and Wang (2007) developed economic-order-quantity model (EOQ)-based models with perishable items to evaluate the impact of a form postponement strategy on the retailer in a supply chain.

Owing to the fact that this study investigates the impact of data inaccuracy on perishable inventory, it will be meaningful to mention about the past studies about inventory inaccuracy. Several researchers focusing on inventory management have dealt with the effect of inventory errors on supply chain performance, and investigated the effect on performance factors of decreasing inventory inaccuracy. In this context, Delanuay et al. (2007) classified the errors causing inventory discrepancies in supply chains and defined four types of errors. The first is permanent shrinkage in the physical stock due to theft, obsolescence, or breakage. The second is misplacement, which is temporary shrinkage in the physical stock that can be replaced after every counting or after every period. The others are the randomness of the supplier yield and the transaction type. The random yield of the supplier is a permanent loss or surplus in the physical inventory due to supplier errors, and transaction type errors affect the information system differently than the first three errors, which modify the physical inventory.

Most studies in this area have used the simulation method to measure the effects of inventory inaccuracy on supply chain performance. Kang and Gerschwin (2005) used simulations to emphasize the problem of shrinkage in physical inventory that may increase lost sales because of items being unexpectedly out of stock. They found that with an error rate of theft as small as 1% of the average demand, the disturbance led to 17% of demand lost. Fleisch and Tellkamp (2005) examined the relationship between inventory inaccuracy and performance in a retail supply chain, considering more error types than the previous study. They simulated a three echelon supply chain with one product in which end-customer demand is exchanged between the echelons, and studied how incorrect deliveries, misplacement, theft, and unsaleable goods affect inventory inaccuracy, the out-of-stock level, and the costs related to inventory inaccuracy. The results of the study showed that inaccuracies caused by theft appear to have the biggest impact on supply chain performance compared to inaccuracies caused by unsaleable goods or low process quality. Lee et al. (2004) used simulations to study the effects of inventory accuracy on inventory reduction and level improvement in a three echelon supply chain considering the (s,S) policy decisions, unlike other studies. They found that using automatic identification technology, average inventory held decreased by 16%, and total back orders decreased by 22% when the (s,S) policy decisions are made with accurate inventory information. Rekik et al. (2008) optimized an inventory management model by considering a single period Newsvendor problem with inaccuracies in the inventory. They compared three approaches. In the first approach, the retailer is unaware of errors in the store. In the second approach, the retailer is aware of the errors and optimizes its operations by taking this issue into account. The third approach deals with the case where the retailer deploys an advanced automatic identification technology to eliminate errors. They concluded that getting information on misplacement errors and taking them into account when optimizing the ordering decision can lead to important savings and does not necessitate the deployment of a particular system, the retailer can benefit from this improvement by adjusting his ordering quantity

There are many papers addressing the perishable inventory systems. To the best of our knowledge, there exists no paper studying the impacts of data inaccuracy on perishable inventory of which product lifetime is finite. In this paper, we will investigate the impacts of data inaccuracy on retailer's perishable inventory for different levels of product lifetime, demand and lead time uncertainty to fill this gap in the literature. Using a simulation model, the lost sales, product spoilage, average inventory and order quantities are calculated to investigate the retailer's performance.

3. SIMULATION MODEL

In our simulation model, we worked on a two-echelon supply chain which is composed of a retailer and manufacturer. Depending on customer demand, the retailer places orders with the manufacturer. The manufacturer delivers the product with fixed product lifetime (t) as soon as possible and doesn't hold any inventory. The Economic Order Quantity (EOQ) method is used as the inventory model at the retailer (Eq 1). The inventory replenishment point (s) is determined depending on the average lead time (L') and average demand (D') (Eq 2). Products at the retailer are placed on the shelves based on FIFO principle.

$$EOQ = \sqrt{\left(2 * D' * c_{order}\right) / c_{inventory}} \quad (1)$$

$$s = L' * D' \quad (2)$$

In our simulation model, the retailer fulfills the end customer demand daily basis and counts the inventory for different periods (p). It is expected that a gap will occur between physical and system inventory since the retailer is unaware of the outdated products (Y) until next counting date.

