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A simulation study to determine the parameters of medicine inventory policy

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Abstract. Inventory management for the healthcare system is a very important issue as it is directly related to human lives. A medical warehouse in Kuwait was facing several challenges related to inventory management. Stock-out or overstock of some medications can occur occasionally. Simulation model using Arena was used to study the current inventory system. The model was modified to propose a new continuous review (s, S) control policy for efficient inventory system to fix monthly supply. Optimization problem was formulated using Arena OptQuest tool in order to determine the optimal parameters for the policy that would give high availability of medicines with the lowest total cost.

Key words: inventory policy, discrete event simulation, optimization, supply chain management, healthcare systems.

1. INTRODUCTION

In healthcare systems, proper inventory management of medicine is very important to avoid stock-out and overstock. Poor inventory systems could increase the cost and/or decrease the availability of stocks. If stock-out occurs, there is no inventory of a certain item to fulfill the customer's order [1] but in case of overstock the number of stock items exceeds customer's demand [2]. In a medical warehouse in Kuwait, medicine inventory system needed improvement as there was often stock-out or overstock of some types of medicines. As there were changes in the demand pattern and the medicine availability from the supplier, modelling and simulation were suitable tools to establish the most appropriate inventory policy for medicine supply chain [3,4]. The objective of this research was to increase the availability of drugs with satisfying demand from the customers and minimizing the overall costs by decreasing the backordering costs, holding costs, and ordering costs.

2. LITERATURE REVIEW

Inventory policies are classified into two major categories depending on the review period. The first category is the continuous review, in which the inventory position is continuously monitored to make

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a new order. The second category is periodic review – the inventory position is reviewed after fixed period of time. Most applications regarding the healthcare try to optimize the management and financial performance of drugs warehouse [5]. A wide variety of research papers that study the inventory management in supply chain use simulation modelling that consists of three parts: suppliers, central warehouse, and hospitals. The authors of the paper [6] simulated inventory system to identify the optimal reorder point and reorder quantity in order to reduce the inventory level in the warehouse. Other researches constructed a simulation model in order to study the impact of continuous and periodic review policies. The paper [7] evaluated the performance of several inventory policies based on total costs and patients' safety. Krzyzaniak [8] used optimization to address optimal inventory policies for pharmaceuticals in individual care by minimizing the unexpected replenishment orders and maintaining acceptable service level.

3. SYSTEM DESCRIPTION

Current inventory policy uses the continuous review system while demand and lead time are stochastic. At the beginning of each month, the manager checks both, the sales forecast and the available free space in the warehouse. If the quantity of inventory in stock decreases to a certain level, an order is placed to replenish the stock inventory. The order quantity is determined by Eq. (1).

$$\text{Order quantity} = (\text{current average monthly demand} \times 15 \text{ months})\,(1.15) - (\text{stock today} + \text{quantity of upcoming order}), \tag{1}$$

where 1.15 is accounted for 15% of safety stock to avoid having shortages during the lead time. Lead time is the time between placing an order and receiving it to the warehouse. The reorder point is triggered whenever the month in stock drops below fifteen months. Orders of the warehouse according to the Eq. (2) are the following:

$$\text{Months in stock} = \frac{\text{Quantity in stock today} + \text{upcoming orders}}{\text{Monthly average of quantity issued}}. \tag{2}$$

4. DATA ANALYSIS

Considering drugs to be the only stock items, the method was tested on three medicines. Monthly customer demand was collected for 2 years and it was found that each medicine followed a certain pattern and the lead time was either constant or variable. A bar chart was implemented for medicine A as shown in Fig 1. This medicine is used to treat the cold and flu that spreads at a specific time of the year.

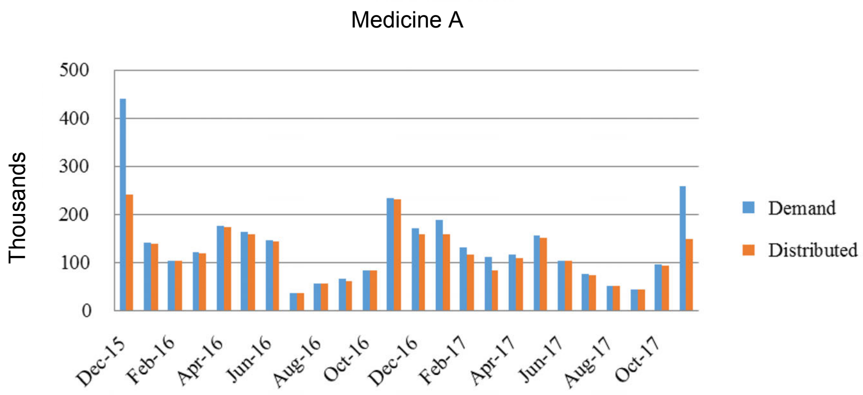

Fig. 1. Medicine A demand behaviour.

