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Original research article

Optimal Medical Inventory Policies for Medical Storage: a Case Study of a Medium-Sized Hospital in Thailand

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ABSTRACT

This study focuses on an improvement in medical storage, which is one of the major expenses in a hospital. Based on a real case study of a medium-sized private hospital in Thailand, the study is conducted in two steps. The first step classifies medical (drug) items into three classes using the ABC analysis. Then, in the second step, a simulation-based optimization method using ARENA with the OptQuest Optimization tool is developed. The method optimizes the inventory policy's parameters, to minimize the total relevant costs of keeping the drug items by combining the ordering and holding costs. We have applied four inventory policies to all samples of the drug items in class A, which contains the highest usage values. Then, a comparison is made with the hospital's current practice to find possible savings. From the findings, cost savings of nearly 50% from the case of current practice can be achieved. The proposed methodology can assist and provide the best decisions in managing the medical inventory of this hospital under an uncertain environment of customer demand and supply lead time.

Keywords: Inventory management; Replenishment policy; Medical storage; Medium-sized hospital; Simulation-based optimization

1. Introduction

Good healthcare is an essential factor in our lives. In fact, the healthcare business keeps growing due to an increase of aging citizens, with more people paying attention to their health. However, the operating cost of a hospital to maintain the good service and quality level has increased nowadays. As a result, only well-managed hospitals can survive in this competitive environment.

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Inventory management plays an important role because healthcare requires a large budget for the inventory cost, which represented approximately 10% of the annual healthcare expenditures in the United States and about $600 billion globally in 2009 [1]. Several researchers have estimated that inventory investments in healthcare range between 10% and 18% of total revenues [2-3]. Essential healthcare items, either directly or indirectly, are required in the patient healing process, with monitoring and control. Hence, inventory control systems need to be aligned with patient conditions [4]. Technically and scientifically, the demand for healthcare items is closely linked to physician recommendations, based on patient conditions [5].

Over-supply or shortages of such medicines would jeopardize the operations of hospitals. As a result, hospitals have to well-manage orders and their inventories to adequately provide medicines to patients with the lowest cost. In most situations, inventory planning becomes more complicated when patient demand behaves stochastically, which causes severe fluctuations in demand. Hospitals need to keep their inventory high enough to minimize the number of drug shortages. However, the storage of surplus drug items costs both time and money. Balancing these two aspects is essential, and it is necessary to find the best policy of how much to replenish and when to replenish.

As a result, this study focuses on the process of selecting an appropriate policy to manage the medical inventory in a medium-sized hospital using a real case study. In this study, several policies of managing the drug inventory in a hospital are introduced and compared by simulation-based optimization. The main contribution of this study is to recommend the best policy with the possible amount of savings for managing medical inventory in a certain business environment.

The rest of this paper is organized as follows. The related literature is provided in Section 2. Then, Section 3 presents the background of the case study. Next, the methodology and simulation experiment are explained in Sections 4 and 5, respectively. Section 6 analyzes and discusses the proposed method. Managerial implications and conclusions are in Sections 7 and 8, respectively.

2. Literature Review

2.1 Inventory model

An inventory model helps businesses to determine the optimum level of inventories that should be maintained by managing the frequency of ordering and deciding on the quantity of goods or raw materials to be stored [6]. The model also assists in tracking the flow of raw materials and goods to provide uninterrupted service to customers without any delay in delivery. It includes various inventory policies attempting to answer when and how much to order. Such questions have a major influence on the amount of inventory a business unit carries and the number of transactions (and corresponding overhead) a unit must support.

Research in inventory management is vast. Some of the related topics (especially related to healthcare service) are introduced here. Beheshti et al. [7] stated that ABC classification analysis is a well-established inventory planning and control method, which is proper to apply in inventory management to reduce the related inventory costs by arranging different classes of inventory based on their total usage values. Kelle et al. [6] tried to improve the current inventory management policy by suggesting the reorder point and order-up-to level, to control an automated ordering system. Their parameters are based on a near-optimal allocation policy of cycle stock and safety stock under a storage space constraint. Uthayakumar and Priyan [8] established a mathematical inventory model that combines a continuous review with production and distribution for a supply chain in a pharmaceutical company and a hospital supply chain. The suggested model can meet the target of the customer service level at the minimum total PSC (Pharmaceutical Supply Chain) inventory cost and can maintain a suitable level of stock.

Moreover, Darwish et al. [9] introduced randomness of demand into their model by assuming that the safety stock is equal to a safety factor, multiplied by the standard deviation of the lead time demand. They generalized the classical stochastic continuous-review inventory-control (Q, R) model for the case when the production rate is finite and unmet demand is partially backordered. Hovav and Tsadikovich [10] then used supply chain concepts and techniques to minimize the total costs of the vaccination supply chain while upholding allocation-related costs (costs associated with the selection of relevant manufacturers and the assignment of the distribution centers to the manufacturers), the distribution center's expenses including the costs of transporting vaccines from the manufacturer to the distribution center, inventory holding costs, service costs, and costs associated with possible vaccine shortage.

2.2 Simulation-based optimization

Simulation modeling basically represents an actual situation. It is the procedure to create and analyze a digital prototype of a physical model for evaluating and predicting its performance. For simulation-based optimization, the mapping from decision variables to objectives and constraints is at least partially implicit, requiring the execution of a computational model. Algorithms typically treat this model as a "black box", iteratively setting parameter values, running the simulation, and adapting based on the objective and constraint information returned. A review of research on simulation-based optimization methods can be found in [11-13]. A problem in simulation-based optimization is to find which set of a large number of sets of model specifications have led to the optimal output performance. However, there have only been a small number of research papers using the simulation methodology to improve the system performance in healthcare businesses. For example, Belciug and Gorunescu [14] used a simulation-based methodology, based on real data collected from the geriatric department of a hospital in the UK. They presented the M/PH/c queuing model for bed-occupancy in hospitals. Their novel evolutionary-based approach optimizes hospital management by providing an efficient way to estimate the system control parameters. It is the approach to obtain the proportion of refused patients, the corresponding average time spent in the hospital, the corresponding average number of patients in the hospital, and the bed occupancy.

Bhattacharjee and Ray [15] stated that properly modeling the patient flows would help the healthcare department to make the right decisions on how to allocate the existing resources. Their model can identify existing problems and provide alternatives for improving the performance of a healthcare system. Simulation methodology is then used due to its flexibility in modeling patient flow complexities and the time-dependent behavior of a system. However, the real-life queuing situations normally have non-Poisson and time-varying arrivals and non-exponential service time distributions. These characteristics need to be incorporated in the patient flow model by combining the optimization techniques with patient flow models for optimizing the performance metric(s).