Daily closing system inventory (I) is calculated by adding the difference between the daily opening system inventory and customer demand (D) to daily incoming items (Q) from the manufacturer (Eq. 3). Physical inventory is calculated in the same way, considering the quantity of outdated products (Eq. 4). As orders are placed depending on the system inventory level, lost sales occur depending on the physical inventory level. At the end of a period (p), inventory is counted and the data are corrected; thus, the system and physical inventories become equivalent (Fleisch and Tellkamp, 2005):

$$I_i^{system} = I_{i-1} - D_i + Q_i \quad (3)$$

$$I_i^{physical} = I_{i-1} - D_i + Q_i - Y_i \quad (4)$$

The model calculates daily lost sales (LS), outdated products (PS) and inventory level (I) for different values of the input variables which are inventory counting period (p), product lifetime (t), standard deviation of lead time (sl) and demand (sd). At the end of the each 365 days (a year), total lost sales (TLS) as a percentage of total customer demand, total quantity of outdated products (TPS), yearly average inventory (AI) and total order quantity (NQ) are reported annually. The process flow of the simulation model is illustrated in Fig. 1.

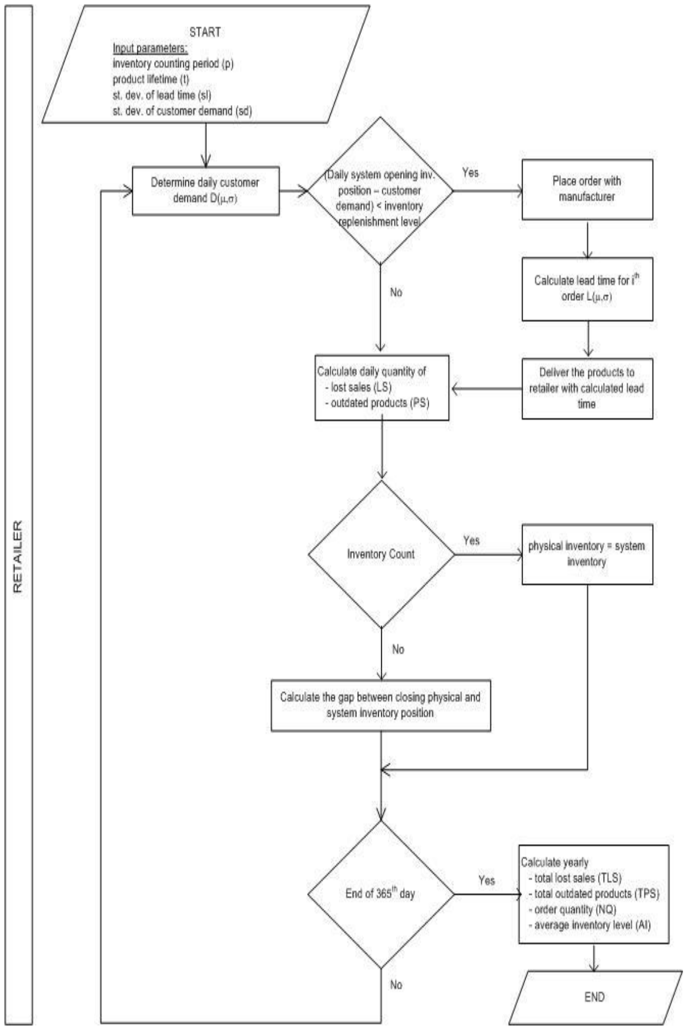

Figure 1. Simulation model process flow

4. EXPERIMENTAL DESIGN

In this study, the experiments are conducted for the products having very short shelf lives. And in order to investigate different levels of inventory inaccuracy, the simulation is run for the cases of that the inventory is counted each day, once a week and once every two weeks (p). The longer the period of inventory counting, the higher the data inaccuracy occurs in system inventory. The demand and lead time uncertainty (sd,sl) are determined as 25%, 50% and 75%. The aim of this study is to show how different levels of data inaccuracy affect the inventory performance of the retailer under uncertainty of the demand and lead time. Additionally, it is also investigated how data inaccuracy affect the inventory performance when the products have different levels of lifetime. In this model, end-customer demand is independently and identically normally distributed, with a daily average (D') of 500 items. The average lead time of the orders (L'), order cost (c_{order}) and inventory holding cost ($c_{inventory}$) are chosen to be 2 days, \$20 and \$0.0014 respectively. Using the simulation model, the lost sales, outdated products, average inventory and order quantities are calculated on yearly basis to investigate the retailer's performance. Different levels of the independent variables of inventory counting period (p), product lifetime (t), standard deviation of lead time (sl) and demand (sd) are given in Table 1.

Table 1. Levels of independent variables

Independent variables	Levels
Inventory counting period (days)	1 -7-14
Product lifetime (days)	8-9-10
Demand uncertainty (st, %)	25-50-75
Lead time uncertainty (sl, %)	25-50-75

5. EVALUATION OF THE SIMULATION RESULTS

The simulations to examine the impacts of data inaccuracy on retailer's perishable inventory are carried out using the commercial software Crystal Ball Version 7.2.1. The independent factors of inventory counting period, product lifetime, standard deviation of lead time and demand were used in 81 (3x3x3x3) combinations. Additionally, the simulations are run 100 times for each combination to minimize the possible errors arising from the random variables. In the simulation model, the lost sales, product spoilage, average inventory and order quantities are calculated to investigate the retailer's performance over a 365 day period. ANOVA analysis is performed to examine the results of the simulation model using SPSS.