It has a low level of criticality as it has many alternatives. There is seasonal demand for that medicine. For example, from August 2016 to October 2016, demand was low as it was not a flu season. From December 2016 to February 2017, demand was high due to the winter season. However, most of the time the warehouse did not meet hospital's demand and that caused a shortage and stock-out in the warehouse.

Medicine B has a moderate criticality – it is important to supply patients with medicine B as it can cause many problems to the patient's health if it is not provided properly. It is used for treating diabetics (adults as well as children). There is need for medicine B all year round. As shown in Fig. 2, a bar chart of medicine B shows that the supplies of the warehouse do not meet the demand of hospitals, which leads to a shortage and stock-out in the warehouse. There is high demand in that medicine almost all year round, which means that medicine B is often needed.

Medicine C has high criticality as its absence during surgery can cause dangerous problems to the patient's health. It is used for decreasing body's immune system while transplanting an organ into the body. As shown in Fig. 3, the bar chart of medicine C illustrates that the warehouse almost met the demand of the hospitals compared to the other medicines. Also, for example in June 2017 and October 2017, demand was shockingly and unexpectedly high since there were many patients having a transplant surgery. Other months like February 2016 and April 2017, demand was low as there were only few patients who needed the medicine.

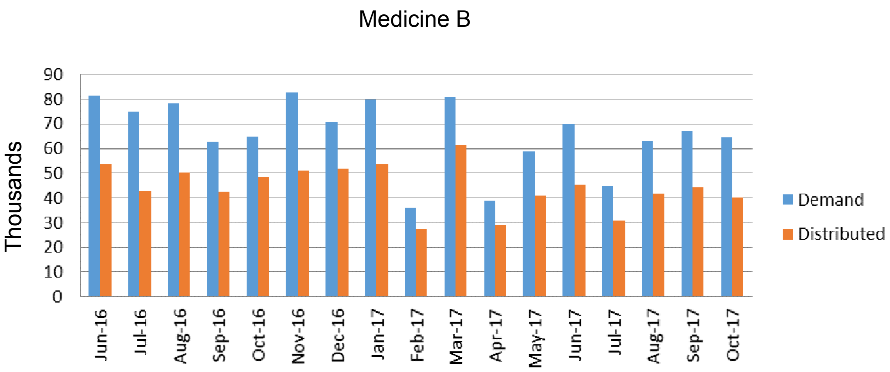

Fig. 2. Medicine B demand behaviour.

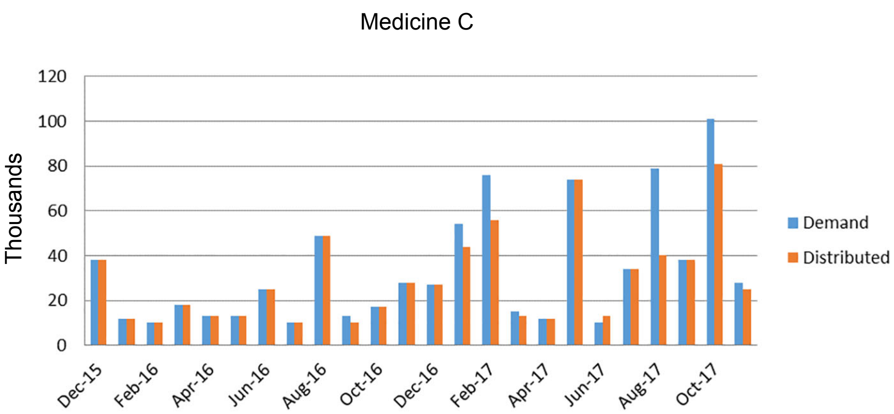

Fig. 3. Medicine C demand behaviour.

