Applying Actual Usage Inventory Management Best Practice in a Health Care Supply Chain

Vijith Varghese[#1], Manuel Rossetti[#2], Edward Pohl[#3], Server Apras[*4], Douglas Marek[#5]

[#] *Department of Industrial Engineering, University of Arkansas*
4207 Bell Engineering Center, Fayetteville, AR 72701
[1]varghese.vijith@gmail.com
[2]rossetti@uark.edu
[3]epohl@uark.edu
[5]douglas.marek@gmail.com
[*]*SAP, Turkey*
[4]sapras@windowslive.com

***Abstract*— This paper lays a foundation for the better understanding of the application and acceptance of Actual Usage Inventory Management within the health care supply chain. Actual Usage Inventory Management consist advanced inventory control practices driven by actual usage data. To determine the possible savings from using Actual Usage Inventory Management, a case study was performed on pharmaceutical products in a large healthcare system in the mid-west. The case study used the (r, Q) inventory policy to model the current inventory system and to propose a more cost-effective inventory control system at each echelon. A multi-echelon inventory control system is also proposed and the cost benefits are measured. Demand forecasting algorithms were applied to forecast demand for inventory control procedures. The results indicate that there is great potential for significant cost savings within the healthcare provider network. It is likely that if other providers adopt such practices that they will be able to better control material supply costs.**

***Keywords*—** *Inventory control; forecasting; logistics modelling; healthcare supply chain; pharmaceutical supply chain*

1. Introduction

Managing cost has been an important concern in the health care industry. According to government statistics [4], the national health care expenditure of the United States was $2.6 trillion, which was 17.6% of the GDP or $8,086 per person. Furthermore, health care costs are expected to grow an average of 6.1% per year between 2009 and 2019.

Supply costs are of particular concern, and according to [9], a typical hospital spends 25-30% of its budget on medical supplies and their handling. Similarly, a recent survey on health care providers [8] found that each year these providers spent more than $100 million on supply chain activities, which was “nearly one-third their annual operating budget.” Furthermore, about half of health care providers had supply chains that were described as “immature” based on those providers’ survey responses. [8] provides information on the average amount in each cost category that large health care providers spend as a percentage of annual operating expenses (approximately $100 million, which is 31% of total costs spent on supply chain activities). From six cost categories considered in the survey, the cost categories Inventory Management and Order Management account for 61% of the supply chain costs (or $61 million per year for a typical large health care provider). Inventory Management and Order Management costs may be reduced through the use of inventory control practices, which is the focus of this paper.

A survey of large retailers [7] showed that on average they have “high success” in both controlling supply chain costs and maintaining flexible capacity to meet market needs. [10] predicted considerable efficiency gains through adoption of retail best supply chain practices in healthcare. This study, Healthcare vs. Retail Gap Analysis identified the use of inventory control practices among ten best supply chain practices,

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which can potentially reduce healthcare supply chain costs. The pertinent supply chain practice was termed as Actual Usage Inventory Management and refered “to capturing actual usage data at the last leg of supply chain at the point of care and incorporating this information into automated replenishment control strategies. Visibility of this information allows for improved forecasting identifying seasonal demand variations, A-B-C item classification, quantity discount management, audit capabilities and optimal automated ordering.”

To determine the possible savings from using Actual Usage Inventory Management, a case study was performed on pharmaceutical products in a large healthcare system in the mid-west (refered to as Health System in this paper). This case study is intended to reduce the two main costs of inventory/order management, which are holding costs and ordering costs. The case study used the (r, Q) inventory policy to model the current inventory system and to propose a more cost-effective inventory control system at each echelon. A multi-echelon inventory control system is also proposed and the cost benefits are measured. Section 2 describes the supply operations of Health System and the scope of operations relevant to the case study. In section 3, the components of Actual Usage Inventory Management best practice selected in this case study are discussed and the results are analyzed. Finally, in section 4, the results are summarized and future results are presented. The appendix to the paper describes the mathematical models underlying the inventory control practices used within the paper.