The rising level of inventory counting period increases the data inaccuracy (Fleisch and Tellkamp, 2005). According to the results of a Tukey test of ANOVA post-hoc analysis shown in Table 2, the rising level of data inaccuracy increases the discrepancy between system and physical inventory and thus the lost sales. Since the level of retailer's physical inventory is lower than the level of the system inventory, the retailer fulfills the customer demand at a lower rate. Additionally the rising data inaccuracy decreases the yearly number of orders placed by the retailer and average inventory level. And the decreasing level of average inventory decreases the yearly quantity of product spoilage.

Table 2. ANOVA Tukey Test for inventory counting period for the retailer

Dependent Variable	(I) Inventory Counting Period	(J) Inventory Counting Period	Mean Difference (I-J)	Std. Error	Sig.
Lost Sales	1	7	-1,9%	0,1%	5,1E-09
		14	-5,4%	0,1%	5,1E-09
	7	1	1,9%	0,1%	5,1E-09
		14	-3,5%	0,1%	5,1E-09
	14	1	5,4%	0,1%	5,1E-09
		7	3,5%	0,1%	5,1E-09
Product Spoilage	1	7	6683	300	5,1E-09
		14	9839	300	5,1E-09
	7	1	-6683	300	5,1E-09
		14	3157	300	5,1E-09
	14	1	-9839	300	5,1E-09
		7	-3157	300	5,1E-09
Average Inventory	1	7	107	5	5,1E-09
		14	200	5	5,1E-09
	7	1	-107	5	5,1E-09
		14	93	5	5,1E-09
	14	1	-200	5	5,1E-09
		7	-93	5	5,1E-09
Number of Orders	1	7	3	0	5,1E-09
		14	5	0	5,1E-09
	7	1	-3	0	5,1E-09
		14	2	0	5,1E-09
	14	1	-5	0	5,1E-09
		7	-2	0	5,1E-09

When we investigate the impact of data inaccuracy for different levels of product lifetime, we notice that the rising level of data inaccuracy increases the lost sales. And the increase rate in lost sales becomes higher for perishables with lower product lifetime, as the trend lines show (Fig 2). However, the rising value of data inaccuracy decreases the number of orders and consequently the yearly average inventory so decreases. And the decreasing yearly average inventory reduces the quantity of product spoilage. Figure 2 also indicates that the perishables with higher product lifetime have higher inventory level and consequently less lost sales and product spoilage.

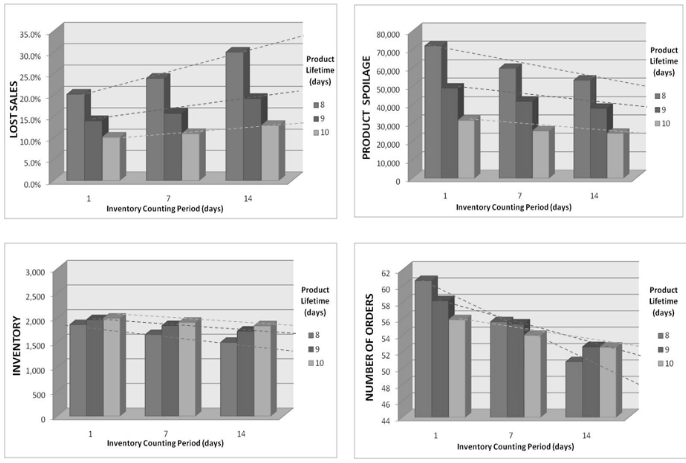

Figure 2. The impact of data inaccuracy for different values of product lifetime

As seen in Figure 3, high level of demand uncertainty increases the number of orders and thus the level of inventory. Therefore high level of demand uncertainty decreases the lost sales but increases the quantity of product spoilage due to higher inventory levels. In our model, when the demand uncertainty exceeds the level of 50%, the number of orders and the average inventory level become much more higher, and therefore the product spoilage increases to higher value. As shown in Figure 3, the rising level of data inaccuracy increases the lost sales and decreases the level of product spoilage. Additionally, with increasing data inaccuracy, the increase rate in lost sales and decrease rate in product spoilage become greater with higher demand uncertainty, as the trend lines show.

