Technology Assessment for an Inventory Management Process in a Hospital Unit

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Abstract

The penetration of Auto Identification and Data Capture Technology (Auto ID DC) in healthcare logistics is low. A recent American Health Association (AHA) study shows that 16% of hospitals use barcode technology for supply chain management purposes, and 3% use Radio Frequency Identification (RFID). Hospital materials managers find it difficult to evaluate the impact of Auto ID DC technologies on current processes in order to make a decision about whether or not to adopt a technological alternative. This paper studies the impact of Auto ID DC technologies on the inventory management process in a hospital unit. In particular we will refer to implantable devices within a catheterization lab. We propose a conceptual design of the system and a quantitative modeling approach to handle these issues, and present our preliminary results from a spreadsheet-based tool.

Keywords

Auto ID DC Technologies, barcodes, RFID, hospital unit inventory management, quantitative modeling

1. Introduction

Auto ID DC technologies have been shown to improve process efficiency and reduce errors associated with transactions and data entry; however, a recent American Health Association (AHA) study shows that only 16% of hospitals are fully using barcode technology for supply chain management purposes and only 3% fully using RFID[1]. Hospital materials managers lack the tools to evaluate the impact of Auto ID DC technologies on current processes and thus find it difficult to show the benefits of the technology and justify its adoption. The purpose of this research is to alleviate this barrier to assessing Auto ID DC technology, so that a hospital system administrator can know whether the technology will be beneficial to their institution.

This paper describes the development of a spreadsheet-based tool to evaluate the impact of Auto ID DC technologies on the inventory management process of a catheterization lab (cath lab). The product and environmental characteristics within this hospital unit represent a challenge for inventory management purposes. Typical items within a cath lab are implantable devices. These items are characterized by high unit costs, short shelf lives, and a large number of stock keeping units (SKUs). The processes used to track these items are complex and may be suitable for improvement via the adoptions of technology. The environment is characterized by high product technology innovation and the frequent introduction of new product models. This causes items to be outdated and makes demand management challenging. The processes that can be improved with technology are the ones related to product consumption at the point of use and replenishment cycle.

A model to establish the impact of Auto ID DC technologies on the outlined processes is the main contribution of this paper. The paper is structured as follows. A review of Auto ID DC technologies in hospitals will be given in Section 2. In Section 3, the conceptual design of the system will be explained followed by the modeling approach in Section 4. The scalability of the model will be discussed in Section 5. The paper ends with preliminary results and the conclusions in Sections 6 and 7, respectively.

2. Review of Auto ID DC Technologies

The basic principle behind Auto ID DC technologies such as barcodes or RFID is identification of the items that flow through a given process and capture the item related information. Then, without any manual data entry, this information is stored in a computer or information system. The aims of using Auto ID DC technology are increasing process efficiency, reducing data entry errors and freeing staff to perform more value added functions [2].

Auto ID DC technology is changing the way the healthcare supply chain operates. Auto ID DC enabled processes can be faster, more efficient and less expensive than human identification alone. Auto ID DC technologies include barcodes, RFID, Optical Character Recognition (OCR), voice recognition, magnetic stripes, and biometrics [3]. Within a specific hospital unit such as a cath lab, the need for automation and control over inventory management processes has lead to the implementation of different technological alternatives. The two most commonly implemented technological alternatives are barcodes and RFID. The inventory management processes supported by a given technology are summarized in the following steps: receiving, storage, counting, reordering, withdrawals, consumption, and reconciliation.

Barcode technology can be found on Pyxis and Omnicell machines, but can also be used independently. With this technology, barcode readers support the receiving and storage functions. Counting and reordering are automatic, and an information system within the machine performs the calculations. This type of technology represents a burden for nurses who have to work through the system in order to get the product they need for patients. RFID technology can be found on enabled cabinets and requires sophisticated control software, which works in a similar way as the barcode enabled machines. The basic difference with RFID is that it does not require line of sight in order to read the information from the item. Implementation of RFID technology can improve inventory management processes by eliminating the need for daily counts, reducing the number of items in inventory (inventory holding costs), and improving the stock reordering levels (par levels). Hospitals currently using RFID technology to control cath lab high value items and to facilitate billing include Heart Hospital Baylor Plano, Collin, TX (2007); Umass Memorial Medical Center, Worcester,MA (2007); Mercy Medical Center, Des Moines, IA (2007); King's Daughters Medical Center, Ashland, KY (2005).