2. System Description

The test site is a large healthcare provider, which as of 2009 has 26 hospitals, 36,900 coworkers, 4,650 medical staff, and 3,638 licensed beds. *Health System* operates its own distribution center (refered to as CSC in this paper) which serves eight hospital systems, where each hospital system has one or more hospitals with a central pharmacy (refered to as CP in this paper). Each CP resupplies the smaller storage locations within that hospital.

Typically, *Health System* purchases inventory from suppliers, which is delivered to and stored in the CSC. The inventory of each CP is resupplied from the distribution center on a daily basis using the healthcare system’s private transportation fleet. This structure of a CSC serving several CPs is called a multi-echelon supply chain, in contrast to a single-echelon supply chain in which a CP is serviced directly by outside vendors. Some inventory does bypass the CSC and is supplied to CPs directly from outside vendors, but that circumstance was ignored for the purpose of the case study.

The CPs of two of *Health System’s* hospital systems were chosen for the case study. The first was a health system based in *Location 1* (with a 200 bed hospital system) and the second was in *Location 2* (a 336 bed acute care hospital). Both hospitals had a large number of inventory items, but the case study limited its scope to items that had the same unit of sell quantity as its unit dosage to ensure accurate data collection. At the *Location 1* hospital there were 927 items available to study, and 1,920 items at the *Location 2* hospital.

3. Analysis and Results

This section describes the benefit of adopting certain components of *Actual Usage Inventory Management* best practices in the two healthcare systems: ABC classification, demand characteristics classification, forecast based demand planning, and inventory control policies using single echelon as well as multi echelon models. Figure 1 summarizes the steps involved in analyzing and implementing *Actual Usage Inventory Management*

3.1 Demand Usage Analysis

An ABC Pareto analysis was done on the items in both hospitals, although only the *Location 2* hospital analysis is shown in this paper. The purpose of this analysis was to select the items that would most likely have an impact in cost reduction [11]. Usually, 20 percent of the items cover approximately 80 percent of the usage value (where usage value is a function of average yearly demand and unit cost). The analysis divided the items into three priority categories (Category A is very important and few in number, category B is important and more in number and category C is less important and most in number) based on each item’s usage value (in dollar value) [12]. These

