Quantifying the Costs of Cycle Counting in a Two-Echelon Supply Chain with Multiple Items

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ABSTRACT

Inventory record errors within a supply chain can lead to problems that cause low customer satisfaction and high operational costs. In this paper, we present a simulation model of a two-echelon inventory system consisting of a retailer, a distribution center, and a supplier that includes multiple item types and the use of cycle counting as the corrective action. An extensive set of cycle counting configurations were examined while observing the trade-off between fill rates, accuracy, and system costs in order to investigate the best possible configuration of cycle counting for two set of experiments that examine high demand-low cost and low demand-high cost items. The results indicate that the correct application of cycle counting will increase record accuracy and provide significant amount of savings for the entire supply chain.

Keywords: cycle counting, supply chain, simulation, inventory inaccuracy

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1. Introduction

Inventory accuracy is one of the key performance measures for retail stores that monitor inventory transactions on a continuous basis; however, most retail stores have major inventory accuracy problems (DeHoratius and Raman, 2006). The errors within the inventory records can lead to problems in supply chain management such as, insufficient organizational planning and replenishment decisions, causing low customer satisfaction and high operational costs. Inventory record inaccuracy is caused by the difference between the actual and the recorded inventory. If an individual inventory record does not match with actual inventory, this reveals the discrepancy which is the difference between recorded and the actual inventory in units. Since a record can be either accurate or not, the inventory record accuracy can be calculated as (Brook and Wilson, 1995).

$$Overall\ SKU\ Accuracy = \frac{Total\ Number\ of\ Accurate\ Records}{Number\ of\ Records\ Checked} \times 100\%$$

The most systematic method of solving inventory accuracy problems, cycle counting, is a well-known approach used to manage inventory inaccuracy (Young and Nie, 1992). It is simply the planned continuous counting of a small set of items during a period. The objective of cycle counting is to determine errors in the process, as well as identify causes for inventory inaccuracy and provide improvement in customer service levels by making the in-store operations more effective (Piasecki, 2003). Muller (2003) emphasized another objective of cycle counting as to provide at least 95% accuracy on all items. The overall goal of cycle counting is defined as improving inventory accuracy (Piasecki, 2003).

Most companies utilize this technique to achieve better inventory control in their business. Although applying cycle counting decreases or removes a considerable amount of inaccurate inventory costs; it is also an additional cost. Civerolo (1996) emphasized the importance of implementing cycle counting in a correct way. Applying cycle counting in a correct way ensures remarkable improvement in the accuracy, whereas incorrect implementation may lead to critical problems due to added variation in the process. Therefore, it is necessary to use this approach as effectively as possible; otherwise, the cost of applying cycle counting can be higher than the benefits to be gained.

One of the main contributions of this research is taking into account the cost while varying the frequency of the process. We study the best configurations of cycle counting with respect to its cost and benefits to a retail supply chain. This is important because accurate inventory records leads to better customer satisfaction via higher product availability, a more effective replenishment process, and an improvement in the overall supply chain performance. This research models the retail supply chain with a simulation model of two echelon inventory system consisting of a supplier, a distribution center (DC), and a retailer with a set of SKUs to cycle count at the retailer. Figure 1 illustrates a simple multi-echelon inventory system.

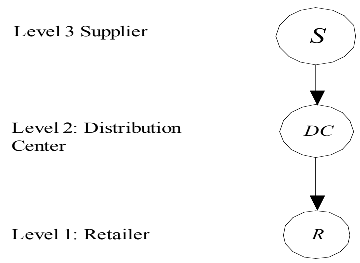

Figure 1 A Simple Multi-echelon Inventory System

We extended the model in Rossetti et al. (2007) by considering a set of items with transportation between inventory holding points (IHP) instead of a single item with no transportation cost. This enables an assessment of the total cost for all the items to be cycle counted. In addition, different configurations of cycle counting are taken into account. As a result, this research illustrates the positive effect of cycle counting in a supply chain by utilizing the system's performance and cost measures.

The remainder of this paper is organized as follows. Section 2 presents the relevant literature on inventory inaccuracy and cycle counting. Section 3 contains the details of the simulation model. Section 4 describes the experimental design and presents the results of simulation experiments in order to examine the benefits of cycle counting under different scenarios. Finally, Section 5 concludes the paper with a summary and directions for future work.

2. Literature Review

Previous studies on inventory accuracy commonly suggest that inventory inaccuracy should be minimized. However, most of the early work utilized analytical classic inventory models of single echelon inventory models to demonstrate the system. Iglehart and Morey (1971) formulated a cost function in a periodic review inventory system which calculates the frequency of counts in order to minimize the total cost and ensure a sufficient buffer stock. Similarly Morey (1986) developed a cost function that can be easily implemented in a spreadsheet. The objective of the study was to minimize the total cost and reach the acceptable stock out level during the cycle count interval. Kumar and Arora (1991) also developed a model that determines the optimal values for cycle counting frequencies. In the single echelon inventory system with an (r, Q) inventory policy, they suggest that inventory miscounts should be minimized to increase customer satisfaction. Kumar and Arora (1992) extend their previous research by considering lead time variability. The relationship between the level of miscounts and the lead-time variability was studied to calculate reorder points. They suggest systematic audit activities to be applied along with taking into account lead time variability.

Alternatively, simulation studies have been widely performed in the previous studies. Young and Nie (1992) proposed a single echelon inventory model that checks the costs of two different inventory policies, ABC and Economic Order Quantity (EOQ), under the effect of cycle counting. They examined the trade-off between cycle counting and non-counting based on the anticipated cost of various scenarios within the hospital industry. While cycle counting has significant labor cost, poor inventory accuracy results in stock-outs, which leads to excessive shipping and extra labor cost. They concluded that while making policy decisions, these costs should be taken under consideration in order to choose the optimum cycle counting frequency.

DeHoratius (2006) examines a periodic review inventory process with unobserved lost sales caused by unrecorded demand, which is called, “Invisible demand”. A single SKU, at a single echelon was simulated to see the effects of discrepancy under three different replenishment policies: “Full” a newsvendor policy assuming retailer knows the actual inventory, “Bayes” in which demand and the probabilistic inventory record are uncertain and updated with a Bayesian procedure and a “Naive” policy which assumes recorded inventory reflects the actual inventory. It was demonstrated that in order to get high service levels, the last two policies require higher inventory levels as compared to the “Full” policy.