Much research has utilized the simulation methodology to determine the optimal operating parameters for other systems such as production, transportation, and supply chain systems. For example, Jung et al. [16] used the simulation based-optimization method to determine the optimal safety stock level in planning and scheduling models. Later, Azadeh et al. [17] presented and integrated the Analytic

Hierarchy Process (AHP) and Genetic Algorithm (GA) with computer simulation for the optimization of operator allocation in a Cellular Manufacturing System (CMS) with weighted variables, to control the material flow of traditional non-hybrid production control systems and hybrid systems under restricted conditions. Kelle [6] determined the reorder point and order-up-to level (called the min and max par levels) that control the automated ordering system. These parameters are based on a near-optimal allocation policy of cycle stock and safety stock under a storage space constraint. Schmitt et al. [18] studied the impact of disruption as an alternative to expediting intervention using the simulation experiment in a four-echelon supply chain. Simulation experiments reveal that the impact of disruption as an alternative to expediting interventions, dynamic order-up-to policies showed promising results as an adaptive mitigation tool. Tsai and Chen [19] proposed a simulation-based solution framework for tackling the multi-objective inventory optimization problem under the goal which to find appropriate settings of reorder point and order quantity. Pacheco and Cannella et al. [20] performed a simulation-based optimization on real-world data with demand variations. They proposed an order-up-to-level policy, which provided better performance, particularly in terms of bullwhip effect reduction and improved the service level. Enhancing a typical periodic review policy with a backroom for perishable products in a retail business under an uncertain environment was carried out by Heng and Chiadamrong [21]. They used the simulation-based optimization with Genetic Algorithm (GA) to search for the best operating parameters in their study.

Based on the health care industry in this study, the simulation and optimization are completed with the ARENA simulation software and the OptQuest optimization tool. Similar to other simulation software embedded with the optimization tool, it requires the specifications of lower and upper values for the input variables that are to be optimized. The OptQuest tool is an iterative heuristic combining three meta-heuristics (i.e., scatter search, tabu search, neural network). Examples of a successful application of scatter search with the OptQuest tool were reported in Bulut [22]. Setyaningsih and Basri [23] also developed the simulation-based optimization model using the OptQuest optimization tool to optimize and improve the inventory system with the periodic review period. Al-Fandi et al. [24] employed the OptQuest tool to manage and optimize the stock-out or overstock of medical supply in a hospital. The continuous review (s, S) policy was used to manage the inventory in their study. Sadeghi et al. [25] integrated design and control phases in a three-echelon supply chain system of a blood sugar strip manufacturer. The OptQuest optimization tool was also used to obtain the lowest total cost by searching the best setting of inventory parameters and expected cell utilization.

3. Background of the Case Study

The hospital in this case study is a medium-sized hospital located in Samutsakorn province in Thailand with a service area of 10,000 square meters. It was established in March 2006 with 100 fully-equipped inpatient beds and 20 examination rooms. The facility provides services for up to 1,000 out-patients per day. One of the main problems in the hospital during our first visit is its drug storage. The hospital is concerned that it did not manage its inventory appropriately, causing over-supply of its stock, resulting in a high amount of drug inventory.

Currently, the hospital has 967 drug items in the main medical storage. There are another 2 sub-storages (located on different floors) for pulling the medical items from the main storage when required. The flow of medical storage is shown in Fig. 1. Its current inventory control policy operates as the max-min concept (see Fig. 2). Orders are issued to suppliers or the main storage every time the inventory level drops to a pre-determined minimum level. The amount of an order is fulfilled up to the pre-determined maximum level. Under such practice, the amount of an order for each drug item should be the same in every order.

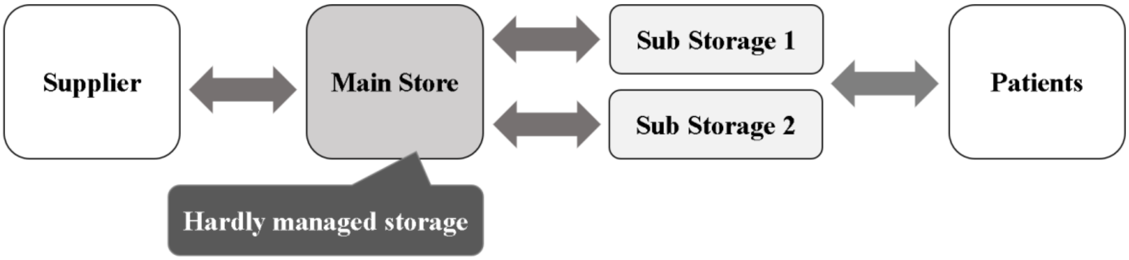

Fig. 1. Components of medical storage.

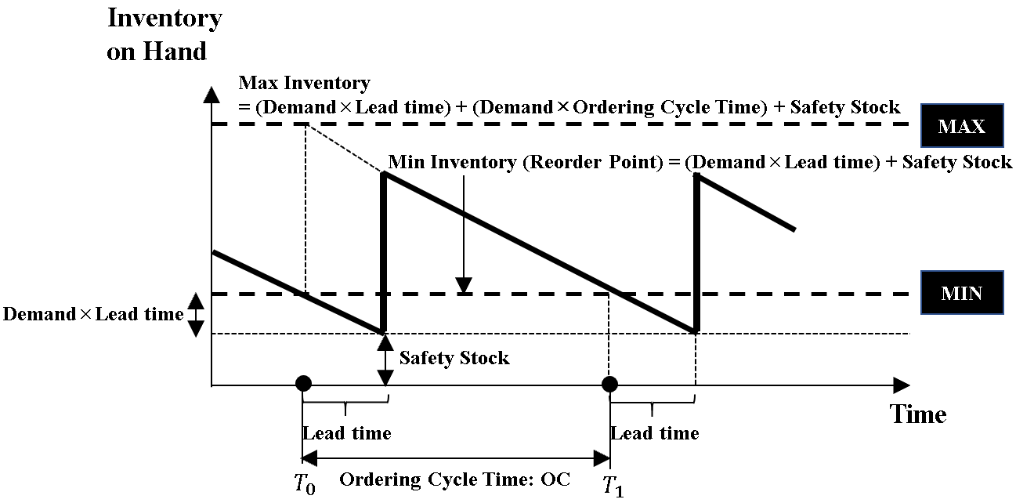

Fig. 2. Current inventory replenishment policy of the hospital (Max-min policy).

However, four main problems could be identified during our investigation and data collection periods.

1. Since the availability of drugs for the patients is critical, the hospital tended to keep too high an inventory level to avoid any possible shortages. It was also found that the maximum levels of some drug items exceeded their pre-determined maximum levels.

2. The ordering amount of drugs varied in every order as the hospital operators did not adhere strictly to the max-min policy. Sometimes, there were multiple orders in one day.

3. Lead times for medical inventory replenishment fluctuated. From the historical records, they could vary from 1 day to 12 days, depending on each drug item and each medical supplier.

4. The max-min policy may not be the most cost-effective method for all drugs as this policy is required to keep a higher level of inventory in relation to other policies. The max-min policy has a mechanism to control and optimize the ordering amount in which this policy needs to make an order in every cycle, which can cause too many unnecessary orders.