3. Conceptual Design of the System

Two basic processes take place within a hospital unit: the primary care process, which is the actual procedure to be performed, and the support processes, which are related in this case to the procurement, replenishment, and storage of the items required during the procedure. For the purpose of the system design, these two components are referred to as the backend and the frontend processes.

The backend process is related to the actual use of the items in a given clinical procedure. The backend processes interface with the patient. Two basic sub-processes within the backend are patient record keeping (clinical system) and billing (billing system). The recording of the clinical procedure takes place along with the material consumption and billing. Data entry is critical in this process. Auto ID DC technology has an impact on data entry and can help to reduce the errors in data entry.

The frontend process is related to the replenishment and storage functions and interfaces with the supplier. The basic sub-processes within the front end are receiving, counting, withdrawal, consumption, and reconciliation. Within the frontend process, two inventory buffers are considered. The first one is calculated to protect against demand variability, and the second one is calculated to protect against discrepancies. Discrepancies are errors within the inventory records that occur when the actual inventory on hand does not match the recorded value of the inventory. The sum of these two buffers equals the par levels. Auto ID DC technology can improve the inventory control process and can help to reduce item par levels.

The backend and frontend processes are connected through the inventory allocation process, when the items are removed from the storage location in order to be used in a given patient. Depending on the technological environment, this pending transfer can be captured by the inventory management system or it will depend upon the consumption information in order to establish the items that were used.

4. Quantitative Approach

For the front end, two buffers are defined. Each one of those buffers is approached with specific theoretical models in order to establish their values. For the demand buffer, different inventory models to find the optimal inventory policy such as base stock, (r,Q) and (s,S) policies are explored. For the discrepancy buffer, the formulation found in [5] is used to calculate the buffer so that the impact of Auto ID DC technologies on discrepancy buffer can be analyzed. The basic idea is to determine the relationship between the results from both inventory buffer calculations with the current item par levels. These par levels are established for a given item within a hospital unit inventory management system, and it is believed those levels can be reduced.

4.1 Demand Buffer in Front End

Due to the nature of the replenishment process within a cath lab, the base stock policy can be used to calculate the inventory policy cost. This policy is often used to control items that have high cost and a small ordering cost compared to the inventory holding cost. The basic idea is to calculate how much inventory to have available (stock level) in order to provide good service (fill rate).

The base stock policy formulation given in [4] has the following assumptions: Items are analyzed individually (1). Demand occurs one at a time, randomly (2). Back ordering is allowed, and if the quantity needed is not available then the unfilled amount gets put on a list to be filled later (3). Lead time is deterministic (4). Whenever a unit is taken from the shelf for a customer, then a replacement is ordered (5). For a given fill rate, the base stock policy is used to determine the stock level, *R*, in order to minimize the total cost of holding and back ordering. The total cost of the inventory policy is given by, $Y(R) = h \times I(R) + b \times B(R)$, where *h* denotes holding cost of one unit over a period of one year, *b* denotes backorder cost of one unit over a period of one year, *I* (*R*) denotes the expected inventory on hand as a function of *R*, and *B*(*R*) denotes the expected number of backorders as a function of *R*.

4.2 Discrepancy Buffer in Front End

Inventory on hand and the inventory recorded in the system do not match most of the time. The difference between the recorded and the inventory on hand is defined as a discrepancy. Let *D(t)* be the discrepancy for time *t*. Let $I_a(t)$ be the actual physical amount of inventory on hand and let $I_r(t)$ be the recorded amount of inventory on hand for time *t*. The discrepancy for a record at time *t* is $D(t) = I_r(t) - I_a(t)$. If $|D(t)| > 0$, then the inventory record is considered to be inaccurate at time *t*. The discrepancy is positive ($(D(t) > 0)$) when the recorded inventory in the system is higher than the actual physical on hand inventory whereas it is negative ($(D(t) < 0)$) in the opposite case.

The inventory records in cath labs are known to be inaccurate, having discrepancies, due to several compliance factors. A compliance factor is defined as a process where there is a risk of discrepancy. These compliance factors and how they contribute to the overall discrepancy are shown in Figure 1. The way the compliance factors affect inventory record inaccuracies is shown in the labels on the arcs in Figure 1. For example, when an item is stolen (shrinkage) from a cabinet or expired in a cabinet, it reduces the physical on hand inventory without any changes being made to the inventory records. Therefore, it adds a positive discrepancy to the inventory system. On the other hand, if a nurse scans an item twice while withdrawing it from the cabinet, then the change in inventory records will be higher than the change in physical inventory, and therefore creates a negative discrepancy.