Inventory accuracy problems can occur in every echelon of a multi-echelon inventory system instead of at a single echelon only. Therefore, considering the total supply chain may give better insights concerning the system. Multi-echelon inventory systems have been broadly studied in the last decade (Fleisch and Tellkamp, 2005, Kang and Gershwin, 2005, Rossetti et al., 2007). Fleisch and Telkamp (2005) presented a simulation model for a three echelon inventory system with one product. Various factors causing inventory inaccuracy were examined where theft is shown as the factor having the most negative impact on the performance measures. They studied several values of these factors and identified the different impacts on supply chain monetary and non-monetary performance measures for two cycle counting policies. In the first base case, inventory inaccuracy was not corrected at any time. In the second case, at the end of each period they eliminate the inventory inaccuracy and investigate the effect on the same performance measures. In contrast to the periodic review policies used in their research, we model a two-echelon supply chain that uses continuous (r, Q) inventory policies.

Similar to our study, Kang and Gershwin (2005) utilized (r, Q) inventory policies with two specific inventory systems as stochastic and deterministic. Stock loss, transaction error, inaccessible inventory, and incorrect product identification are identified to be the main causes of discrepancies. Both stochastic and deterministic simulation models were developed that emphasized the examination of system behaviors under corrective actions and stock-loss error. Moreover, they represent different compensation methods for controlling the error such as safety stock, manual inventory verification, manual reset of the inventory record, constant decrement of the inventory record, and Auto-ID. The study revealed that if no correction is done, even a small error can cause big impacts on system performance.

Rossetti et al. (2007) constructed a simulation model to illustrate the effect of inventory inaccuracy within a supply chain. Cycle counting was used as the corrective action of the incorrect replenishment decisions made on incorrect inventory records. Two cases were modeled with the simulation. In the first case, learning effects were modeled which demonstrates the impact of learning from cycle counting and having less inventory record errors. In the second case, non-compliance was studied. In this situation, one of the IHPs does not follow the cycle counting policy. The results indicate that average system fill rate decreases when error exists. When learning effect is introduced to the system, fill rate increases in both cases and when IHPs do not follow cycle counting average system fill rate decreases. As a result, it is shown that cycle counting is not just increasing inventory record accuracy, but also provides benefits for the supply chain network.

The literature commonly indicates that inventory record inaccuracy should be minimized to improve customer satisfaction and to decrease total supply chain costs. A general approach is to utilize cycle counting. One of the areas explored in our research is the cost of applying cycle counting. Although Fleisch and Tellkamp (2005), and Morey

(1985) discuss the costs of cycle counting, they considered only one item in their models. In addition, they did not consider the transportation between IHPs and did not tabulate the accuracy. This research extends the model developed in Rossetti et al. (2007) in various ways. The most important extension is the examination of multiple item types in the system as well as a more general amount demanded process. In addition, transportation activity between the retailer and the DC is modeled in a detailed way rather than considering transportation just as a deterministic delay. Because, we have multiple item types, the model is able to provide the accuracy and discrepancy measures for the retailers across the item types. We know of no other models in the literature that allow this calculation. Moreover, the total supply chain costs are included in the model in addition to supply chain performances (e.g. system fill rates). The model is able to examine different cycle counting configurations while taking into account the trade-off between fill rates and system costs. Thus, the potential exists to use this model to determine the best possible configuration of cycle counting given a set of SKUs to cycle count.

With this motivation, this research illustrates the positive effect of cycle counting in a supply chain by utilizing the system's performance and cost measures. We develop a multi echelon inventory system given a set of SKUs to cycle count for a store to examine the various configuration of cycle counting while considering the trade-off between fill rates, accuracy, and system costs. In the next section, the research methodology for building the model is presented.

3. Simulation Modeling

The system under study covers the supply chain starting from the retailer level through to the supplier. Under an (r, Q) policy the basic model consists of a supplier, DC, and a retailer. Each inventory holding point follows the same type of inventory policy. Each demand at the retailer consists of a random amount of request for a given type of item.

Once a demand occurs at the retailer, the model first checks the actual-on-hand inventory assuming that the customer can see the shelves in the store. If actual on-hand inventory is enough to satisfy the demand, the customer demand is filled and the recorded on-hand is updated. This occurs when the customer arrives at the counter to checkout. Every time a customer demand occurs, the system updates the inventory position (inventory on-hand + on-order) and when the inventory position (IP) falls under the reorder point a replenishment order is sent to the DC. At that time, two scenarios can occur: In the first, the recorded on-hand is not enough to satisfy the demand indicating a discrepancy. This indicates to the system that there is an opportunity to correct the records (opportunity count). If the IP is less than or equal to the reorder point, the system does not wait to complete the opportunity count to send an order. In the second scenario the recorded inventory is also enough to satisfy the demand. This time the system checks the IP directly without an opportunity count. Similarly, a replenishment order is placed if the IP falls under the reorder point. Moreover in the situation of lost sales, where actual on-hand inventory is not enough to satisfy the demand, the amount that is not filled is considered as lost sales at the retailer (partial fulfillment). The system then checks the recorded inventory and the steps mentioned above are followed similarly for both discrepancy scenarios. (Figure 2)

The orders at the retailer are sent directly to the DC. The DC is assumed to have neither error nor cycle counting in this study. Thus, the DC checks only the recorded on hand inventory. If the recorded on hand inventory is not enough to satisfy the demand, the entire order is backordered, and the retailer waits for the replenishment from the supplier. Otherwise, the order is filled and the system updates the IP to decide whether to send an order to the supplier or not. Trucks perform scheduled deliveries from the DC to retailer. Finally, customer demands are filled from the retailer.