A fishbone diagram (see Fig. 3) was also constructed to systematically analyze the cause and effect of over-supply on drug storage. In this study, we focus on unsuitable methods and inappropriate parameter settings since they are controllable factors and their savings can be tangible, measurable, and substantial. Other causes (people, equipment, materials, environment) are uncontrollable factors or they are caused by human error

4. Methodology

Since the hospital has nearly 1,000 drug items in storage and they did not keep the historical records of all items, especially with low value or rarely used items, a comparison cannot be made of all drug items. This study separates the experiment into two steps. In the first step, this study attempts to classify a total of 967 drug items into 3 groups.

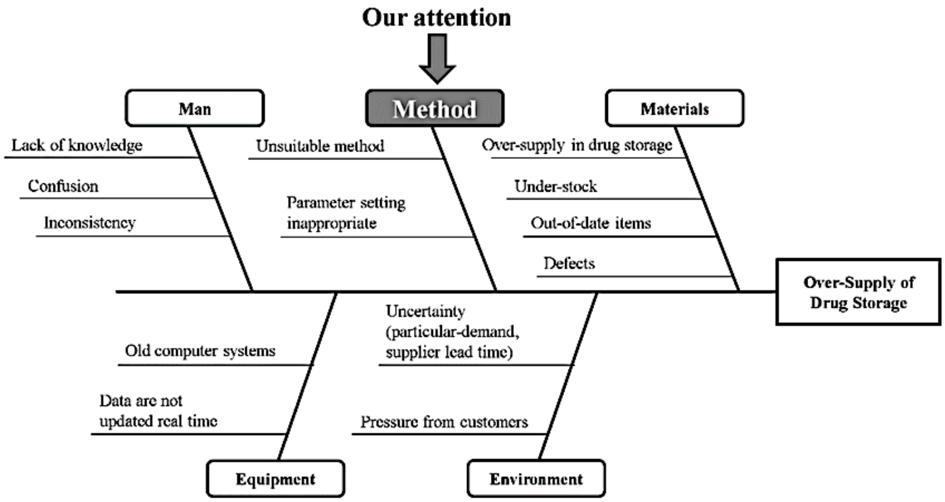

Fig. 3. Fishbone diagram (cause and effect analysis).

This study uses the ABC classification according to total usage values where class A contains 70% of total usage values, class B contains 20% of total usage values and class C contains 10% of total usage values. For the purpose of demonstration, we first put our focus on class A items, as they represent the highest total usage, by using an appropriate sample size from the total number of items in the group.

Equation (4.1) is used to find the appropriate sample size [26]. In this study, a 90% confidence level is used.

$$n' = \frac{NZ^2P(1-P)}{d^2(N-1)+Z^2P(1-P)}, \qquad (4.1)$$

where

n' = sample size with finite population,

N = Population size,

z = z statistic for a level of confidence ($z = 1.28$),

P = Expected prevalence or proportion,

d^2 = Precision.

Under the class A items, with a population size of 94 items and a 90% confidence level, a sample size of 37 units is calculated as follows:

$$n' = \frac{94(1.28)^2(0.9)(1-0.9)}{0.05^2(94-1)+(1.28)^2(0.9)(1-0.9)}$$

$$n' = 37 \; Samples$$

Naing et al. [26] recommended to use P around 10% to 90%. In this case, we used 90%. So, $P = 0.9$ with a precision (d) of 5%.

Next, four main inventory control policies are introduced into all samples to find the most suitable policy for each item. All scenarios are simulated using the ARENA simulation software with the OptQuest, optimization tool, to determine the optimal levels of the operating parameters. The tool can ascertain that each policy operates at its optimal or close to its optimal level, where the total relevant costs (ordering + holding cost) are the cheapest. Finally, the current practice is compared with other policies to find possible savings from such an implementation. Fig. 4 depicts a flow chart of the method of how the best policy is identified.

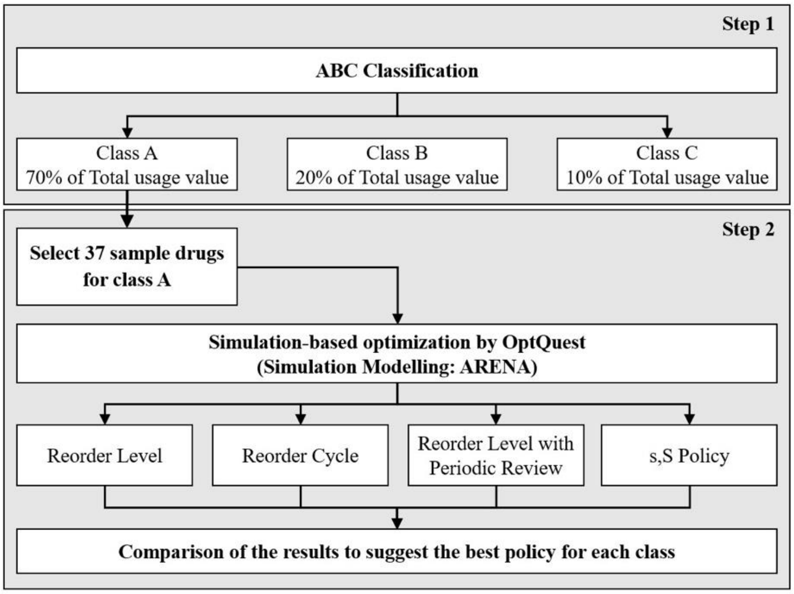

Fig. 4. Methodology.

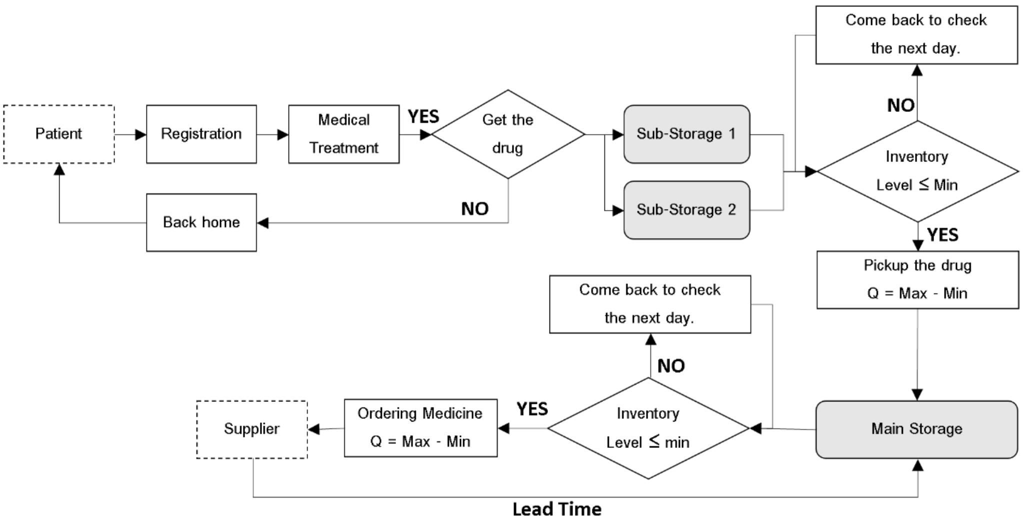

Fig. 5. Current Policy.