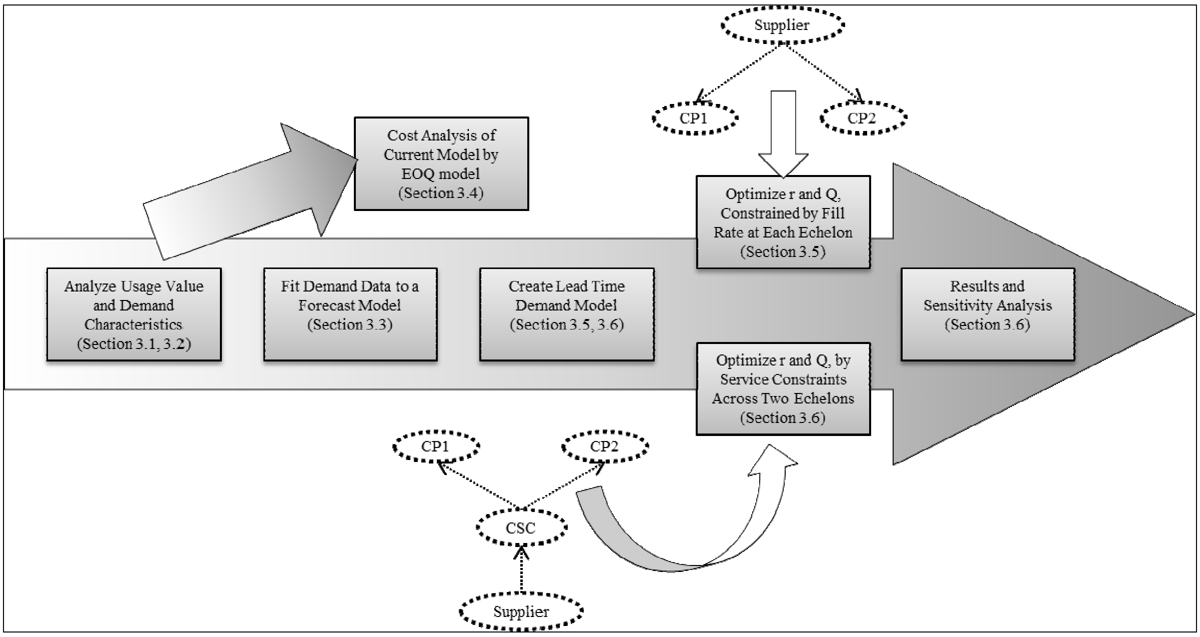

Figure 1. Actual Usage Inventory Management Analysis

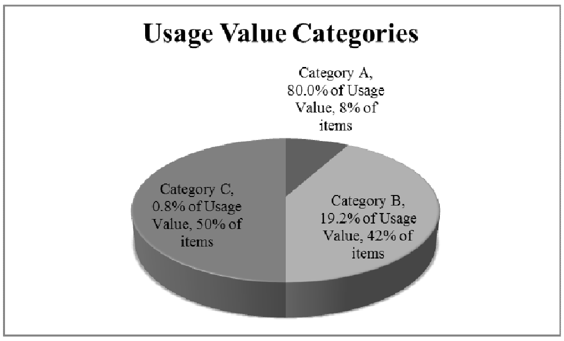

Figure 2. Usage Value Categories, *Location 2* Hospital

results are shown in Figure 2, which is a pie chart of the percentage of items that are in each category.

Note that usage value is not even close to being uniformly distributed, as Category A contains a full 80% of the usage value even though it has only 8% of the items. The majority of items are in the B and C categories, which is typical of most inventory systems.

3.2 Demand Characteristics Analysis

In addition, a second analysis was done to determine demand frequency and variability, and this analysis divided the items into categories of erratic (E), intermittent (I), lumpy (L), and smooth (S). [3] [13] categorized items based on their mean inter-demand interval and the variation of demand size. According to [3] [13], an erratic demand item has a highly variable demand size, an intermittent demand item has infrequent demand occurrences, a lumpy demand item has intermittent demand that is highly variable when it occurs, and a smooth demand item has neither intermittent demand nor highly variable demand. These demand classes are summarized in Table 1.

Figure 3 shows a pie chart of the percentage of items in each demand class. Note that most of the items do not have smooth demand, which increases the difficultly of making accurate forecasts and accurate estimates of the item fill rates. A combined table of the usage value analysis and the demand frequency analysis is shown in Table 2.

Table 1. EILS Demand Classes

	Frequent Demand Occurrences	**Infrequent Demand Occurrences**
High Demand Variability	Erratic	Lumpy
Low Demand Variability	Smooth	Intermittent

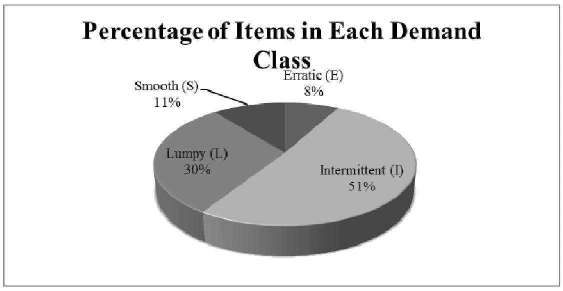

Figure 3. Demand Classes, *Location 2* Hospital

Table 2. Percentage of Items in Each Category and Demand Class, *Location 2* Hospital

	Demand Class				
Category	**E**	**I**	**L**	**S**	**Total**
A	0.4%	3.9%	0.7%	3.0%	8.0%
B	3.5%	24.5%	8.7%	5.2%	42.0%
C	3.9%	23.5%	20.4%	2.3%	50.0%
Total	7.8%	51.9%	29.8%	10.5%	100.0%

A sample of items was chosen for the rest of the analysis in the case study. In the *Location 1* hospital, 34 out of 927 inventory items were chosen, and 36 out of 1920 items were chosen in the *Location 2* hospital. The items chosen had a variety of demand characteristics. The CSC was also studied as part of a multi-echelon analysis. The CSC analysis used 24 items that were common to both the *Location 1* hospital analysis and the *Location 2* hospital analysis.

3.3 Forecasting Analysis

The goal of the forecasting process is to find the best fitting forecasting model for the selected items and to obtain the mean and variance of the predicted weekly demand from the forecasting process. Demand was classified as weekly to get enough periods for forecasting. For additional information on the effect of aggregating demand periods on inventory forecasting, please see [14].