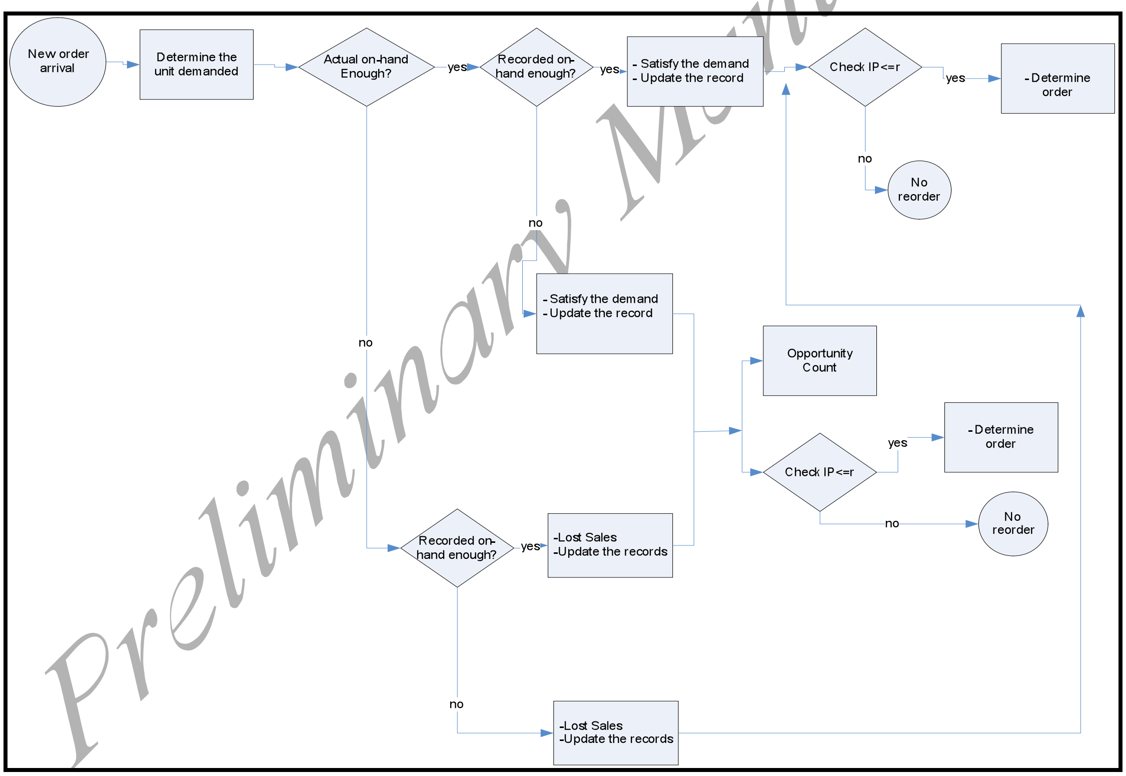

Figure 2 Retailer System.

3.1 Error Modeling

Two main errors can occur in this system: Stock loss error and transaction error at the retailer level. Although both error types can occur at any level, we consider the DC as essentially being accurate. The reason for this assumption is that the best practice for DC operations requires cycle counting and often results in accuracies over 99%. Stock loss error, described as the unrecorded loss of inventory because of shrinkage, destruction, theft, etc tends to occur more often at the retailer level due to theft and other causes (Kang and Gershwin, 2005). Transaction errors are the errors that occur when the retailer receives any shipment from the DC (suppliers) that may have discrepancies. These types of errors are typical mistakes (typos, misprints, miscounts…etc.) associated with the transactions (Kang and Gershwin, 2005).

The probability of stockloss error for each item type has the same distribution with the probability of demand for the corresponding item type. The underlying assumption is; the more the demand for an item, the higher the probability of having stockloss error due to theft. The amount of the loss is a Poisson distribution with a mean proportional to the demand rate. Mean stockloss quantity is determined as a percentage of the mean total demand that should occur until the stockloss event. Let i be the item type. Then stockloss amount is calculated as: *Poisson ((Mean Total Demanded (i) * Stockloss Percentage).* Since it is not possible to lose more than actual on-hand inventory, the amount of stock-loss is set to the actual on-hand inventory, when the stock-loss error quantity is greater than the on-hand inventory.

Transaction error is modeled as series of probabilistic processes. The probability of transaction error occurrence does not depend on the item type. But transaction error amount depends on the level and the item type; different order quantities in each level cause different transaction errors. Transaction error occurs when the retailer is replenished by the DC. The probability of transaction error occurrence is modeled via discrete distribution with a percentage assumed in order to get common industry accuracy levels. The amount of transaction error is calculated via a Poisson distribution with mean equal to a certain percentage of the order quantity. Since every item type has different order quantities, transaction error amount is dependent on item type.

Poisson (Retailer Reorder Quantity (i) Retailer Receipt Error Percentage))*

We have assumed the chance of occurrence of an unintentional gain or loss as 50% (Rossetti et al., 2007).

3.2 Cycle Counting Modeling

We consider two types of counting in our system: One is scheduled cycle counting, while the other is “opportunity counts” that occur when there exists an obvious opportunity to correct the records. The operation of the system can lead to two types of opportunity counts. The first case happens when demand occurs while there is actual inventory on the shelf but the recorded inventory is not enough to fulfil the demand (positive discrepancy). In a physical retail environment, this situation presents an opportunity to correct the record, because the customer can actually see the items on the shelf. The customer demand is satisfied although the record would have indicated a lost sale; this presents an opportunity to correct the record. The second case involves the situation in which a demand arrives and there is not enough actual inventory on the shelf to satisfy the demand but the recorded inventory record is showing a positive balance (negative discrepancy). In this case, it is impossible to fill the customer demand fully because there is not enough stock available. This situation leads to lost sales although records would have shown the opposite. In our system, these opportunities for counting are noted until enough item types indicate that opportunity counts are available. This method allows us to take advantage of economies of scale when counting more than one item type. For scheduled cycle counting, the correction of inventory records occurs only when a cycle count is performed regardless of opportunity counts.

Both counting types utilize a learning curve to model the reduction in the errors via cycle counting. Mathematical equations with a logarithmic approach were developed to model this learning effect as a reduction in the annual rate of stock loss error arrival. The learning curve formula is modified as:

$$R_N = R_1(\#\_CC^b)$$

Where R_N = Annual arrival rate of the errors

R_1 = Annual arrival rate at the beginning of the simulation

b = (Log of the learning rate)/ (Log2) = slope of the learning curve

Assuming a learning rate of 85%, $b = -0.322$

Thus; as the number of cycle counts increase the annual rate of arrival of the errors decreases. This rate is then converted to the time between arrivals by using the formula

$$Time\ Between\ Arrival\ of\ Errors = \frac{366}{R_N}$$

3.3 Demand Generation

The time between arrival of demand is assumed to follow an exponential distribution; hence the demand process is a Poisson distribution for the retailers. In the model, we have 12 different item types having different demand rates. A discrete distribution with different probabilities for each item type was utilized to select the item type for the corresponding demand. After the customer arrival and item type selection, the amount of each demand is required to be identified. A lognormal distribution was selected as the amount of demand. The demand rate also drives the unit cost of the specific item type. In general, inventory systems of consumable items include high demanded and low unit cost items. We assume that the higher the demand, the lower the cost and vice versa. Therefore, demand rate and unit cost are inversely proportional.