5. Simulation Experiment

5.1 Model configuration

In the current practice, the hospital operates on the max-min concept (see Fig. 5) where orders are issued to suppliers every time the inventory level drops to the pre-determined minimum level or the Reorder Level (ROL) that can be calculated by Eq. (5.1).

The amount of an order will increase the inventory level up to the pre-determined maximum level that can be calculated by Eq. (5.2), where the amount of safety stock is calculated by Eq. (5.3). The hospital currently uses these equations to set its Max-Min policy parameters for its current practice, with a service level of 99.9% ($Z = 3$). This is to make sure that the hospital holds sufficient stock to avoid any possibility of shortages. In fact, this service level leads to a probability of 0.1% that the lead time demand is higher than the safety stock.

$$MIN\ or\ ROL = (D \times LT) + SS, \tag{5.1}$$

where
D = Average customer demand per period,
LT = Lead-time for a supplier to replenish the item requested,
SS = Safety stock.

$$MAX\ \ or\ TSL = D \times (LT + T) + SS, \tag{5.2}$$

where
D = Average customer demand per period,
LT = Lead-time for a supplier to replenish the item requested,
T = Ordering cycle time (Review period),
SS = Safety stock.

$$Safety\ Stock = z \times \sqrt{LT \times \sigma_D^2 + D^2 \times \sigma_{LT}^2} \tag{5.3}$$

where
Z = Appropriate value from a table of standard normal distribution probabilities,
LT = Average supplier lead time,
D = Average customer demand per period,
σ_D = Standard deviation of the demand per period,
σ_{LT} = Standard deviation of the supplier lead time.

For comparison, four typical inventory models, which are the Reorder Level, Reorder Cycle, Reorder Level with Periodic Review, and (s,S) policies are applied (see Tersine [27] for more details). For the Reorder Level Policy (as shown in Fig. 6), an order is issued every time the amount of ending stock reaches the minimum level (Reorder Level (ROL)) with an equal amount of the Economic Order Quantity (EOQ). The amount of the EOQ can normally be calculated by Eq. (5.4). However, this calculated EOQ is subject to certain customer demand with no lead time. With an uncertain customer demand and varying suppliers' lead times in our case, Eq. (5.4) no longer yields the optimal ordering size. Thus, the OptQuest optimization tool is introduced to search for the best amount to meet the objective function value.

$$EOQ = \sqrt{\frac{2 \times RC \times D}{HC}}, \tag{5.4}$$

where
RC = Ordering cost per order,
D = Average customer demand per period,
HC = Holding cost per unit per period.

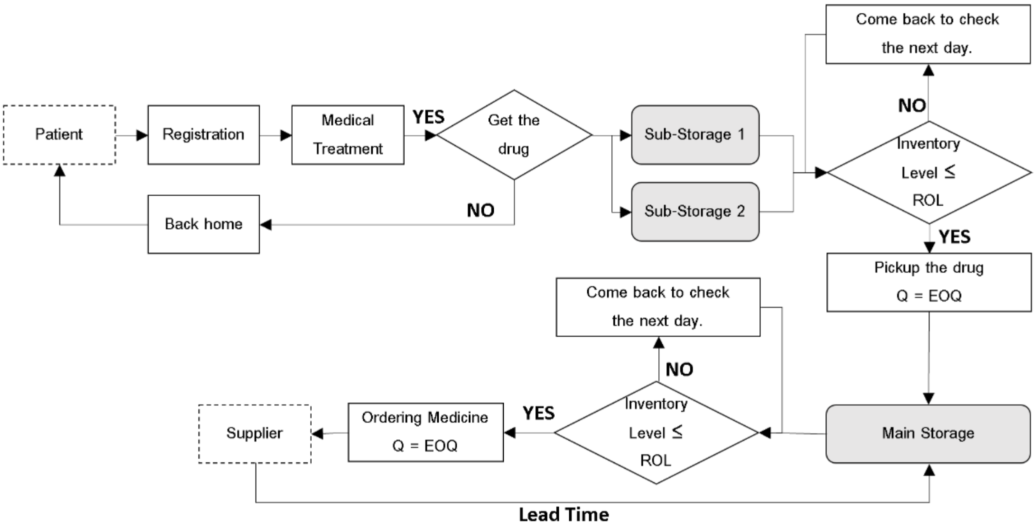

Fig. 6. Reorder level policy.

For the Reorder Cycle policy (see Fig. 7), the depleted items are ordered in every fixed time interval, known as the ordering cycle time, with the amount equal to the gap between the Target Stock Level (TSL) (also searched by the OptQuest optimization tool) minus the Stock On Hand (SOH). In this study, the ordering cycle time is set to be one week.

The Reorder Level with Periodic Review policy reviews the stock at every fixed time interval on a weekly basis. However, when the amount of ending stock reaches the ROL level at each review period, an order is issued with an amount equal to the EOQ. The concept of the Reorder Level with Periodic Review policy is shown in Fig. 8.

For the (s, S) policy, the stock is reviewed at every fixed time interval, which is every week. However, when the amount of ending stock reaches the ROL level at each review period, an order is issued with an amount equal to the TSL minus SOH. The concept of the (s, S) policy can be seen in Fig. 9.

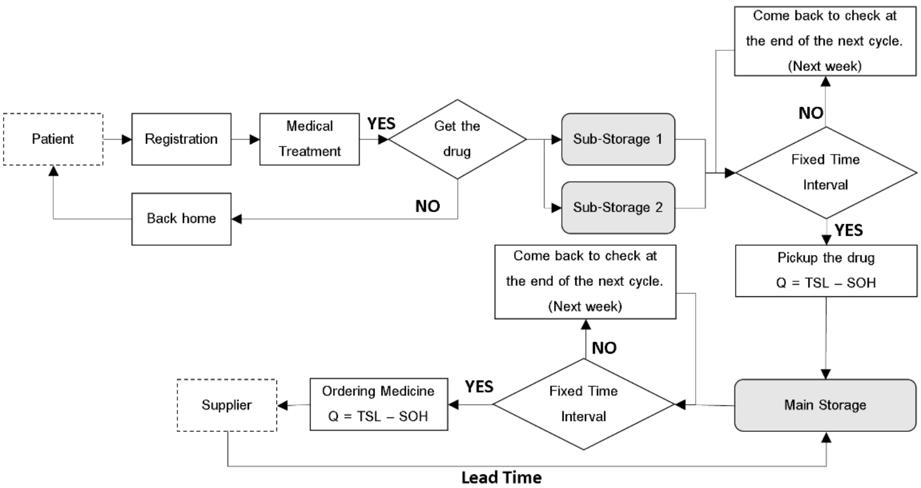

Fig. 7. Reorder cycle policy.