The following steps were used to determine the most appropriate forecasting model: (1) plot the data, (2) interpret the results based on the information from the data plotted, (3) define demand patterns, such as trend, seasonality, and (4) fit the forecasting model based on forecasting error, Mean Absolute Error (MAE). MAE is the average mean absolute errors between actual and predicted demand.

Forecasting was performed for each selected item for *Location 1* and *Location 2*, respectively. There were no significant trends or non-stationary patterns for any of the selected items. In most cases, ARIMA models, which predict future values of a time series by a linear combination of its past values and a series of errors, worked well for the items. Figure 4 shows the summary of percentage of items at CP in *Location 1* and *Location 2* hospitals for which each forecasting techniques were appropriate.

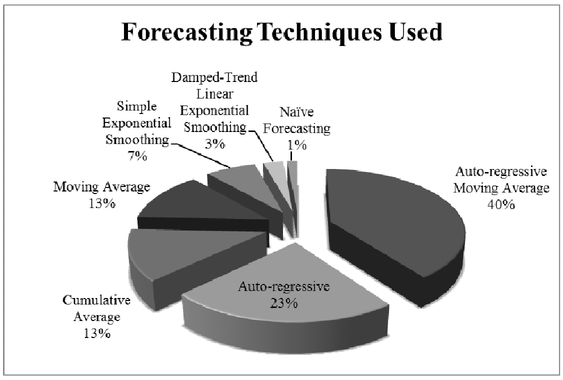

Figure 4. Forecasting Techniques Used, *Location 1* and *Location 2* Hospitals (Combined Data)

4. Results

4.1 Current Inventory Model

The inventory policy used by *Health System* is called the "par-level" method in which the stocking quantity (the par level) is defined for each item based on average usage and the desired number of days supply. *Health System*'s current inventory system attempts to keep an overall average of 14 days of supply for its items, and has a desired fill rate of at least 98.5%. To model *Health System*'s inventory system, a standard (r, Q) model was used (Appendix A gives more details on a standard (r, Q) model).

For the model of the current system, the supply period was assumed to be 14 days for all items. In other words, the order frequency was once every two weeks. Lead time from the CSC to the CPs was assumed to be one day. The inventory carrying cost rate was assumed to be 25%. The unit costs and average demand for all items were based on historical records.

The cost per order was the most difficult cost to estimate. To find the implied cost per order of each item, the economic order quantity (Q*) was assumed to be known based on the assumption that 14 days was the optimal order frequency. Then the equation for the economic order quantity was solved for the cost per order for the item. The overall cost per order (K) was calculated as the average of all the implied values of the cost per order of all the items (discussed in Appendix A). The overall cost per order was estimated to be $34.14 for the *Location 1* CP and $13.57 for the *Location 2* CP. Because of the indirect way in which this cost was calculated, a sensitivity analysis for the overall cost per order was done on the results of both hospitals. Once all the inputs for the (r, Q) model were determined, the values for r and Q could be computed, as well as values for safety stock and average inventory level, from which total cost can be computed (discussed in Appendix A and C). The total cost for the sampled items was $837 at *Location 1* CP (34 items) and $768 at *Location 2* CP (36 items).

4.2 New Inventory Management Process

An inventory analysis was conducted for CPs and CSC, respectively. First, an inventory model was developed and applied for each CP separately, and then the CSC and CPs were integrated for a multi-echelon analysis.

4.2.1 Model for Inventory policy of single echelon between CP and CSC

A new inventory management process was considered, also based on most of the same assumptions as the current model. The main difference was that in the new process, each item could use any number of days of supply, so better values could be determined for the variables r and Q in order to reduce total cost. To determine r and Q, a mathematical optimization model was selected that minimized total cost for each item subject to a fill rate constraint of 98.5% (discussed in Appendix A and B). The optimization calculations of the total costs were done using an Excel spreadsheet and VBA.

In addition, forecasting techniques were used to further aid in optimizing the r and Q values. In order to determine the best forecast model for each item, the demand data was plotted and then fit to a number of different forecast models and MAE was used to help determine the best model for each item. Seasonal trends and other non-stationary patterns were also tested for, but no significant trends were found in any of the selected items.