5. SIMULATION MODEL

Arena simulation software was used to construct ($\mathbf{s}_{\mathbf{mos}}$, $\mathbf{S}_{\mathbf{mos}}$) inventory policy, which is (s, S) inventory policy in terms of months of supply (mos) as demand is varying from month to month. (s, S) is a control policy in which the inventory level on hand falls below a minimum (s), replenishment will restore inventory on hand to a target (S). These parameters are specified in number of months. An (s, S) control policy in terms of months of supply identifies that an order will be placed up to ($\mathbf{S}_{\mathbf{mos}}$) when the inventory position (IP) falls below the reorder point ($\mathbf{s}_{\mathbf{mos}}$). So, when demand (D) occurs, the system checks the availability in stock, if the stock on hand (OH) is enough for the order, the demand will be fulfilled and the quantity on hand is decreased. Otherwise, if the stock on hand is not enough to fill the order, it will be placed as backorder (BO). Backorder will be filled on first-come, first-served basis after the arrival of replenishment order. Inventory position (IP) was calculated using Eq. (3):

$$\text{Inventory position (IP)} = \text{inventory on hand (OH)} + \text{scheduled receipt (SR)} - \text{backorder (BO)}. \quad (3)$$

Every time the order has arrived, the system checks if inventory position (IP) falls below the quantity that is enough for s months of supply ($\mathbf{s}_{\mathbf{mos}}$), an order is placed to restore inventory on hand up to S months of supply ($\mathbf{S}_{\mathbf{mos}}$). There is certain time from placing an order until it arrives, which is called lead time. After the lead time, the order will be replenished and quantity on hand (OH) is increased. A signal for backorder queue is sent to fill the backorder (BO), and the inventory on hand (OH) is decreased. If the inventory position (IP) is below the reorder point ($\mathbf{s}_{\mathbf{mos}}$), a new order will be placed. Figure 4 summarizes the conceptual model for (s, S) policy.

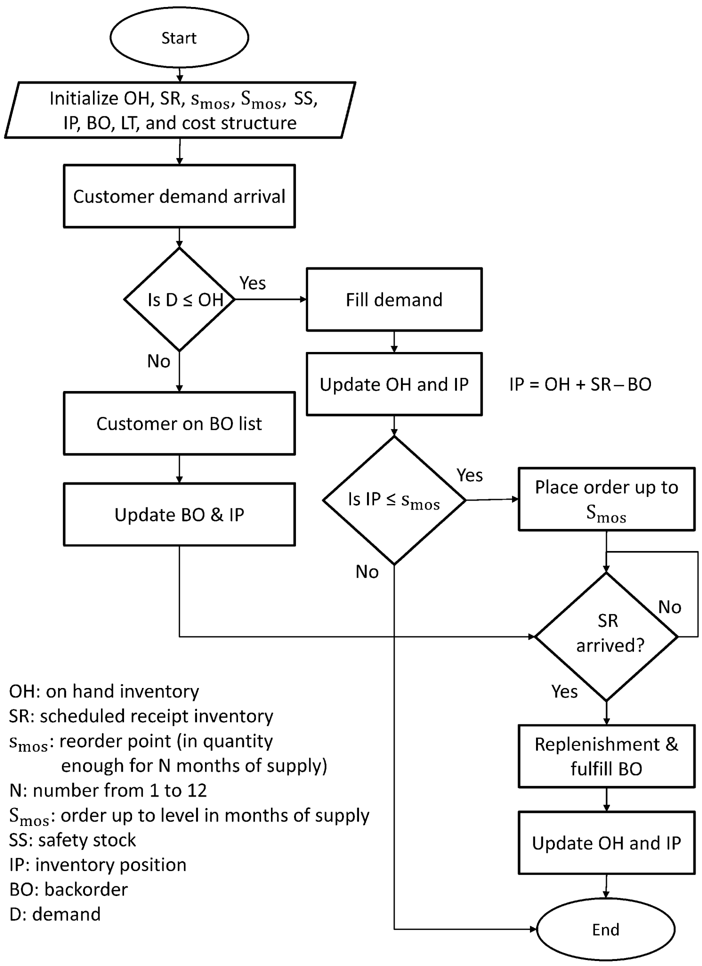

Fig. 4. Conceptual model for (s, S) inventory control policy.