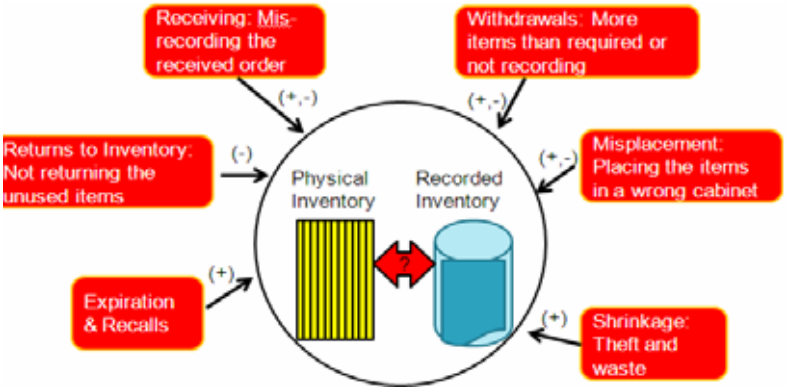

Figure 1: Compliance Factors and Their Effects to Overall Discrepancy

The discrepancies in the inventory records force hospital units to carry more inventory than required, because replenishing the inventory based on inaccurate records could result in stock outs which are not acceptable for hospitals due to safety concerns. A discrepancy buffer is introduced into the model in order to minimize the effect of inaccurate records. The closed-form formula that is presented in [5] is used to compute the discrepancy buffer. There have been other efforts in computing the optimum cycle counting and buffer on an environment facing to inaccurate records. A policy is presented by [6] to determine the minimum actual protection level in terms of the buffer stock to be maintained and the number of periods between them. A work by [7] studied how to obtain optimal cycle counting frequency and the optimal increment in safety stock level for each item. The magnitude of the cycle

counting effort in terms of the number of cycle counts and number of full time cycle counters required per day to maintain a desired accuracy level on a specified number of items in inventory is determined by [8]. Another work by [9] is an application of probabilistic branching logic to the inventory record accuracy and determines the minimum cycle length in days and number of cycle counts per day to maintain the desired accuracy level.

While computing the discrepancy buffer, withdrawal, returns to inventory, receiving and expiration compliance factors from Figure 1 are considered. Each of these compliance factors are modeled as independent and identically normal distributed random variables. Let *P* be a point of use error having a $N\left(0,\sigma_P{}^2\right)$ distribution. Point of use incorporates the withdrawal and returns to inventory compliance factors. Let *R* be a receiving error with $N\left(0,\sigma_R{}^2\right)$and *E* be the number of expired products with $N\left(\mu_E,\sigma_E{}^2\right)$ where $\mu_E > 0$. Let *A* be the aggregate error which is modeled as independent and identically distributed random variables with mean μ_A and variance σ_A. Since $A = P + R + E$ and all the random variables are normally distributed, $E[A] = E[P] + E[R] + E[E]$ and $Var[A] = Var[P] + Var[R] + Var[E]$. Let *D* be mean demand per period. Assuming demand occurs on a per unit basis, standard deviation of total error per period, σ is $\sqrt{\sum_{i=1}^{D}\sigma_A{}^2}$. After determining the distribution parameters ($\mu_A, \sigma_A{}^2$) for the aggregate error per unit demand and computing σ for total error per period, the formulation introduced in [5] is used to minimize total counting and holding cost per period to find the optimal reconciliation frequency (cycle counting) and the corresponding discrepancy buffer to protect against discrepancies. Let *n* denote the number of periods between inventory counts. Each inventory count reconciles the true and observed inventory position with a random residual error of R_j, $j = 1, 2, \mathrm{K}, M$ where *M* represents different types of counts. Let $\mu_j = E(R_j)$, and $\sigma_j = \sigma^2(R_j)$ for every *j*. Let $B_j(n)$ be the discrepancy buffer stock kept when counting type *j* is performed and α be the probability of aggregate error depleting the buffer stock between inventory counts. Using these inputs, the authors in [5] derive the simple, closed-form formula for the buffer stock in equation 1.

$$B_j(n) = \sigma\Phi^{-1}\left[(1/2 + (1-\alpha)/2(1-k^{-2})\right]\sqrt{n} + k\sigma_j + \mu_j \qquad (1)$$

The constant *k* in equation (1) is equal to $1/\alpha$. The total expected cost per period is $C_j(n) = K_j / n + hB_j(n)$, where *K* is the fixed inventory counting cost and *h* is the holding cost per item per period. $C_j(n)$ with respect to *n* is minimized to obtain the best $B_j(n)$. Then we select the type of count which yields the smallest total cost per period. Let $X(n)$ be the smallest total cost per period, so $X(n) = \min_{j=1\mathrm{K}M}\left(C_j(n)\right)$.