Since each item type has different demand characteristics, we needed to calculate the policy parameters for each item type. If the parameters are not set to optimal values, then it will be difficult to interpret the effect of other factors within the model. For example, the system which is set to carry more inventory than it is supposed to will hide the effects of errors. Arena's OptQuest was utilized to find policy parameters for the item types. The optimization model for OptQuest was setup to determine the policy parameter values that minimize the ordering, holding, asset, and transportation cost subject to providing 90% fill rate at the retailer and at the DC. OptQuest for Arena is an application that changes model inputs and then runs a sequence of simulations to find a combination of these inputs that appears to be optimal based on output performance. OptQuest utilizes Tabu Search as its basic meta-heuristic approach. For more details about demand modeling, setting policy parameters, and optimization model we refer the reader to Gumrukcu (2007).

Two steps are followed for validation. The model was first validated for a single echelon with the model developed in (Tee and Rossetti, 2002). The next validation was performed with the model built in Rossetti et al. (2007). As stated earlier the model under study is built upon the model built in that study. Step by step validation of performance measures was performed while building the new model.

3.4 Performance Measures from the Simulation Model

One of the goals for this research is to examine various configurations of cycle counting while considering the trade-offs between fill rates, accuracy and system costs. Therefore, the system performance measures can be grouped in three categories.

1) Performance
   a) Accuracy
   b) Discrepancy (negative, positive, absolute)
2) System
   a) Fill Rate (Retailer, DC, and System): Percentages of demand filled immediately.
   b) Probability
      i) Lost Sales: Probability of demand not satisfied at the retailer
      ii) Backorders: Probability of demand not satisfied immediately at DC.
      iii) Lost Sales due to Errors: Probability of demand not satisfied caused by errors.
   c) Inventory (Average on-hand, number of lost sales, number of back orders)
3) Cost (annual average)
   a) Holding: Cost of carrying inventory (On hand Inventory * unit cost * holding charge)
   b) Asset: Cost of the actual worth of the item (On hand Inventory * unit cost)
   c) Lost Sales : Cost of unsatisfied demand (Amount of Lost Sales * unit cost)
   d) Transportation: Cost of transportation (Amount shipped * handling unit cost)
   e) Cycle Counting: Fixed cost of counting + Number of units counted * cost of counting per unit

f) Total Cost: Holding Cost + Asset Cost + Lost Sales Cost + Transportation Cost + Cycle Counting Cost

These performance measures are used to assess the system under the effect of various scenarios.

4. Experimental design

The simulation experimentation was performed in two primary phases. In phase 1, factorial experiments were designed to evaluate the effect of each factor individually, and possible interactions between factors. In phase 2, three special scenarios were introduced and their effect on system performance explored. The following are the basic modeling assumptions used in model building.

- All IHPs follow (r, Q) continuous review policy for inventory replenishments.
- The demand process follows a Poisson process.
- All unsatisfied demands at the DC are backordered, conversely any demand that can not be satisfied is considered as lost sales at the retailer. While no partial fulfillment of orders are allowed at the DC, the retailer accepts partial fulfillments.
- The DC is modeled neither with error nor with cycle counting.
- The replenishment delay from the supplier to DC and from DC to retailer is assumed to be constant. In addition, the supplier is assumed as an unlimited source.
- Truck capacities and the fixed cost of transportation are neglected.
- The time for cycle counting is neglected. On the other hand, the cost of counting is considered.

One important issue to understand about the model is that it is non-stationary due to the introduction of record errors in the system. Remember that, the inventory orders are determined based on the recorded inventories, which are not reflecting the actual on-hand inventory when the system has errors. The accumulation of errors causes this non-stationary behavior. In a real system, this non-stationary behavior will not occur because of interventions by those people running the system. Within the simulation model, we must deal with this behavior by confining our analysis to yearly performance. Thus, the simulation model is not a steady-state model; however, it still must be initialized. We run the simulation model for 720 days with a warm-up period of 360 days. This enables us to "reset" the system's performance measures at the end of the first year and confine any non-stationary (out of control) behavior to a yearly interval. In our simulations, we do not turn on the error generation processes during the warm up period. The warm up period of 360 days is appropriate since in most cases a financial audit of a retail environment must occur on a yearly basis due to tax and accounting reasons. After the simulation has been warmed up, the model is run for additional 360 days in order to collect performance on a yearly basis. During the experiments, each case is then replicated 30 times.

4.1 Factorial Experiments

The performance of the multi-echelon inventory system with multiple item types having different characteristics maintained by different factors is discussed in this section. The factors to be examined were selected based on the item type. From the large amount of inputs we have selected demand as the most essential input, which drives almost all of the system behavior. Another factor is the time between scheduled counts. It is obvious that, the more often the counting, the better the system fill rate but also the higher the cost. The last factor is the number of accumulated opportunity counts across items types in order to trigger an opportunity count for the set of items. The lower the trigger number, the higher the frequency of overall counting. The experimental design with factors, their levels, and descriptions are given in Table 1.

Table 1 Experimental Design

Factor	Level	Level Description
Item Type Demand	2	All low, All high
TBA Scheduled Counts (days)	4	45, 90, 180, none
Number of items trigger Opportunity Count	4	1,6,12, none

All these experiments compare the different configurations of cycle counting. Most retailers prefer carrying more inventory rather than implementing cycle counting. For that reason, we include the cases where policy parameters are adjusted in order to get the desired fill rate for each demand type. Thus, in addition to the 32 (2 x 4 x 4) cases implied by Table 1, the experimental design consists of one more experiment for each demand type, resulting in 34 experiments. In the rest of the document, "Re-optimized case" is what we call these two experiments. In order to interpret the effect of these factors some inputs are kept unchanged during the experiments. These system baseline parameters are given in Table 2.