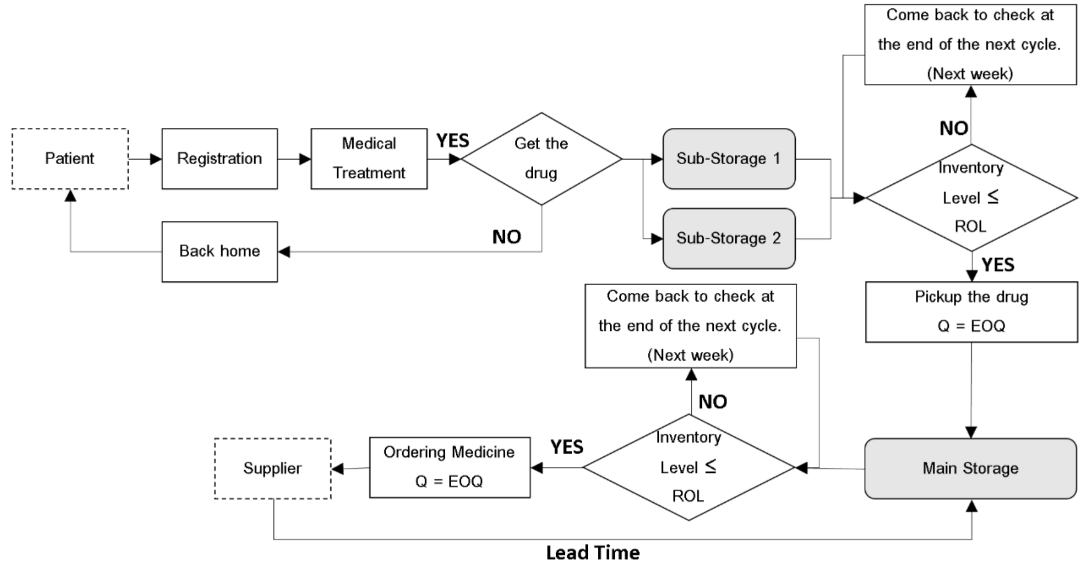

Fig. 8. Reorder level with periodic review policy.

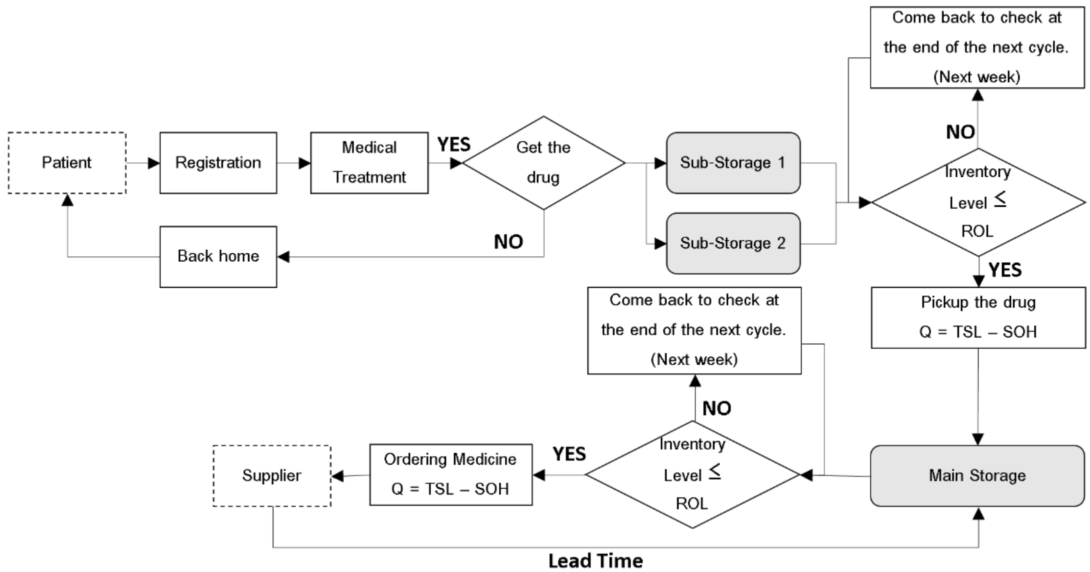

Fig. 9. (s, S) Policy.

5.2 Decision variables

Each replenishment policy requires different decision variables, as shown in Table 1. These decision variables explain when and how much of an order should be placed. Their optimal settings are searched by the OptQuest optimization tool embedded in the ARENA simulation software, to minimize the objective value, which is the total relevant costs.

Table 1. Decision variables for each inventory policy.

Policies	Decision Variables	How much in an order?	When to place the order
(1) Reorder Level	EOQ, ROL	EOQ	When the stock reaches ROL
(2) Reorder Cycle	TSL	TSL-SOH	In every ordering cycle
(3) Reorder Level with Periodic Review	EOQ, ROL	EOQ	Review at every ordering cycle and when the inventory level falls below ROL
(4) (s, S) policy	TSL, ROL	TSL-SOH	Review at every ordering cycle and when the inventory level falls below ROL

Table 2. Setting values of lower bound and upper bound.

Class	Bound	Inventory Policy						
		Reorder Level		Reorder Cycle	Reorder Level with Periodic Review		(s,S) Policy	
		EOQ (units)	ROL (units)	TSL (units)	EOQ (units)	ROL (units)	s (units)	S (units)
A	Lower	0	0	0	0	0	0	0
	Upper	5,000	5,000	10,000	5,000	5,000	5,000	10,000

Table 2 presents the searching bounds of each decision variable where the bounds of the lower limit and upper limit are set. They are guaranteed to be large enough to ensure that the optimal values fall between the lower and upper bounds.

5.3 Analytical model formulation

Even though the model is constructed by the simulation method, the analytical model formulation is presented below to clarify the objective function and important constraints in the hospital operations.

Notations

Indexes:

- i index of drug items ($i = 1,...,I$),
- j index of storages ($j = 1,..., J$),
- t index of time periods ($t = 1,...,T$).

Parameters:

- b_{ijt} Backlog unit of drug item i at storage j in period t (Units),
- BC Backlog cost (THB),
- bc Backlog cost per unit (THB),
- D_{ijt} Patient demand of drug item i at storage j in period t (Units),
- e_{ijt} Average stock level of drug item i at storage j in period t (Units),
- f_{ijt} Frequency of ordering of drug item i at storage j in period t (Units),
- h Unit holding cost per year (%),
- HC Holding cost (THB)
- o Ordering cost per order (THB),
- OC Ordering cost (THB),
- POR_{ijt} Order quantity of drug item i at storage j in period t (Units),
- s_t Staff salary per period (THB),
- SOH_{ijt} Stock on hand of drug item i at storage j in period t (Units),
- TRC Total Relevant Costs (THB),
- v_{ijt} Value of drug item i at storage j in period t (THB).