Use of Auto ID DC technologies will reduce the probability of making an error at the point of use and during receiving compared to manual systems. For example, when a nurse withdraws an item from an RFID-enabled cabinet, readers installed in the cabinet will read the item's tag and decrement the inventory. Another example is when items are received, they are required to be scanned if barcode technology is used at receiving. Moreover, the use of technology will increase the visibility in the system, so number of expired products will decrease. For example, an RFID implementation enables the system to be aware of the due dates of the items at any time by supplying real time information. Reduced probability of making an error at point of use and receiving and increasing visibility implies lower standard deviation of total error per period (σ) in the formulation. Reduction in total error per period will lower the discrepancy buffer (*B*(*n*)) and give a lower resulting total expected cost period (*C*(*n*)).

4.3 Back End

The compliance factor, missing/duplicating items at data entry is modeled with a triangular probability function with having minimum likely error rate (*a*), most likely error rate (*b*) and maximum likely error rate (*c*). Let γ be probability of missing items at data entry and assume a triangular distribution with parameters (a_1, b_1, c_1). Let β be probability of duplicating items at data entry and assume a triangular distribution with parameters (a_2, b_2, c_2). Let *c* be item cost and *Z* be the total cost of missing and duplicating items. Number of missing items per period is ($D^*\gamma$)

whereas number of duplicating items per period is ($D * \beta$).If we multiply these terms by item cost (*c*) and add them up, we find Z. In addition to these, clinical records get safer as the number of missing/duplicating items at data entry is reduced.

4.4 Model Output

The model outputs include the cost of keeping inventory for the demand uncertainty and discrepancies in the front end and the cost of missing/duplicating items in the back end. Let *TC* denote the total expected cost from front and back end operations. Hence, $TC = Y(R) + X(n) + Z$. Consignment will reduce $Y(R)$ since the hospital does not pay for the items on the shelf until they are used. However, there is still a certain amount of holding cost due to storage. The technologies used for the processes in the front and back end will definitely have a positive impact on the compliance factors; therefore, $X(n) + Z$ heavily depends on the technology configuration.

5. Scalability of the Model

In order to facilitate the analysis, items are grouped in classes and sub classes. A class is defined as a group of items having same ownership (owned/consigned), price and shelf life. A subclass represents the items within a class with similar demand velocity (fast, normal, slow). The quantitative model has parameters that are scalable for different sizes of cath labs. Scalable parameters are number of classes and subclasses, demand rate per subclass per period, average cost of a typical item in a class, holding cost per period and lead time. Besides scalable parameters, there are technology parameters (non-scalable) that represent the discrepancy rates for each compliance factor and the technology impact factors.

Operational savings from adopting a new technology in the front end model are calculated from possible inventory reductions. Inventory reduction times the cost of an item will give the inventory reduction cost per period. If we add cost savings from the back end model, we determine the operational savings from introducing technologies in the front end and back end per period. After annualizing operational savings, a hospital administrator can compare the results with the technology investment ($$) and finalize the economic evaluation of the technology alternative.

6. Preliminary results

The proposed quantitative model was tested in the following scenario: A cath lab unit with 2,000 procedures per year and an average consumption rate of 1.8 coronary stents per procedure. Only stents are considered for inventory management purposes as a representative item type in the cath lab since they have short shelf life and new product models are frequently introduced. Drug eluting stents (class 1 and class 2) are consigned whereas bare-metal stents (class 3 and 4) are owned. Table 1 gives the scalable parameters used in this scenario. The first three columns of Table 1 display the class number, name and the subclasses within each item class for the test scenario. The rest of the columns show weekly demand rate, item cost, lead time (week) and holding cost per week for each subclass within each item class. The input parameters were estimated to illustrate a range of values.

Table 1: Scalable Parameters

Class #	Class Name	Sub-Class Name	Demand Rate/Week	Item Cost	Lead Time (Week)	Holding Cost/Week
1	(Consigned, Short Shelf Life)	Fast Moving	10	3000	0.43	$230.77
		Normal Moving	5	3000	0.43	$230.77
		Slow Moving	1	3000	0.43	$230.77
2	(Consigned, Long Shelf Life)	Fast Moving	10	3000	0.43	$230.77
		Normal Moving	5	3000	0.43	$230.77
		Slow Moving	1	3000	0.43	$230.77
3	(Owned, Short Shelf Life)	Fast Moving	15	800	0.43	$307.69
		Normal Moving	7	800	0.43	$307.69
		Slow Moving	2	800	0.43	$307.69
4	(Owned, Long Shelf Life)	Fast Moving	15	800	0.43	$307.69
		Normal Moving	7	800	0.43	$307.69
		Slow Moving	2	800	0.43	$307.69