Table 2 System Baseline Parameters

System Baseline Parameters		
Number of Item Types	12	
Mean Demand Amount	3	unit
Std Dev. Demand Amount	1	unit
Retailer Lead Time	3	days
DC Lead Time	7	days
Probability of Transaction Error	10%	
Receipt Error Percent	5%	
Stockloss Error Amount Percent	50%	
Holding Charge	0.24	$/$/year
Cycle Count Variable Cost	0.25	$/unit
Cycle Count Fixed Cost	5	$/count
Handling Cost	0.1	$/unit
Accuracy observation TB	30	days

Since this analysis is based on a relative comparison, the specific values assumed are not critical to the overall conclusions. We refer reader to (Gumrukcu, 2007) for more detail on the parameter selections. The average annual demand is assumed to have values in ranges that can be classified as high and low demand. A rule based approach was followed to obtain 12 item types having different demand rates for each case (Gumrukcu, 2007). As each item type has different demand rates, policy parameters should be recomputed for each item type in each case. For the re-optimized cases, the reorder point and reorder quantities were recomputed in order to get the same fill rates when the system is subjected to error conditions whereas the parameters for the other cases are found in the "perfect case".

As all the conditions of low demand high cost items and high demand low cost items are different, the experimental design explained in the previous section was performed in two separate phases: experiments of low demand-high cost items and experiments of high demand-low cost items. The first case is the "perfect case" where the system is not subject to any kind of error. In other words it is the desired system, 100% accurate. Since supply chain systems are subject to both error types in a retail environment, this is not a realistic case. Therefore the retailers carry more inventory in order to provide the same fill rate as the "perfect case". This case is the "re-optimized case" where the policy parameters are adjusted for each item type to achieve the desired fill rate without applying cycle counting. Another case is the "pessimistic case" where the system does not do anything to increase the system fill rate. Because the retailers will never allow such low fill rates, this case is not realistic either. But in order to show the real affect of errors it is included in the cases for comparison purposes. The remaining 15 cases are applying different configurations of cycle counting rather than carrying more inventory to be closer to the "perfect case". These are called "cycle counting cases". Cases differ from each other by the number of items triggering opportunity count and time between cycle counts. In each set of experiments, we first compare the "cycle counting cases" with the re-optimized case. This comparison explains whether cycle counting is worth applying rather than carrying more inventory. If so, the second comparison is performed in order to select the best configuration of cycle counting out of the remaining 15 cases.

1st Set of Experiments

In this section the experimental results for low demand high cost items are presented. Table 3 and Table 4 show the results of all the 18 cases explained above. From the table below, it can be easily seen that, in terms of accuracy and fill rate the perfect case is the best case. The re-optimized case is also providing the same fill rate but with a very low accuracy. In addition, although there is not much lost sales in that case, the majority of the lost sales are derived from the errors in the system. The influence of the errors can also be noticed in the amount of discrepancy, which is very high. But all these effects can be hidden by carrying more inventory, which leads to higher holding costs as illustrated in Table 4.

Table 3 Experimental Results of Low Demanded High Cost Items

	TB	OC	Accuracy	Retailer Fill Rate	DC Fill Rate	System Fill Rate	P(Lost Sales due to Error)	Abs. Disc.
Perfect	none	none	100.0%	90.3%	90.4%	90.3%	0.0%	---
1	none	none	94.4%	84.9%	89.3%	86.4%	11.9%	6.502
2	45	1	92.5%	83.6%	88.8%	85.4%	11.3%	8.667
3	45	6	92.3%	83.3%	87.9%	85.0%	14.8%	8.999
4	45	12	91.7%	81.7%	89.1%	84.4%	17.3%	9.656
5	45	none	91.6%	84.1%	89.2%	85.9%	14.4%	10.13
6	90	1	79.7%	80.1%	88.9%	83.2%	29.1%	25.84
7	90	6	79.6%	79.2%	88.8%	82.5%	25.3%	26.07
8	90	12	77.8%	78.3%	86.8%	81.4%	28.2%	28.74
9	90	none	89.6%	83.1%	87.7%	84.7%	20.6%	12.35
10	180	1	69.8%	73.1%	87.5%	78.1%	39.9%	40.72
11	180	6	62.8%	72.4%	88.4%	77.9%	44.9%	50.78
12	180	12	63.6%	70.4%	88.2%	76.4%	48.2%	53.18
13	180	none	89.9%	81.8%	89.2%	84.4%	19.4%	11.88
14	none	1	73.1%	77.3%	89.2%	81.5%	35.3%	34.76
15	none	6	38.2%	56.4%	88.8%	66.1%	68.1%	95.77
16	none	12	33.2%	55.8%	88.8%	65.5%	70.3%	104.3
RO	none	none	24.0%	91.8%	87.7%	90.9%	80.5%	192.4

*RO: Re-optimized case

Table 4 tabulates the costs associated with each case. Instead of only showing the total cost, the components of total cost are also included to indicate the reasons of cost differences and components that are causing the highest cost.

Table 4 Annual Costs of Low Demanded High Cost Items

	Annual Cost										
	Holding		Asset		Lost		Ordering				
	Ret.	DC	Ret	DC	Sales	Hand.	Ret	DC	SC	OC	Total
Perfect	$722	$1,004	$1,342	$2,708	$1,563	$55	$4,369	$2,680	$0	$0	$14,443
1	$680	$1,001	$1,297	$2,635	$1,606	$55	$4,386	$2,696	$137	$40	$14,532
2	$681	$1,009	$1,296	$2,650	$1,589	$56	$4,370	$2,688	$130	$0	$14,469
3	$673	$1,012	$1,308	$2,664	$1,680	$57	$4,485	$2,753	$134	$0	$14,764
4	$667	$997	$1,301	$2,649	$1,831	$57	$4,491	$2,737	$138	$0	$14,868
5	$684	$992	$1,319	$2,665	$1,669	$56	$4,454	$2,747	$61	$49	$14,697
6	$641	$1,002	$1,296	$2,682	$1,912	$57	$4,533	$2,775	$58	$7	$14,962
7	$652	$1,006	$1,296	$2,739	$1,843	$56	$4,476	$2,774	$57	$0	$14,899
8	$646	$997	$1,269	$2,716	$1,825	$55	$4,427	$2,686	$56	$0	$14,676
9	$667	$1,002	$1,321	$2,700	$1,760	$56	$4,423	$2,723	$23	$72	$14,746
10	$617	$998	$1,203	$2,708	$2,221	$54	$4,357	$2,652	$22	$20	$14,852
11	$602	$997	$1,269	$2,674	$2,365	$55	$4,460	$2,731	$20	$0	$15,174
12	$601	$1,007	$1,204	$2,746	$2,330	$54	$4,328	$2,618	$18	$0	$14,906
13	$668	$1,013	$1,327	$2,685	$1,674	$56	$4,392	$2,705	$0	$75	$14,594
14	$641	$988	$1,254	$2,590	$2,068	$55	$4,349	$2,678	$0	$14	$14,638
15	$503	$1,000	$1,070	$2,931	$3,225	$49	$4,081	$2,474	$0	$4	$15,336
16	$488	$1,003	$1,037	$2,838	$3,206	$50	$4,225	$2,534	$0	$0	$15,380
RO	$1,467	$1,651	$4,674	$4,667	$708	$67	$2,824	$2,377	$0	$0	$18,435

As expected, the re-optimized case is the one with the highest cost. The biggest impact on this high cost comes from retailer holding and asset cost due to carrying more inventory. On the other hand, lost sales and ordering costs decrease since the retailer achieves high fill rates by having less frequent high volume orders. The reduction in these costs cannot offset the increase in the holding and asset costs. Case 1 and Case 2 are found as the best cases for most of the performance measures, revealing that increasing the number of scheduled cycle counts with more opportunity cycle counts provides the best savings opportunities for low demand high cost items.