In order to more precisely meet the fill rate requirements, a probabilistic model was considered that estimated the stock out frequency during lead time. The amount of demand during lead time was modelled using a Gamma distribution, which was created using the mean and standard deviation of the demand during lead time from the item's chosen forecast model (discussed in Appendix B).

In order to simplify the forecasting process, the case study also explored using simple exponential smoothing on all the items. The results produced only slightly less cost savings than the multiple forecast models approach. The simplified process could therefore be used in situations where fitting a separate forecast model to each item is unrealistic. However, all of the results in this paper use the multiple forecast model approach.

4.2.1.1 Single Echelon Inventory Analysis for CP in Location 1 and CSC

In this section, the results of inventory analysis are presented for CP in *Location 1*and CSC. In the CP in *Location 1* the new inventory management process (in Appendix B) was found to reduce the cost by 67% in comparison with the current model (from $837 to $278 for a sample of 34 items). The results related to the proposed inventory model were based on sample of 34 items transacted between CP in *Location 1*and CSC and sample of 36 items transacted between CP in *Location 2*and CSC. Table 3 shows the number of days of supply that were determined for each item in the new management process, and Figure 5 shows a sensitivity analysis of how the cost per order affects the total cost of the both the current model and new management process.

In Table 3, there are a variety of values for the number of days of supply for each item because of the varying demand characteristics of the items. The average number of days of supply is 114 days, the median is 56 days, the minimum is 12 days, and the maximum is 478 days. It is interesting to note that the average number of days of supply in the new process is greater than the baseline 14 days for almost all of the items, suggesting that for the given model inputs, keeping more inventory would actually save money.

Table 3. New Inventory Management Process Results for *Location 1*CP

Item No.	**Turnover per year**	**Days of supply**	**Item No.**	**Turnover per year**	**Days of supply**
1	30.46	12	**18**	9.02	40
2	18.46	20	**19**	7.38	49
3	15.78	23	**20**	8.99	41
4	11.15	33	**21**	5.80	63
5	16.18	23	**22**	5.83	63
6	17.61	21	**23**	1.57	233
7	11.66	31	**24**	8.88	41
8	21.72	17	**25**	1.46	251
9	19.73	18	**26**	0.97	375
10	20.80	18	**27**	1.62	225
11	4.29	85	**28**	11.29	32
12	5.54	66	**29**	1.63	224
13	2.99	122	**30**	1.64	222
14	19.73	18	**31**	2.40	152
15	5.80	63	**32**	1.57	233
16	2.70	135	**33**	0.88	414
17	12.77	29	**34**	0.76	478

Figure 5 illustrates how sensitive the total costs for both models are to changes in the cost per order. These total costs are further divided into holding cost and ordering cost. Note that in the current model, the holding cost remains exactly the same regardless of the cost per order because the number of days of supply is fixed at 14 days for all items. In the new inventory management process, both the holding cost and ordering cost change for different values of the cost per order, because the number of days of supply for the items is not fixed. The new process always has a cost savings over the current model, even if the cost per order is as low as $1, because the new model optimizes the days of supply for each item.

In the CP in *Location 2*, similar results were found. The new model reduced cost by 51% (from $768 to $375 for a sample of 36 items) over the current model. The number of days of supply for the items was generally lower than the *Location 1* CP, most items still had a number of days of supply greater than the baseline of 14 days, suggesting that keeping more inventory would save money for the *Location 2* hospital as well.