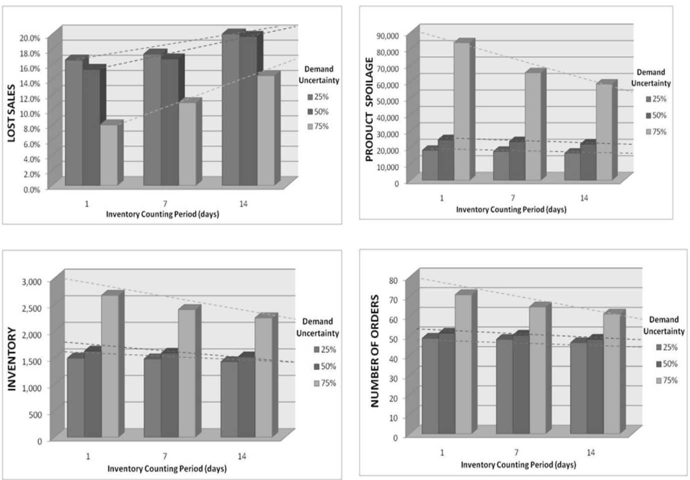

Figure 3.The impact of data inaccuracy for different values of demand uncertainty

As seen in Figure 4, high level of lead time uncertainty increases the quantity of product spoilage. However it decreases the number of orders and thus the level of inventory. Therefore the lost sales are greater in higher level of lead time uncertainty. As shown in Figure 4, the rising level of data inaccuracy increases the lost sales and decreases the level of product spoilage. And Figure 4 also indicates that the increase rates in lost sales become slightly greater with increasing lead time uncertainty, as the trend lines show.

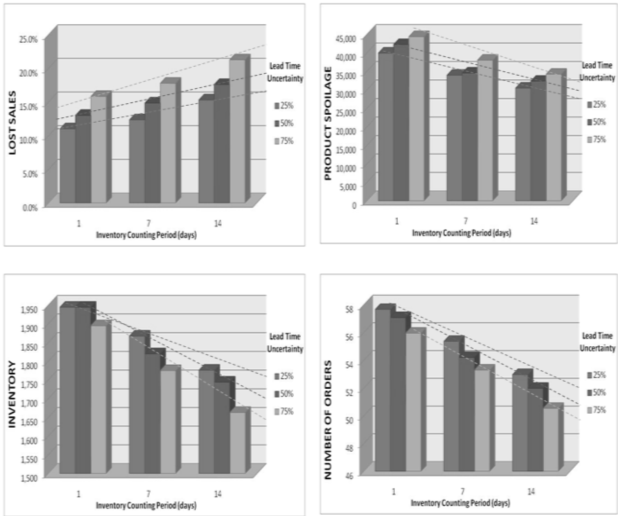

Figure 4. The impact of data inaccuracy for different values of lead time uncertainty

In summary, the results of the simulation study show that the inventory inaccuracy is much more critical for perishables with lower product lifetime under higher demand and lead time uncertainty. Selling perishables with lower product lifetime, the retailer has higher lost sales and product spoilage. The lower the product lifetime, the greater the impact of data inaccuracy is on retailer’s inventory performance. Under higher demand uncertainty, the lost sales become lower but the product spoilage higher. And the data inaccuracy affects the retailer’s inventory performance much more with increasing demand uncertainty. Under higher lead time uncertainty, the retailer becomes higher lost sales and product spoilage. And the increasing data inaccuracy affects the inventory performance much more with increasing lead time uncertainty.

6. CONCLUSION

Perish ability of either raw materials or finished products is a major problem for companies. Due to the limited product lifetime, an ineffective inventory management at each stage in the supply chain from production to consumers can lead to high system costs including ordering costs, shortage costs, inventory handling costs, and outdating costs. Without alignment of physical inventory and information system inventory, inventory information becomes inaccurate due to product spoilage and the supply chain performance decreases. However, the power of information technology can be harnessed to help supply chain members increase their operation performance (Yu et al., 2001). Advanced Auto-ID technologies can be used to decrease the data inaccuracy across the supply chain.

The purpose of this research is to contribute to the literature on perishable inventory systems by investigating how the data inaccuracy affects the retailer's inventory performance for different levels of product lifetime, demand and lead time uncertainty.

Using a simulation model, the lost sales, product spoilage, average inventory and order quantities are calculated to investigate the retailer's performance. It is shown here that the impact of data inaccuracy on retailer's inventory performance becomes greater with lower product lifetime. And the data inaccuracy affects the retailer's inventory performance much higher with increasing demand and lead time uncertainty.

In conclusion, the results show that decreasing data inaccuracy is much more important for perishables with lower product lifetime under higher demand and lead time uncertainty to increase the inventory performance. In a future study, the impact of data inaccuracy on perishable inventory systems will be investigated on a three echelon supply chain.

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