2^{nd} Set of Experiments

The second set of experiments includes high demand and low cost items. As seen in Table 5, promising performance measure levels can be obtained by cycle counting.

Table 5 Experimental Results of High Demand Low Cost Items

	TB	OC	Accuracy	FR Ret	FR DC	Sys FR	P(LostSales DuetoError)	Abs Disc
Perfect	none	none	100.0%	93.4%	89.8%	93.3%	0.0%	---
1	45	1	93.7%	93.4%	89.4%	93.3%	1.2%	18.35
2	45	6	88.3%	92.8%	89.4%	92.7%	5.7%	26.28
3	45	12	86.9%	92.9%	89.0%	92.8%	8.2%	31.37
4	45	none	85.9%	92.8%	89.9%	92.7%	8.6%	33.11
5	90	1	92.6%	93.3%	90.7%	93.2%	1.4%	20.16
6	90	6	85.4%	93.2%	89.8%	93.0%	7.3%	37.01
7	90	12	71.4%	92.2%	90.3%	92.1%	20.9%	74.23
8	90	none	71.7%	92.3%	89.8%	92.2%	20.5%	71.11
9	180	1	92.9%	93.3%	90.1%	93.2%	1.6%	20.07
10	180	6	82.9%	92.9%	89.6%	92.8%	10.2%	44.29
11	180	12	66.7%	91.5%	89.8%	91.4%	27.9%	86.85
12	180	none	53.8%	89.5%	90.0%	89.5%	46.3%	134.14
13	none	1	91.9%	93.2%	89.0%	93.1%	1.6%	21.59
14	none	6	81.7%	93.0%	89.9%	92.9%	10.1%	43.37
15	none	12	64.9%	90.5%	89.6%	90.5%	31.7%	99.33
16	none	none	22.8%	79.7%	90.0%	80.0%	78.0%	256.49
RO	none	none	13.0%	89.3%	89.5%	89.3%	87.6%	613.52

In addition to high performance levels, high cost increases come from cycle counting which is summarized in Table 6. The resulting dollar savings for high demand low cost items are significantly different than the low demand high cost items. The re-optimized case, which appeared as the worst case for the low demanded items is one of best performing cases for high demand low cost items in terms of total cost. Moreover case 1 which was selected as the best case in the first experimental design is the worst case based on total costs. Therefore, one can conclude that cycle counting leads to additional and unnecessary effort to improve retail system performance in this situation. Case 16 with the lowest fill rate generates the highest lost sales cost. Moreover, the re-optimized case has the retailer carrying more inventory, which causes an increase in holding and asset costs. Since these items are very low cost items, total cost does not significantly vary and does not generate major differences between any cases.

Table 6 Annual Costs of High Demand Low Cost Items

	Holding		Asset		Lost		Order				
	Retailer	DC	Retailer	DC	Sales	Hand.	Retailer	DC	SC	OC	Total
Perfect	$149	$476	$513	$1,464	$1,277	$2,040	$11,132	$5,685	$0	$0	$22,734
1	$148	$476	$511	$1,477	$1,250	$2,046	$11,161	$5,716	$807	$462	$24,053
2	$148	$476	$507	$1,475	$1,285	$2,048	$11,162	$5,702	$770	$120	$23,691
3	$147	$474	$506	$1,475	$1,276	$2,045	$11,160	$5,691	$796	$0	$23,569
4	$147	$474	$506	$1,471	$1,290	$2,047	$11,158	$5,698	$773	$0	$23,565
5	$148	$476	$507	$1,466	$1,268	$2,042	$11,136	$5,690	$358	$594	$23,684
6	$148	$476	$507	$1,464	$1,260	$2,043	$11,152	$5,698	$377	$160	$23,285
7	$146	$475	$503	$1,475	$1,338	$2,040	$11,128	$5,680	$337	$54	$23,175
8	$146	$476	$505	$1,474	$1,280	$2,029	$11,062	$5,652	$353	$0	$22,977
9	$148	$475	$511	$1,470	$1,258	$2,037	$11,112	$5,674	$150	$714	$23,549
10	$148	$475	$507	$1,476	$1,288	$2,039	$11,128	$5,690	$158	$177	$23,087
11	$145	$476	$499	$1,474	$1,349	$2,034	$11,107	$5,684	$158	$98	$23,024
12	$141	$477	$487	$1,488	$1,522	$2,021	$11,053	$5,643	$125	$0	$22,955
13	$149	$476	$511	$1,478	$1,273	$2,040	$11,118	$5,678	$0	$769	$23,491
14	$147	$475	$508	$1,475	$1,271	$2,042	$11,142	$5,692	$0	$198	$22,950
15	$144	$477	$495	$1,466	$1,398	$2,024	$11,098	$5,670	$0	$84	$22,855
16	$124	$485	$426	$1,470	$2,168	$1,909	$10,645	$5,429	$0	$0	$22,655
RO	$161	$447	$563	$1,278	$1,095	$2,081	$11,553	$5,958	$0	$0	$23,136

In all cycle counting configurations wherein any of scheduled and opportunity counting is applied individually or together, opportunity counting is found as a better alternative for these highly consumed fast items

Overall, low demand-high cost items show potential for high performance measure values and dollar savings through cycle counting. Comparing scenarios in the first experimental set indicates that increasing the frequency of both counting types provides the best opportunities for system improvement. Projected savings from the cycle counting analysis range between $3,567 and $3,966, or 19.3% and 21.5% in the scenarios having greater than 80% fill rates. Cycle counting does not offer such promising results for high demand low cost items. The resulting savings from cycle counting range between -$917 and $281, and -3.9% and 1.2% respectively, satisfying desired fill rate values.