Decision variables:

EOQ_{ij} Fixed economic order quantity of drug item i at storage j (Units),

ROL_{ij} Minimum reorder level of drug item i at storage j (Units),

TSL_{ij} Maximum target stock level of drug item i at storage j (Units).

Objective Function

Minimizing the total relevant costs is the objective function of this study and it can be defined as follows:

$$MIN\ TRC = OC + HC + BC, \tag{5.5}$$

Subject to:
Financial constraints

$$OC = \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{i=1}^{I} o \cdot f_{ijt} \tag{5.6}$$

$$HC = \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{i=1}^{I} h \cdot e_{ijt} \cdot v_{ijt} \tag{5.7}$$

$$BC = \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{i=1}^{I} bc \cdot b_{ijt}. \tag{5.8}$$

Ordering cost(OC) as stated in constraint 5.6, is the cost incurred when the main storage places an order to its suppliers. The ordering cost per order (o) was obtained by the hospital. It was calculated by the total procurement operations including staff salary (st), which is estimated at 70,000 THB per month divided by the annual frequency of ordering $\left(f_{ijt}\right)$, 11,325 times per year as explained below.

$$o = \frac{\sum_{t=1}^{T} s_t}{\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{i=1}^{I} f_{ijt}} = \frac{70,000 \times 12}{11,325} = 74.17\ THB\ per\ order. \tag{5.9}$$

Holding cost $\left(HC\right)$ as stated in constraint 5.7, is the cost of holding medical items in storage. In this case, the holding cost (h) is estimated to be at 30% of the medical value per year. All holding costs are calculated based on an average level of inventory.

Backlog cost $\left(BC\right)$ as stated in constraint 5.8, is the cost of shortage for medical items that have not been shipped based on patient requirements. As the hospital policy is to avoid any shortage, the backlog cost per unit was deliberately set with a high value so as to avoid any chance of occurring in the study.

Inventory balance constraints

Inventory balance constraints control the flow of inventory (drug) in the hospital.

$$SOH_{ijt} = SOH_{ijt-1} + POR_{ijt} - D_{ijt}, \forall i, j, t. \tag{5.10}$$

Constraint 5.10 is the inventory balance constraint for its respective units of interest, ensuring that the drug items entering plus the inventory from the previous period equal the drug items leaving plus the inventory stored at the end of that period.

For the reorder cycle policy (periodic review) and (s, S) policy at the end of each review period.

$$POR_{ijt} = \max\left\{\left(TSL_{ijt} - SOH_{ijt}\right), 0\right\}, \forall i, j, t. \tag{5.11}$$

According to constraint 5.11, the order quantity in each cycle for each drug item is equal to the gap between the Target Stock Level (TSL) minus its inventory on hand in that cycle. The TSL is one of the decision variables required to be searched for its optimal setting.

For the reorder level policy and the reorder level with periodic review policy when $SOH_{ijt} \leq ROL_{ij}$.

$$POR_{ijt} = EOQ_{ij}, \forall i, j, t. \tag{5.12}$$

According to constraint 5.12, whenever the stock on hand falls below the minimum stock level set by ROL, an order will be issued equal to EOQ. The order quantity in any period for each drug item and ROL are the decision variables, which need to be searched for their optimal settings.

5.4 Simulation experimental conditions

Ten replicates were simulated with a replication length of 356 days or one year per replicate. Based on 10 replicates, the 95 percent confidence interval of the throughput had a width of less than 5 percent of its mean. The patient demand in all models has been set equal to the actual patient demands, which were recorded by the hospital in the past year. The initial level of inventory of each drug item has also been set at the actual inventory level of each drug item from the current practice. As a result, all policies start with and are comparable under the same initial conditions, with similar patient demand throughout the simulation period.

A	B	C	…	N	O	R	S	T
No	Name of Medicines	Usag Values (Baht)			Total Usage Values (Baht)	Total Usage Values (%)	Cumulative %	Group
		Jan	…	Dec				
1	MCELET1	159,841.95	…	156,741.09	1,915,445.52	4.75%	4.75%	A
2	MCEF3I8	45,577.72	…	280,402.06	1,635,348.41	4.06%	8.81%	A
3	MACTII1	41,730.00	…	-	229,515.00	0.57%	9.38%	A
4	MIPDI1	99,296.00	…	109,639.33	1,163,831.87	2.89%	12.26%	A
5	MDYNAI1	87,251.01	…	89,722.71	1,151,220.84	2.86%	15.12%	A
6	METORT3	48,164.52	…	72,208.79	840,446.95	2.08%	17.20%	A
7	MPENTAI1	64,345.91	…	85,707.00	837,450.09	2.08%	19.28%	A
8	MAUGMET6	57,111.25	…	59,946.75	740,882.50	1.84%	21.12%	A
9	MCEFSS1	48,720.00	…	81,120.00	671,520.00	1.67%	22.78%	A
10	MVENTOS1	41,700.58	…	38,067.93	594,264.13	1.47%	24.26%	A
…	…	…	…	…	…	…	…	…
31	**MELOME1**	15,095.03	…	38,240.73	312,970.19	0.78%	45.24%	A
…	…	…	…	…	…	…	…	…
93	MGARSI1	12,381.42	…	4,127.14	109,369.21	0.27%	69.64%	A
94	MCONTT1	11,842.31	…	3,710.25	108,532.39	0.27%	69.91%	A
95	MHEPVI2	10,432.50	…	8,025.00	104,325.00	0.26%	0.26%	B
96	MBUSCT1	6,968.70	…	10,213.61	104,028.32	0.26%	0.52%	B
…	…	…	…	…	…	…	…	…
261	MDILATRT1	3,812.00	…	922.77	28,600.91	0.07%	19.94%	B
262	MSINGT4	-	…	3,129.75	4,761.50	0.01%	19.95%	B
263	MHIBSC2/4	2,700.00	…	2,580.00	28,300.00	0.07%	0.07%	C
264	MFOSMI1	-	…	2,953.20	4,675.90	0.01%	0.08%	C
…	…	…	…	…	…	…	…	…
966	MREGELC1	-	…	-	-	0.00%	10.14%	C
967	MSICFM1	-	…	-	-	0.00%	10.14%	C

Fig. 10. ABC Classification in Microsoft Excel.

6. Analysis of the Results

6.1 Step 1: ABC Classification

Having classified all drug items into three classes based on their total usage values, Fig. 10 presents the ABC classification in which there are 94 medical items (70% total usage values) in class A, 168 items (20% of total usage values) in class B, and 705 items (10% of total usage values) in class C. As the drug items in class A share the highest total usage value (70%), we use these class A items to be a sample and a benchmark, for comparison.

6.2 Step 2

6.2.1 Sampling

The appropriate number of samples in each class of drug items is shown in Table 3.

Table 3. Number of sample of drugs in each class.

Medical Class	Population Size	Sample Size
A	94	37
B	168	44
C	705	55

Table 4. Information on the samples of drug items in class A.