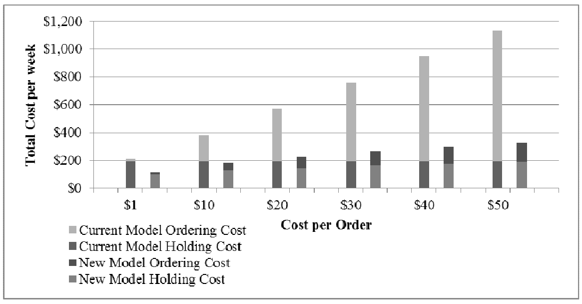

Figure 5. Sensitivity Analysis of Ordering Costs for *Location 1* CP

4.2.1.2 Multi-echelon Inventory Model Analysis

In the previous section, an independent analysis by location for the CPs in *Location 1* and *Location 2* was discussed. This section presents the multi-echelon analysis integrating CSC and CPs in *Location 1* and *Location 2*. The multi-echelon analysis models the supply chain based on a modification of [5] by [6]. [5] approximates the service level including fill rate and backorders of multi-echelon supply chain (consisting one warehouse that supplies N retailers) by assuming (r, Q) policies with stationary Poisson demand. [6] aggregates ordering process for central warehouse (CSC) and assumes that the demand process in the regional warehouse (CP) is characterized by the sequence of customer orders with random inter-arrival times and random order sizes.

The results related to the multi-echelon model were based on sample of 24 items transacted between CP in *Location 1* and CSC and between CP in *Location 2* and CSC. Demand to the CSC was assumed to occur according to a Poisson process involving the aggregate demand of the *Location 1* CP and the *Location 2* CP. The amount of demand during lead time was assumed to occur according to a Gamma distribution. The cost per order was estimated to be $8.81, the inventory carrying rate was assumed to be 18%, and the lead time from suppliers was 3 days. For the current model, it was assumed that 14 days of supply were kept at the CSC. The new process was allowed to vary the days of supply for each item.

The cost of the new process was found to be 28% lower (from $551 to $394 for a sample of 24 items) than the current model. The number of days of supply for each item is shown in **Error! Reference**

source not found., and the sensitivity analysis for the cost per order is shown in Figure 6.

In **Error! Reference source not found.**, the average number of days of supply is 138 days, the median is 91 days, the maximum is 610 days, and the minimum is 19 days. Note that the number of days of supply is higher than the baseline of 14 days for all items. The number of days of supply at the CSC is generally higher than both the *Location 1* CP and the *Location 2* CP, and this makes sense because the demand is much higher so more inventory should be kept to prevent stock outs.

Table 4. New Inventory Management Process Results for the CSC

Item No.	Turnover per year	Days of supply	Item No.	Turnover per year	Days of supply
1	19.10	19	**13**	3.79	96
2	11.25	32	**14**	3.44	106
3	11.14	33	**15**	3.25	112
4	6.99	52	**16**	3.14	116
5	6.93	53	**17**	2.53	144
6	6.27	58	**18**	2.50	146
7	6.22	59	**19**	2.43	150
8	5.33	69	**20**	2.33	156
9	4.86	75	**21**	1.99	183
10	4.58	80	**22**	1.70	215
11	4.53	81	**23**	0.63	583
12	4.27	86	**24**	0.60	610

Figure 6 shows the sensitivity analysis of the total costs for both models in the CSC. Again, in the current model the holding cost remains fixed regardless of the cost per order, but in the new model both holding and ordering costs change based on the cost per order.

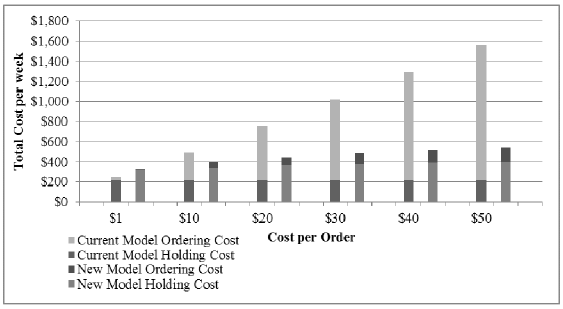

Figure 6. Sensitivity Analysis of Ordering Costs for CSC

According to the results, the new process does not save money over the current model for a cost per order of $1. However, this is due to the fact that the new model must meet the 98.5% fill rate requirement, while the current model is not specifically constrained by that requirement.

5. Conclusion and Future Research

The case study indicates the importance of applying inventory control model for the healthcare supply chain, and examines of multi-echelon inventory control within the health care supply chain with the objective of cost reduction and supporting good inventory management. In this case study, the inventory analysis optimizes the amount of inventory held to reduce the total cost, which includes holding costs and ordering costs. A model was made of the current inventory system, where the number of days of supply was kept constant at 14 days for all items, and no forecasting was used. A newer inventory management process was developed that allowed the number of days of supply to vary for each item, and a different forecast model was generated for each item. The results from CPs, CSC, and multi-echelon analysis indicate the importance of using analytical inventory models to get cost savings.