4.2 Special Scenarios

In the second phase of the experimental analysis, three special scenarios are examined: (1) *bad item(s),* (2) *opportunity response*, and (3) *more often scheduled counting.* Since it was found that cycle counting is recommended for low demand-high cost items, these special scenarios are all applied to low demand-high cost items to further investigate potential savings from cycle counting.

The bad item(s) scenario examines the effect of one or more potential problematic item types on the rest of the supply chain. This is modeled by not performing any kind of cycle counting for the one or more item types selected. Our interest in the bad item(s) case is to understand what will be the effect if there are some bad actors within the low demand items. In this scenario, 5 unique cases are carried out having respectively none, 3, 6, 9, and all the item types not included in the cycle counting activity. As scheduled counting with 45 days time between and opportunity counting for every opportunity is indicated as the best case for low demanded high cost items, the impact of bad items are investigated with these settings.

Table 7 Performance Measures of Bad Item(s) Scenario

Bad Items	Accuracy	Fill Rate			P(lost sales due to error)	Discrepancy		
		Retailer	DC	System		Abs.	Neg.	Pos.
0	94.4%	84.9%	89.3%	86.4%	11.9%	6.502	6.427	0.075
3	88.7%	84.5%	88.7%	86.0%	18.1%	12.687	11.408	1.279
6	84.6%	83.4%	88.8%	85.3%	24.3%	17.268	14.79	2.478
9	79.6%	81.5%	88.7%	84.0%	29.5%	24.523	20.394	4.129
12	33.2%	55.8%	88.8%	65.5%	70.3%	104.3	94.506	9.794

Accuracy and fill rates decrease as the number of item types not included in the cycle counting activity increases whereas discrepancy and probability of lost sales caused by errors increases.

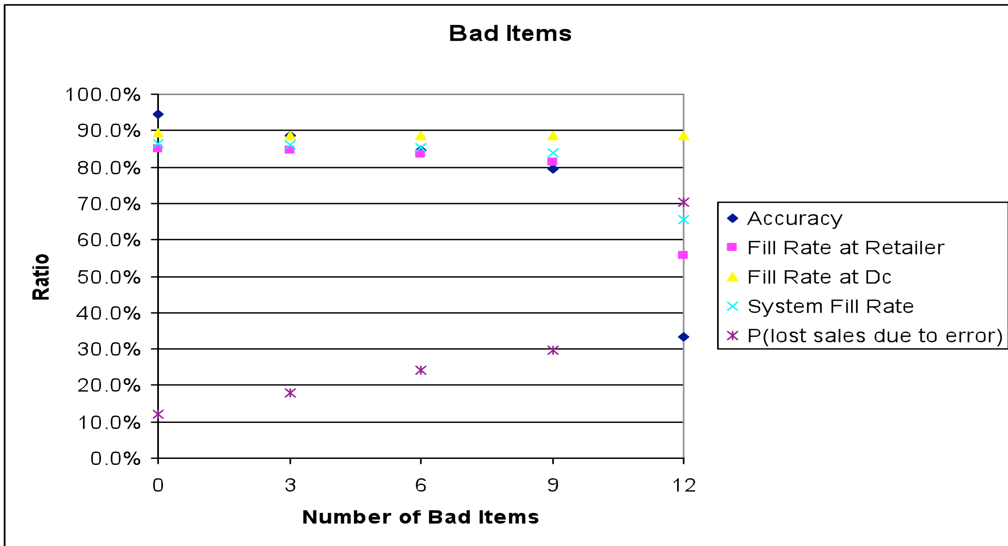

Figure 3 Illustration of Bad Item(s) Scenario Performance Measures

Figure 3 illustrates how the performance measures are affected as the number of bad items increases. Excluding the last scenario, in which none of the item types are counted, the remaining scenarios display a linear decreasing trend in terms of fill rate at the retailer and for the system. As mentioned previously, the fill rate at the DC is not affected by the changes at the retailer. Therefore, the fill rate at the DC represents a steady behavior with a slope close to zero. All performance measures get worse drastically in the last case.

This scenario brings out a kind of Pareto analysis. That is, counting 25% of item types (9 bad item types) are able to generate promising performance measure values. Total cost comparisons of the cases can provide useful insights regarding the analysis of the bad items.

The other special scenario analyzes different responses whenever an opportunity to count a low demand item type exists. Recall that, the model under study captures two types of discrepancy. This scenario examines what-if one of the discrepancy capturing types does not trigger a count. This case is performed to be aware of which of the discrepancy types are more critical. This scenario is modeled by performing cycle counting only whenever an opportunity is captured. In order to interpret the effect of the different opportunity responses on the performance measures, four possible cases were tested as given in Table 8.

Table 8 Opportunity Response

		Fill Rate			P(Lost Sales due to Error)	Discrepancy		
	Accuracy	Ret.	DC	System		Abs.	Pos.	Neg.
No Count	33.2%	55.8%	88.8%	65.5%	70.3%	104.295	96.506	7.954
Counting when actual is enough, recorded is not enough	47.1%	63.5%	90.1%	71.4%	59.4%	79.167	72.981	6.512
Counting when actual is not enough, recorded is enough	89.5%	81.7%	89.2%	84.3%	19.6%	12.31	10.568	1.742
Counting in both cases	89.9%	81.8%	89.2%	84.4%	19.4%	11.884	10.098	1.786

The first case has neither type of opportunity count. It demonstrates the worst performance measures as expected. The next case triggers a count only if customer demand is satisfied, while records indicate stockloss. Counting in this situation does not improve the system performance significantly. The latter case, where a cycle count is triggered when actual on-hand inventory is enough, but the records indicate a loss, provides a considerable improvement in all the performance measures. This scenario reveals two essential results. The first is that the majority of the errors at the retailer are caused by having less actual inventory than recorded, which results in significant lost sales. Typically discrepancy tends to be negative since stockloss always causes negative discrepancy and transaction error is generating both positive and negative discrepancies. The second result is that whenever a negative discrepancy is identified the most impact from cycle counting can be achieved.

The last special scenario extends the experimental design of low demand high cost items. Remember that, in terms of retailer fill rate the best possible case is the re-optimized case having 90% fill rate. The best cycle counting can achieve is 84.9% with the given configurations. In this scenario, we examine other time between scheduled counts in order to get a similar fill rate as the re-optimized case and compare the costs. In Table 9 the performance measures of the 3 additional settings for only scheduled counting are summarized.