Medicine No	Main Storage (units)		Sub-Storage 1 (units)		Sub-Storage 2 (units)		Best fit Distribution of Leadtir and its Parameters
	Min	Max	Min	Max	Min	Max	
1	30	50	5	10	2	4	TRIA(2.5, 3.3, 9.5)
2	26	48	7	12	5	10	2.5 + LOGN(2.22, 1.92)
3	27	47	3	7	4	9	UNIF(1.5, 8.5)
4	70	100	5	15	4	9	UNIF(1.5, 9.5)
5	39	76	1	2	10	20	UNIF(1.5, 7.5)
6	50	90	5	15	10	20	TRIA(1.5, 5.6, 7.5)
7	240	480	30	50	15	25	TRIA(0.5, 4.75, 6.5)
8	150	300	20	50	-	-	TRIA(1.5, 5, 7.5)
9	84	140	-	-	-	-	TRIA(4.5, 5.5, 6.5)
10	280	560	60	340	-	-	TRIA(1.5, 4, 7.5)
11	98	406	30	72	-	-	UNIF(2.5, 7.5)
12	112	168	28	56	60	88	TRIA(1.5, 6.86, 7.5)
13	150	300	10	20	10	20	NORM(5.29, 1.16)
14	100	200	50	150	-	-	1.5 + WEIB(4.24, 1.64)
15	240	480	100	220	-	-	1.5 + ERLA(1.33, 2)
16	150	300	80	110	-	-	TRIA(1.5, 5.1, 7.5)
17	90	180	10	28	12	24	2.5 + LOGN(1.42, 1.54)
18	60	100	20	40	-	-	2.5 + WEIB(2.22, 1.51)
19	150	300	60	120	-	-	TRIA(1.5, 6, 8.5)
20	200	700	30	130	76	126	UNIF(3.5, 7.5)
21	560	1680	350	462	28	84	TRIA(1.5, 5, 7.5)
22	1442	2884	322	462	60	102	TRIA(1.5, 5.17, 7.5)
23	3900	7800	900	1400	-	-	TRIA(1.5, 5.37, 7.5)
24	840	1540	280	420	-	-	TRIA(0.5, 6, 7.5)
25	3000	5000	500	700	55	95	1.5 + ERLA(1.21, 3)
26	720	1320	130	280	-	-	1.5 + ERLA(0.755, 4)
27	350	658	98	168	-	-	TRIA(0.5, 4, 16.5)
28	240	450	70	190	-	-	TRIA(1.5, 7, 7.5)
29	1110	2370	240	390	-	-	1.5 + GAMM(0.767, 3.88)
30	240	460	100	140	5	15	UNIF(2.5, 7.5)
31	196	364	168	280	-	-	1.5 + ERLA(0.85, 4)
32	145	299	30	60	20	40	TRIA(2.5, 6.2, 7.5)
33	40	80	3	6	10	20	TRIA(1.5, 5.31, 7.5)
34	100	150	25	45	1	3	2.5 + LOGN(2.37, 2.39)
35	129	248	15	30	10	20	TRIA(1.5, 7, 7.5)
36	150	300	15	35	15	30	UNIF(2.5, 5.5)
37	20	40	2	4	5	15	UNIF(1.5, 7.5)

6.2.2 Current practice with the Max-Min policy

The hospital uses the Max-Min policy for controlling their drug storage in the current practice. The max-min levels and daily patient demands of all 37 sample drugs in class A can be collected as shown in Table 4 from the hospital by the assistance of the hospital manager. Then, we attempt to build the simulation model (following the flow diagram presented in Fig. 5) to represent the current practice of the hospital's drug storage system and use it as a benchmark for comparison. These obtained max-min levels are set in the simulation model and used with the real, daily patient demand with the appropriate supplier lead time. These parameters are fitted by the best distribution recommended by the ARENA output analyzer with $p \leq 0.05$. The performance of the system as a whole, in terms of the total relevant costs, can then be obtained. The result shows that the total relevant costs of using the Max-Min policy in the hospital's current practice are 496,980 THB with 350,313 THB of holding cost and 146,667 THB of reordering cost. Details of each drug item are shown in Table 5.

Table 5. Classification of the total relevant costs of the samples of drug items in class A.

No.	Holding Cost (THB)	Reorder Cost (THB)	Total (THB)	No.	Holding Cost (THB)	Reorder Cost (THB)	Total (THB))
1	15,575	5,540	21,115	20	5,998	2,165	8,163
2	7,194	3,270	10,464	21	12,966	3,078	16,044
3	3,206	4,294	7,500	22	20,834	5,043	25,877
4	6,570	5,154	11,724	23	51,476	4,769	56,245
5	3,172	3,827	6,999	24	9,124	4,005	13,129
6	1,474	4,554	6,028	25	26,004	3,886	29,890
7	6,189	3,218	9,407	26	5,404	5,243	10,647
8	4,275	2,447	6,722	27	11,814	5,080	16,894
9	3,912	3,545	7,457	28	12,295	3,782	16,077
10	8,783	3,270	12,053	29	23,178	4,769	27,947
11	4,852	2,581	7,433	30	6,217	4,138	10,355
12	3,805	2,588	6,393	31	7,691	5,496	13,187
13	3,382	2,328	5,710	32	8,732	4,613	13,345
14	4,895	2,870	7,765	33	3,202	3,938	7,140
15	6,588	3,411	9,999	34	8,475	5,177	13,652
16	3,833	4,709	8,542	35	15,526	4,190	19,716
17	1,916	1,564	3,480	36	20,557	3,330	23,887
18	1,277	6,148	7,425	37	6,139	4,168	10,307
19	3,783	4,479	8,262	**Total**	**350,313**	**146,667**	**496,980**

6.2.3 Simulation-based optimization

Four replenishment policies (i.e., Reorder Level, Reorder Cycle, Reorder Level with Periodic Review, and (s, S) policies) have been applied in the simulation model of the hospital inventory system. With the actual daily patient demand and best-fitted distribution of the supplier lead time of each drug item, the OptQuest optimization tool can suggest the optimal settings of the parameters from each model that can minimize the total relevant costs. Tables 6 - 9 present the total relevant costs and the best settings of each replenishment policy's parameters obtained from the OptQuest optimization tool with an example of a drug item (MELOME1) in the class A.

6.2.4 Comparison of total relevant costs

With all 37 sample drug items, it was found that the Reorder Level policy cannot give the lowest total relevant costs while the Reorder Cycle policy gives the lowest total relevant costs of 7 items. The Reorder Level with Periodic Review policy also gives the lowest total relevant costs of 8 items, and the (s, S) policy gives the lowest costs of 22 items. If all samples are applied with their best policy, the overall cost savings are 235,429 THB or 47.37% from the cost of the current practice, as reported in Table 10. These savings are a result of applying the right policy with the appropriate setting parameters under an uncertain environment. With the deterministic inventory models, a set of assumptions is required in the calculation, to obtain the operating parameters. These assumptions could conflict with the real working environment. For instance, the normal distribution must be used to describe uncertainty in both the demand during the replenishment lead time and the supplier's lead time. However, in real practice, this may not always be the case, as they are rarely deterministic or normally distributed (see Table 4). Thus, the obtained parameter values are not guaranteed to have the best expected outcome as intended.