This case study used real data and recommended r and Q values and forecast models that are realistic to actual hospital inventory systems. Furthermore, the case study looked at the issue of inventory control from a multi-echelon perspective, which is especially important for the inventory of the CSC.

Table 5. Cost Savings Summary

	Total Cost per week for *Location 1*	Total Cost per week for *Location 2*	Total Cost per week for CSC
Current Model	$ 837	$ 768	$ 456
New Process	$ 278	$ 375	$ 394
% Cost Savings	67%	51%	14%
# of Items Studied	34	36	24
Cost Savings per Item	$ 16.44	$ 10.92	$ 2.58

The cost savings of the new process were significant in comparison to the current model. A summary of the cost savings is shown in Table 5. According to these results, an inventory system of 1000 items would save $16,440 per week in the *Location 1* hospital, $10,920 per week in the *Location 2* hospital, and $2,580 in the CSC. For all three locations combined, this would be a total of about $30,000 per week or $11 million per year.

Naturally, the actual savings may not be this high. The main reason would be if the current inventory system already had a somewhat optimized system that did not keep a fixed number of days of supply for all items. However, there are several other important factors not taken into account in this case study.

First, a real inventory system is constrained by physical space, so increasing the amount of inventory may not be practical in hospitals with limited space. Second, backordering cost was not considered, so if a stock-out of an item requires an expensive rush delivery, then days of supply might need to be higher than this analysis would suggest. A third issue is that some items such as medications may expire, so a hospital might consider keeping a lower number of days of supply for those items where this becomes an issue.

Another concern is determining the appropriate costs involved. The ordering costs are especially difficult to determine and not well understood, which is why the results for this case study used a sensitivity analysis. But it is important for a hospital to analyze what the costs of holding and ordering inventory items really are, so that the analysis can give the correct recommendations.

Despite these issues, the results clearly indicate that large savings may be possible by optimizing the parameters that control each item's inventory level. These parameters can be readily determined with a basic mathematical model such as the (r, Q) model instead of being arbitrarily determined. Furthermore, adjusting the inventory control parameters in a hospital is a fairly simple change that doesn't involve significant costs such as retraining workers or buying expensive technology. Therefore, health care providers should consider implementing inventory control practices in their own hospitals.

Future research includes studying the impact of *Actual Usage Inventory Management* best practice by identifying other components that improve the inventory management. The proposed approach includes developing a goal tree with the strategic objective to improve inventory management. This could be used to developing a readiness model for evaluating the readiness of an organization in adopting *Actual Usage Inventory Management* best practice. This could also serve as a roadmap for organizations considering the adoption.

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Appendices

Appendix A

Computing total cost and average ordering cost for the (r, Q) policy: The notations used in the model are as follows:

i	**Index for items (i=1,2,….,n)**
u_i	Unit cost of item i
c	Inventory carrying rate
A_i	Ordering cost of item i
r_i	Reorder point for item i
Q_i	Order quantity for item i
I_i	Average inventory for item i
OF_i	Order frequency of item i
K	Cost per order
TC_i	Total cost for item i
FR	Observed fill rate
L	Lead time

$TC_i = (Holding\ Cost) + (Ordering\ Cost = (I_i * c * u_i) + (OF_i * K)$

How to compute the average ordering cost? Assuming that Q_i is equal to economic order quantity (EOQ), $Q_i = \sqrt{\frac{2*A_i*\lambda_i}{h_i}}$. The average ordering cost can be calculated by $\hat{A} = \frac{1}{n}\sum_{i=1}^{n} A_i$, where $A_i = \frac{h_i * Q_i^2}{2*\lambda_i}$

Appendix B

Optimizing (r, Q) model with a fill rate constraint: The proposed model for single echelon analysis is based on (r, Q) model with a fill rate constraint. In this paper, Gamma distribution is assumed to be appropriate for modeling the demand during lead time distribution.