Table 9 More Often Scheduled Counting Results

TB	Accuracy	Retailer Fill Rate	P(Lost Sales due to Error)	Abs. Disc.	Total Cost
7	99.6%	88.3%	1.7%	---	$15,331.62
14	98.8%	87.6%	2.8%	1.544	$14,897.60
28	98.7%	85.7%	7.9%	1.744	$14,740.51

When the time between of scheduled counts increases, accuracy decreases and eventually fill rates decrease.

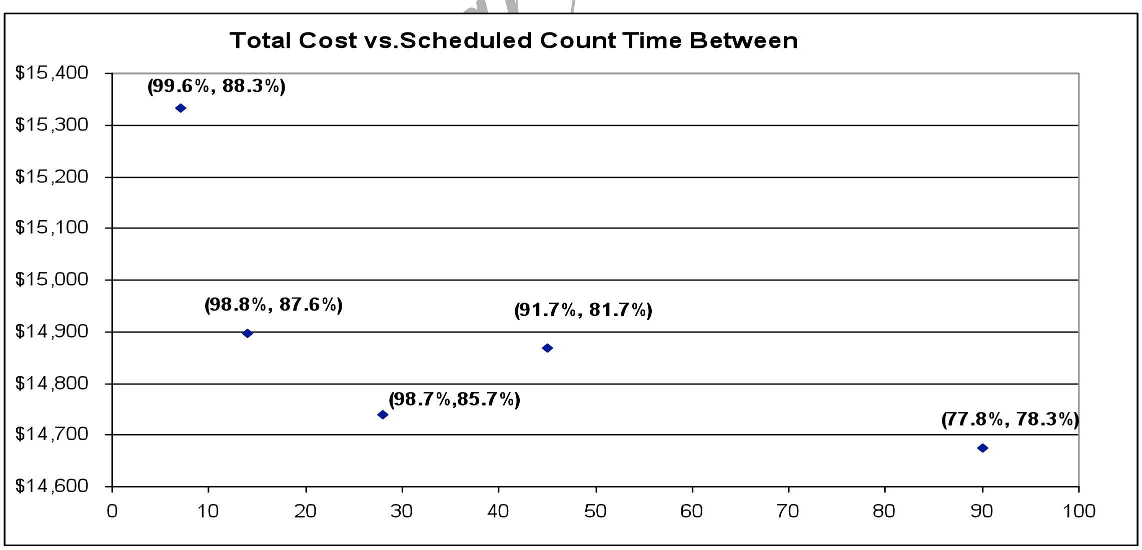

Figure 4 Total Cost vs. Scheduled Count Time Between

Figure 4 summarizes all findings by each scenario examined. The points in the graph indicate the total cost of the supply chain for the corresponding time between cycle counting. In parenthesis, the first number states the accuracy while the next one represents the fill rate at the retailer. Although the lowest cost is achieved for a 90-day cycle counting interval, it provides 77.8% accuracy with a 78.3% fill rate. Such accuracy and fill rate values are not very satisfactory. The case of a 7 day cycle counting interval provides the highest fill rate, which is almost the same as the re-optimized case obtaining $3,104, a 16.8% cost savings. As a result, if the objective is to satisfy a 90% fill rate, cycle counting is still applicable with a substantial improvement in the cost savings.

5. Summary and Future Research

Inventory record inaccuracies cause poor customer service levels with increased inventory costs at the retailers. One method of hiding the inventory record accuracy problem is to carry more inventory in order to satisfy customer needs. Among the various methods to solve the inventory inaccuracy problems, cycle counting is the most popular. But it is also a well known fact that cycle counting by itself is an additional cost. In this research cycle counting is investigated to observe the potential benefits that can be gained. The comparison between the cost of carrying additional inventory and applying cycle counting is demonstrated.

A simulation model for a multi echelon inventory system was developed. The important feature of the model is its ability to simulate more than one item type within a multi echelon inventory system as well as a more general demand amount process. To our best knowledge, none of the models in the literature examine multiple item types in such a detailed way. Consequently, the model is also able to provide accuracy and discrepancy measures for the retailer across the item types. The transportation activity from the retailer to the DC is modeled by scheduled deliveries, while previous studies assume transportation just as a deterministic delay. Furthermore, the total supply chain costs are included in the model in addition to supply chain performance measures such as system fill rates. Probability of lost sales caused by errors is also investigated in the analysis, and has not been previously examined in the literature. An extensive set of cycle counting configurations were examined while observing the trade-off between fill rates and system costs. The objective is to examine the best possible configuration of cycle counting given a set of SKUs to cycle count.

The performance of the system varies depending on the characteristics of the item types carried by the retailer. This study examines two general kinds of item types which commonly exist in a retail environment: high demand-low cost items and low-demand-high cost items. It is shown that cycle counting is essential for low demand-high cost items providing substantial savings with high fill rates. The study captures enough evidence to suggest that applying scheduled and opportunity count frequently is quite beneficial for these slower moving high cost items. On the other hand, for high demand low cost item types, cycle counting results in trivial savings. Thus, one can choose to carry more inventory instead of implementing cycle counting, since operational changes might generate additional costs which are out of the scope of this study. For these fast moving low cost item types, cycle counting can be an unnecessary effort. From our research on the high demand item types, we can also make the conclusion that opportunity counting performs better for these item types, if it is ensured that promising savings are attainable from cycle counting.

It may not be feasible to count every low demand high cost item type at the retailer. The cases tested by introducing the bad items indicate that as we increase the number of item types that are not included in the cycle counting, the system performance degrades. Cycle counting can generate significant improvements even when it is applied for a sub-set of the item types. Typical errors at the retailers result in negative discrepancies, causing less actual on hand inventory than the recorded. Consequently, it was shown that applying opportunity counts whenever actual on hand is less than recorded provides major savings compared to the case in which the positive discrepancy triggers a cycle count.

We have identified several areas of potential future research. Further research may consider modeling demands in terms of orders (a set of demands for multiple types of items). Moreover high demand high cost, and low demand low cost item types can be further investigated. Another area for future research is the optimal timing and sample size for cycle counting programs within a supply chain in order to minimize cycle counting costs while still maintaining overall supply chain inventory record accuracy and system fill rate objectives. Future research can also utilize RFID as a practical tool for cycle counting.

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