In addition, applying different policies to different drug items could cause confusion for operators. Even with only one common policy in the current practice, the operators are regularly reported to make mistakes and are confused with when and how many to order. Implementing many policies at the same time would definitely cause more mistakes, as different operating parameters (amount and timing) are required from different polices. These could mix-up the operation, especially during a busy period of the day. As a result, it was recommended that a common policy should be applied to all items to avoid such confusion for the operators. Table 11 shows the cost savings from applying one common policy to all samples, in which the (s, S) policy shows the highest cost savings. It can help to reduce the total relevant costs by 195,054 THB, or a savings of 39.25% from the current practice. Even though it does not save as much as applying the best policy for each item, it makes the operation run more appropriately.

Table 6. Parameters of an example drug item for the reorder level policy.

MELOME1	Optimization		
	Total Relevant Costs (THB)	**Parameters (units)**	
Reorder Level Policy	16,044	Order Quantity (Main Storage)	6
		Order Quantity (Sub-Storage 1)	6
		Order Quantity (Sub-Storage 2)	4
		Reorder Level (Main Storage)	8
		Reorder Level (Sub-Storage 1)	5
		Reorder Level (Sub-Storage 2)	5

Table 7. Parameters of an example drug item for the reorder cycle policy.

MELOME1	Optimization		
	Total Relevant Costs (THB)	**Parameters (units)**	
Reorder Cycle Policy	14,936	Target Stock Level (Main Storage)	15
		Target Stock Level (Sub-Storage 1)	25
		Target Stock Level (Sub-Storage 2)	9

Table 8. Parameters of an example drug item for the reorder level with periodic review policy.

MELOME1	Optimization		
	Total Relevant Costs (THB)	**Parameters (units)**	
Reorder Level with Periodic Review Policy	15,004	Order Quantity (Main Storage)	17
		Order Quantity (Sub-Storage 1)	11
		Order Quantity (Sub-Storage 2)	12
		Reorder Level (Main Storage)	10
		Reorder Level (Sub-Storage 1)	23
		Reorder Level (Sub-Storage 2)	4

Table 9. Parameters of an example drug item for the (s, S) policy.

MELOME1	Optimization		
	Total Relevant Costs (THB)	Parameters (units)	
(s,S) Policy	13,431	Target Stock Level (Main Storage)	21
		Target Stock Level (Sub-Storage 1)	23
		Target Stock Level (Sub-Storage 2)	9
		Reorder Level (Main Storage)	10
		Reorder Level (Sub-Storage 1)	20
		Reorder Level (Sub-Storage 2)	4

Table 10. Comparison of total relevant costs and cost reduction for the best solution.

Policy	Number of drug items showing the best policy	Total Relevant Costs (THB)	Total Cost Reduction (THB)	Total Cost Reduction (%)
Current practice		496,980		
Reorder Level	0	261,551	235,429	47.37%
Reorder Cycle	7			
Reorder Level with Periodic Review	8			
(s, S) Policy	22			

Table 11. Comparison of total relevant cost and costs reduction for each policy.

Policy	Total Relevant Costs (THB)	Total Cost Reduction (THB)	Total Cost Reduction (%)
Current Practice	496,980		
Reorder Level	349,062	147,918	29.76%
Reorder Cycle	334,428	162,552	32.70%
Reorder Level with Periodic Review	328,434	168,546	33.91%
(s, S) Policy	301,926	195,054	39.25%

7. Managerial Implications

This study shows that it is essential to include uncertainties in the optimization algorithm. By incorporating the uncertainties, the stochastic nature of the system can cause inaccuracy in the calculation of the basic deterministic inventory model. As a result, integrating the simulation model with the optimization tool (simulation-based optimization) is applied in this study. While the simulation model determines the impact of uncertainties on the objective value, the optimization tool then finds the best settings to achieve the best objective value.

With a large number of inventory items, ABC classification helps to identify the items that contain the highest total usage values as they are the main items to be investigated. From the results of this study, it can be concluded that the best performance of this hospital's drug replenishment policy depends on each drug. However, it is difficult to operate with several policies at the same time as it would create confusion for the operators. As a result, selecting one common policy, which gives the highest cost savings among all possible alternatives, is recommended in this case. The (s, S) policy is selected in this study since it dominates other policies as the best policy among the sample drug items in class A and gives the highest amount of cost savings (up to 39.25%). This amount of savings could be increased if a similar methodology is applied to all drug items and to all classes. However, it should be noted that different classes of drug items can lead to different best-replenishment policies, as they have different characteristics. Again, a similar methodology can be applied to the sample drug items in classes B and C, as this study has used only the drug items in class A (the highest usage values) for the demonstration.

8. Conclusions

The medical inventory problem presents a large expense and a large chance of savings in the hospital business. Under an uncertain situation, different sources of uncertainty in a hospital can exist, encompassing suppliers, service processes, and patients. These sources can be identified with the inclusion of different types of uncertainties (e.g., demand, lead time, and process). In most situations, to compensate for these uncertainties, hospitals tend to keep their stock too high to minimize the number of lost sales. The main contribution of this study is to improve the existing inventory management policies and recommend the best policy for managing medical storage in a hospital business. In this study, several policies were compared and benchmarked with the Max-Min policy, as it is the policy currently implemented in the hospital by means of simulation-based optimization. Simulation models were constructed to simulate the replenishment policies, subject to real patient requirements (customer demand) and uncertain suppliers' lead time. This is more realistic than the result given by the deterministic analytical model where it is solved without operating uncertainties.

Our current results are useful for hospitals that face a high level of inventory inaccuracy. Hospitals can then examine procedures or technologies to eliminate them. To give some guidelines, the results of our methodology indicate that the elimination of over-stock and inventory inaccuracy can reduce the cost by up to 40%. Additional savings can also be expected if awareness building for operators and process improvements can be carried out. For instance, automatic identification technologies such as RFID will be, and in many cases have been, adopted in leading hospitals to replace the old barcode systems.

The limitations and further research directions of this study are as follows:

- More mechanisms can be added into the proposed simulation-based optimization, to improve the effectiveness and timing of the computation.
- A sensitivity analysis of the cost structure can be done, to see the effects of varying each cost on the conclusion.
- Other parameters that may influence the outcome, such as buying discounts from suppliers, can also be considered.
- Lastly, there is a concern about the number of decision variables in each policy. Having too few decision variables can give poor results but adding too many variables can interfere with the searching process to find an optimal solution, resulting in a long computational time. Thus, the number of significant decision variables for each policy is another issue worth considering.

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