The order frequency, which shows how often *Health System* orders the items is known. The ordering frequency is once in two weeks. The formula for the order frequency is as follows:

λ_i: mean demand per week for item i

$\mathrm{OF_i} = $ Order frequency of item i

Q_i: order quantity for item i

$$\mathrm{OF_i} = \frac{\lambda_i}{Q_i} \quad (B.1)$$

from the equation, Q_i can be computed, since we know $\mathrm{OF_i} = 0.5$.

$$Q_i = 2 * \lambda_i \quad (B.2)$$

Assuming that Q_i is equal to economic order quantity (EOQ).

$$Q_i = \sqrt{\frac{2 * A_i * \lambda_i}{h_i}} \quad (B.3)$$

The Gamma distribution is commonly used since demand is always positive and this distribution is flexible due to its shape and scale parameters. Forecasting analysis provides the estimated weekly demand and MAE of forecasting errors, which are starting points for the first phase of inventory analysis. First, it is necessary to obtain the standard deviation of forecasting error by using the equation (B.4), since this formula is usually used for many forecasting models (Axsater, 2006).

$$\sigma_i = \mathrm{MAE_i} * \sqrt{\frac{\pi}{2}} \quad (B.4)$$

The next step is to calculate the variance of forecasting error from the equation (B.4) by squaring of standard deviation. The mean lead time demand (μ) and variance of the demand during lead time (σ^2) are necessary to calculate the parameters of Gamma distribution, which are shape (α) and scale (β) parameters. The equations (B.5) and (B.6) show the formulas for calculation of the shape and scale parameters. These parameters are used to calculate the mean and standard deviation of the demand.

$$\alpha = (\mu/\sigma)^2 \qquad (B.5)$$

$$\beta = \mu/(\sigma)^2 \qquad (B.6)$$

Gamma distribution has mean (α*β) and variance ($\alpha * \beta^2$) to be used in the following phase.

The second phase of inventory analysis is the calculation of stock-out, average inventory level, order frequency, holding cost, and ordering cost to determine the order quantity and the re-order point in order to minimize total cost with the fill rate constraint. The calculations of performance metrics are shown in the equations from (B.7) to (B.10).The model with the objective of minimizing the total cost with 98.5% of fill rate for each item is as follows.

Minimize $TC_i = I_i * u_i * c + OF_i * \hat{A}_i$

Subject to

$FR \leq 1.00$

[Upper bound for the fill rate]

$FR \geq 0.985$

[Lower bound for the fill rate]

$Q_i \geq 1$

[Minimum order quantity]

$Q_i, r_i \geq 0$

[Non-negativity]

$\overline{SO}_i$ = average stocout frequency for CP_i

$\overline{B}_i$ = average backorders for CP_i

$\overline{I}_i$ = average inventory for CP_i

$\overline{FR}_i$ = fill rate for CP_i

$$\overline{SO}_i = \frac{1}{q_i}[G^1(r_i) - G^1(r_i + q_i)] \qquad (B.7)$$

$$\overline{B}_i = \frac{1}{q_i}[G^2(r_i) - G^2(r_i + q_i)] \qquad (B.8)$$

$$\overline{I}_i = \frac{1}{2}(1 + q_i) + r_i - \lambda_i L + B_i \qquad (B.9)$$

$$\overline{FR}_i = 1 - \overline{SO}_i \qquad (B.10)$$

G^1 and G^2 represent the first-and second-order loss function of the demand during lead-time distribution.

Appendix C

Cost computation for current model: This section shows computing the results for the current model by determining the order quantity, safety stock, average inventory level, and order frequency, ordering and holding costs based on the policy of 14 days of supply. If all items have a safety stock (SS) set equal to the same number of supply periods then the safety stock can be determined for all items.

Assume that all items have T periods of supply, which is the safety stock.

$$SS_i = \lambda_i * T \qquad (B.11)$$

The equation (B.2) would be the approximate reorder point.

$$r_i = \lambda_i L + \lambda_i T \qquad (B.12)$$

Under this model, the average inventory level for the current model is shown in the equation (B.3) (Ballou, 1999).

$$I_i \cong \frac{Q_i}{2} + SS_i \qquad (B.13)$$

The calculation of the total cost for the current model has the same logic as in Appendix A.