In addition to scalable parameters, technology parameters are required to be fed into the model. For this purpose, the standard deviations $(\sigma_P, \sigma_R, \sigma_E)$ are computed based on the probability of making an error at point of use, receiving and probability of an item expired, respectively. These probabilities vary with technology. Following the steps described in Section 4.2, σ is derived from the computed standard deviations. Back end parameters γ and β are 0.03 and 0.01, respectively for the manual data entry. For computing the discrepancy buffer, $\alpha = 0.1$, $K = \$15$ (one worker counting per hour) and $\sigma_1 = 0.02$ (one type of count is assumed). Manual and RFID alternatives throughout the systems are evaluated. It is assumed that RFID reduces discrepancy rates by 90%.

Based on the given scenario, the following results are calculated from the spreadsheet-based tool which the quantitative approach presented in Section 4 is built in. Figure 2 displays the annualized results on a chart. Results show that the inventory policy buffer costs are reduced by consignment, and lost revenue grows with product value. Moreover, the benefit of Auto ID DC technology is implicit since RFID saves discrepancy costs and also reduces lost revenue from unbilled patient bills.

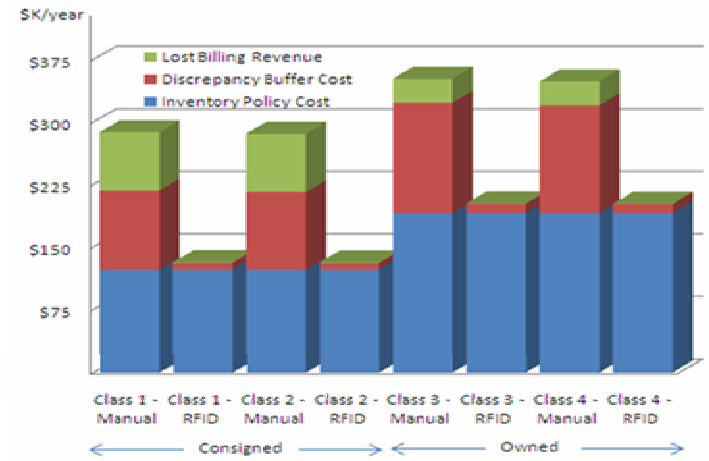

Figure 2: Sample Scenario Results

7. Conclusion

In this paper, we described a preliminary model that can be used to assess Auto ID DC technologies for inventory management of implantable devices in a cath lab. A cath lab is an environment that faces high inventory holding cost, lost billing revenues and errors in clinical records. After giving a review of Auto ID DC technologies in hospital units, we introduced a conceptual design of the system. A modeling approach was presented which quantifies the buffers defined in the conceptual design. The scalability of this model is discussed, and preliminary results are given which illustrate the potential gains of adopting Auto ID DC technologies for an inventory management process in a hospital unit. As future research, the optimum inventory policy and the optimum discrepancy buffer can be determined while considering the risk pooling between two buffers. Moreover, dynamic programming approaches may be used to optimize inventory process over time. Finally, the technology parameters and their impacts can be refined and future testing can be done with real data from various sizes of hospital units.

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References

1. American Hospital Association Survey 2007, Hospital Use of IT.
2. Eastern Research Group, Inc., 2006. “Unique Identification for Medical Devices, Final Report”, prepared for the FDA.
3. Bix L., Clarke R., Lockhart H., Twede D., and Spink J., 2007. “The Case for Global Standards”, The GS1 Global Healthcare Users Group.
4. Heizer/Render. Principles of Operations Management, 7e Chapter 12.
5. Iglehart, D. L., Morey, R. C., 1972, “Inventory Systems with Imperfect Asset Information”, Management Science, 18(8), 388-394.
6. Morey, R. C., 1985, “Estimating Service Level Impacts From Changes in Cycle Count”, Buffer Stock or Corrective Action, Journal of Operations Management, 5(4), 411-418.
7. Morey, R.C., 1986, “Determining Optimal Cycle Count Frequency”, Production and Inventory Management, 27(1), 66-74.
8. Neeley, P.S., 1983, “A Framework for Cycle Counting”, Production and Inventory Management, 24(4), 23-32.
9. Neeley, P.S., 1987, “Since Mathematics Applied to Inventory Accuracy”, Production and Inventory Management, 28(3), 64-68.