6. PERFORMANCE MEASURES

Two performance measures were identified to represent the performance of the inventory policy: fill rate and total cost. The fill rate is the fraction of customer demand that is met through immediate stock availability. Therefore, the higher the fill rate value, the more customers are satisfied (Eq. (4))

$$\textbf{fill rate} = \frac{\text{demand met}}{\text{demand met} + \text{demand not met}} \times 100, \tag{4}$$

$$\textbf{total cost} = \text{ordering cost} + \text{holding cost} + \text{backorder cost}. \tag{5}$$

Equation (5) shows the total cost, where ordering cost is the cost associated with placing purchase orders and it was estimated to be 70.15 $ per order. Holding cost is the cost associated with storing inventory that remains unsold and it was estimated to be 52% of the unit cost [9]. Backorder cost is the cost associated with not having inventory in stock and it was estimated to be 40% of the unit cost. It increased in case of critical drugs.

7. MODEL VALIDATION

Baseline scenario results of fill rate were compared to the actual results from the real life. Table 1 shows that the process is valid as the actual fill rate for each medicine falls within the confidence interval (CI) generated from the simulation model for the three types of medicines.

8. IMPROVED SCENARIO

After validation of the baseline scenario, the model was modified to enable dealing with different s and S values. The optimal parameters for the control policy that gives the lowest total cost and the highest fill rate were estimated by the Arena OptQuest optimization tool. The goal was to minimize the total cost. There were constraints having (1) the fill rate at least 90% to guarantee sufficient amount of different medicines; (2) $\mathbf{s_{mos}} < \mathbf{S_{mos}}$, as in case the inventory position decreases to or below ($\mathbf{s_{mos}}$) orders will be placed up to the maximum level ($\mathbf{S_{mos}}$); (3) integers for $\mathbf{s_{mos}}$ and $\mathbf{S_{mos}}$ values as orders are placed monthly. The optimal parameters for ($\mathbf{s_{mos}}$, $\mathbf{S_{mos}}$) control policy for each drug were identified as shown in Table 2. From results of optimization, it can be seen that the values of the control policy changed depending on the type of drug. The reason for this variation was different demand pattern of these medicines.

Table 1. Validation test

Type of medicine	Actual fill rate, %	95% confidence interval
Medicine A	62.5	(58.18, 64.18)
Medicine B	91.67	(87.1, 96.1)
Medicine C	75	(73.5, 80.4)

Table 2. Results of OptQuest optimization tool

Inventory policy	Type of medicine		
	Medicine A	Medicine B	Medicine C
s_{mos}	6	4	2
S_{mos}	9	7	5

Table 3. Simulation results

Type of policy	Type of medicine					
	Medicine A		Medicine B		Medicine C	
	Fill rate, %	Total cost, $	Fill rate, %	Total cost, $	Fill rate, %	Total cost, $
Current policy (baseline scenario)	61	12.526	89	90.245	75	2.541
Optimized (s_{mos} , S_{mos}) (improved scenario)	**90***	12.022	92	**87.031***	**93***	2.629

* The difference is statistically significant at α = 0.05.

The results of simulation of the total cost and the fill rate for each medicine are shown in Table 3. Simulation modelling was useful for determining the parameters of the inventory system. The results for medicine A and C show significant improvement at α = 0.05 in the fill rate with no significant change in the cost. For medicine B, the cost significantly improved with no significant increase in the fill rate.

9. CONCLUSIONS

This research utilized simulation modelling and optimization to determine the inventory policy parameters for different kind of medicines. At first, the simulation model was developed using Arena simulation software to measure the performance of the current management policies. Then, Arena OptQuest optimizer was used to determine the best values of both, s and S that provide high fill rate while minimizing the total cost. The results show statistically significant improvements in the cost and fill rate for each medicine. The approach implemented in this paper could be applied not only in medical fields but also in different fields of industry.

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Simulatsiooniuuring meditsiinivarude parameetrite määramiseks

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Tervishoiusüsteemi varude haldamine on väga oluline teema, kuna see on otseselt seotud inimeluga. Kuveidi meditsiiniladu seisis silmitsi mitmete probleemidega, mis olid seotud varude haldamisega. Sageli puudus osal ravimitest laojääk või neid oli laos liiga palju. Praeguse inventeerimissüsteemi uurimiseks kasutati Arena simulatsiooni mudelit. Seejärel muudeti mudelit, et välja pakkuda uus, efektiivne varude haldamise süsteem ühe kuu ulatuses. Optimeerimisprobleem formuleeriti Arena OptQuesti tööriista abil, et määrata selle süsteemi optimaalsed parameetrid, mis annavad kõige väiksemad kogukulud ja ravimite hea kättesaadavuse.